



**HAL**  
open science

# Visualisation Immersive et Interactive de Données 3D Temporelles

Gwendal Fouché

► **To cite this version:**

Gwendal Fouché. Visualisation Immersive et Interactive de Données 3D Temporelles. Synthèse d'image et réalité virtuelle [cs.GR]. INSA de Rennes, 2022. Français. NNT : 2022ISAR0035 . tel-04529934

**HAL Id: tel-04529934**

**<https://theses.hal.science/tel-04529934>**

Submitted on 2 Apr 2024

**HAL** is a multi-disciplinary open access archive for the deposit and dissemination of scientific research documents, whether they are published or not. The documents may come from teaching and research institutions in France or abroad, or from public or private research centers.

L'archive ouverte pluridisciplinaire **HAL**, est destinée au dépôt et à la diffusion de documents scientifiques de niveau recherche, publiés ou non, émanant des établissements d'enseignement et de recherche français ou étrangers, des laboratoires publics ou privés.



Distributed under a Creative Commons Attribution 4.0 International License

# THÈSE DE DOCTORAT DE

L'INSTITUT NATIONAL DES  
SCIENCES APPLIQUÉES RENNES

ÉCOLE DOCTORALE N° 601  
*Mathématiques et Sciences et Technologies  
de l'Information et de la Communication*  
Spécialité : *Informatique*

Par

**Gwendal FOUCHÉ**

## **Immersive and Interactive Visualization of Temporal 3D Data**

Thèse présentée et soutenue à Rennes, le 05 Décembre 2022

Unité de recherche : Inria, Centre Inria de l'Université de Rennes (Inria-Rennes)

ISAR 34 / D22 - 34

### **Rapporteurs avant soutenance :**

Christophe HURTER    Professeur, ENAC, Toulouse, France  
Tobias ISENBERG    Directeur de Recherche, Inria Saclay, Paris, France

### **Composition du Jury :**

Président :	Emmanuel DUBOIS	Professeur, Université de Toulouse, France
Examineurs :	Nancy RODRIGUEZ	MCF, Univ. Montpellier, France
	Christophe HURTER	Professeur, ENAC, Toulouse, France
	Tobias ISENBERG	Directeur de Recherche, Inria Saclay, Paris, France
Dir. de thèse :	Charles KERVRANN	Directeur de Recherche, Inria, Rennes, France
Encadr. de thèse :	Ferran ARGELAGUET	CRCN Inria, Rennes, France
	Emmanuel FAURE	CRCN CNRS, LIRMM, Montpellier, France



# ACKNOWLEDGEMENT

---

Ainsi ces trois ans et quelques mois sont déjà passés. Trois ans à approfondir des problématiques scientifiques et techniques avancées, mais aussi trois ans de progression personnelle dans des domaines qui m'animent, et trois ans de travaux qui seront résumés dans ce manuscrit. Bien sûr, ce parcours, ces travaux, je ne les ai pas faits seul, et je profite de cette préface pour remercier tous ceux qui m'ont encadré et accompagné pendant cette longue, et pourtant si courte période.

Tout d'abord, je souhaite remercier les membres du jury : Pr. Emmanuel Dubois, qui m'a fait l'honneur de présider le jury, Pr. Christophe Hurter et Dr. Tobias Isenberg pour avoir accepté le rôle de rapporteur, ainsi que Nancy Rodriguez pour avoir accepté le rôle d'examinatrice pour ma soutenance. Je vous remercie pour votre lecture attentive de mon manuscrit ainsi que vos retours et questions, intéressantes et pertinentes, auxquelles j'ai sincèrement apprécié être confronté lors de ma soutenance.

Je souhaite ensuite remercier chacun de mes encadrants. Merci Charles de m'avoir accordé ta confiance pour travailler sur le projet Naviscope, qui fut pour moi une occasion de travailler à l'intersection entre la réalité virtuelle et la biologie. Merci Emmanuel de m'avoir prêté ton logiciel MorphoNet, grâce auquel nous avons pu prototyper et expérimenter chacune des méthodes conçues lors de cette thèse. Merci à vous deux de m'avoir permis de travailler avec des biologistes, pour apporter un sens plus concret à ces travaux. Enfin et surtout, merci Ferran. Du moment où tu es venu me chercher dans une salle en haut de Supélec pour voir ce que je bricolais en projet de fin d'étude sur de la réalité virtuelle, jusqu'à cette dernière répétition, le dimanche la veille de la soutenance, ces réunions régulières aux discussions captivantes, ambitieuses ou rassurantes quand il le fallait, tu as toujours fait preuve d'une très forte implication et de soutien dans mon encadrement. Encore une fois, merci à vous trois, vous m'avez guidé tout au long de ce parcours, vous avez été parfaits !

Mes remerciements s'adressent ensuite à l'ensemble des collaborateurs biologistes et bioinformaticiens avec qui j'ai eu le plaisir de travailler. Tout d'abord, je tiens à remercier les chercheurs du CRBM, en particulier Christophe Lemaire et Benjamin Gallean, qui m'ont énormément aidé lors des expériences. J'aimerais également exprimer ma gratitude envers l'équipe Salamero de l'Institut Curie, composée de Jean Salamero, Cesar Augusto Valades et Ludovic Leconte, pour

---

leur apport scientifique ainsi que ces grandes réussites qu'ont été les journées de démonstrations de réalité virtuelle. Enfin, je souhaite remercier tous les autres collaborateurs qui ont participé aux expériences et apporté leurs retours pertinents.

Je remercie également mes collègues qui m'ont entouré pendant cette thèse, et m'ont également beaucoup soutenu par ce contact que nous avons pu garder pendant des années COVID particulières. Je remercie tout d'abord Anatole Lécuyer, chef de l'équipe Hybrid, acteur dans cette cohésion d'équipe tant professionnellement que relationnellement, et Nathalie Denis, notre assistante d'équipe, qui a parfaitement géré tous nos besoins pour les déplacements et rencontres avec toutes les personnes impliquées dans les travaux, répartis un peu partout en France. Je souhaite aussi remercier tout particulièrement mes deux collègues de bureau, Adrien Reuzeau et Alexandre Audinot, qui étaient présents pour m'aider à me former sur des points techniques poussés, ainsi que pour tous les moments de frustration que ça a pu engendrer. Je remercie aussi Thomas Howard, Víctor Rodrigo Mercado et Anthony Mirabile, avec qui nous avons pu faire preuve de beaucoup de créativité en de nombreuses occasions, et même parfois au travail ! A eux, ainsi que l'ensemble des collègues que j'ai pu rencontrer pendant ces trois ans, stagiaires, doctorants, ingénieurs, post-doc et permanent, à travers les réunions d'équipe et les discussions techniques, mais aussi à travers les pauses, les visios, les sorties, les soirées jeux, un grand merci à vous tous, je garde de précieux souvenirs de cette vie dans l'équipe.

Je tiens également à remercier ma famille, qui a été un pilier pour moi pendant ces trois années. Mes parents, qui m'ont permis de poursuivre de longues études dans d'excellentes conditions et ont été tout particulièrement présents durant ces années thèse. Je remercie ma sœur pour sa présence, notamment ces soirées jeux qui ont été une bouffée d'oxygène et une pause bienvenue ; mes frères, en particulier Gaëtan, qui a été d'un grand soutien moral, et Eymeric avec qui nous avons enchainé quelques solides marathons de gaming qui m'ont tout autant laissé de bons souvenirs et été des moments de détente. Je voudrais remercier ceux qui étaient plus éloignés mais dont je sais qu'ils ont pensé à moi, notamment ma marraine Marie-Laure. Merci d'avoir été là pour moi, comme vous l'avez toujours été !

Je remercie finalement tous mes amis, ceux proches que je voyais régulièrement pour des soirées de jeux et de détente, Lilian, Catherine, Marie-Christine, Didinski, Barnabé, Ludovic ; ceux plus éloignés mais quand même présents malgré cette distance, Nic-nic, Julien, Louis, Romain, Bélis, Son Dorian, Deli. Je te mets à part Vincent, le meilleur pour la fin, un grand, grand merci à toi, pour ta présence inconditionnelle, ces appels à des heures et aux durées indéterminées, bref, merci d'être la personne sur qui je peux compter depuis maintenant 13 ans...

Encore une fois, merci à vous tous !

# TABLE OF CONTENTS

---

<b>1</b>	<b>Introduction</b>	<b>9</b>
1.1	Why this thesis? . . . . .	9
1.2	Context of the thesis . . . . .	11
1.3	Research issues . . . . .	12
1.4	Scientific Challenges . . . . .	13
1.5	Approach and Contributions . . . . .	14
<b>2</b>	<b>Related Works</b>	<b>17</b>
2.1	Definitions and Background . . . . .	17
2.1.1	Visualization and Visual Analytics . . . . .	18
2.1.2	Immersive Analytics: Virtual Reality and 3D Interaction . . . . .	21
2.1.3	3D Temporal Data: Towards the Notion of 4D Objects . . . . .	27
2.2	Visualization Techniques for Temporal Data . . . . .	32
2.2.1	High Dimensional Data Visualization . . . . .	32
2.2.2	Temporal Visualization: Dynamic vs Static Approaches . . . . .	33
2.2.3	Space-Time Cube Visualization . . . . .	35
2.2.4	Timeline Visualization . . . . .	37
2.3	Immersive Visualization for Temporal Data . . . . .	40
2.3.1	Immersion for Scientific Visualization . . . . .	40
2.3.2	Immersion for Information Visualization . . . . .	41
2.3.3	Collaborative Mixed Reality . . . . .	43
2.4	Conclusion . . . . .	48
<b>3</b>	<b>Immersive and interactive visualization of 3D spatio-temporal data using a Space Time Hypercube applied to biological imaging data</b>	<b>49</b>
3.1	Space-Time Hypercube Visualization . . . . .	51
3.1.1	Generalizing the STC in 4D . . . . .	51
3.1.2	Extracting a 3D STC from a 4D STH . . . . .	52
3.1.3	Visualization: 3D Rendering and Quantitative Data . . . . .	53

## TABLE OF CONTENTS

---

3.1.4	Interacting with the STH and STC . . . . .	55
3.1.5	Generation and Interaction Performance . . . . .	59
3.2	Use Case: Application for Morphogenesis . . . . .	59
3.2.1	VR Visualization Application . . . . .	59
3.2.2	Use Cases . . . . .	60
3.3	Evaluation . . . . .	62
3.3.1	Tasks and Hypotheses . . . . .	63
3.3.2	Apparatus and Participants . . . . .	64
3.3.3	Experiment . . . . .	65
3.3.4	Results . . . . .	66
3.3.5	Discussion . . . . .	67
3.4	Expert Feedback . . . . .	68
3.5	Additional examples . . . . .	70
3.6	Conclusion . . . . .	70
<b>4</b>	<b>Timeline Design Space for Immersive Exploration of Spatial 3D Temporal Data</b>	<b>73</b>
4.1	A Timeline in a 3D Environment . . . . .	74
4.1.1	Extending the 2D Timeline Design Space . . . . .	75
4.1.2	Interacting with 3D Timelines . . . . .	81
4.1.3	Choosing a Timeline Design . . . . .	83
4.2	Evaluation . . . . .	84
4.2.1	Dataset and Task Design . . . . .	84
4.2.2	Hypotheses . . . . .	85
4.2.3	Apparatus and Participants . . . . .	86
4.2.4	Independent and Dependent Variables . . . . .	86
4.2.5	Experimental Protocol . . . . .	87
4.2.6	Results . . . . .	87
4.2.7	Discussion . . . . .	91
4.3	3D Timelines to Explore 3D Temporal Imaging . . . . .	91
4.3.1	Application and Timeline Design . . . . .	92
4.3.2	Finding Regions of Interests in Large Datasets . . . . .	93
4.3.3	Comparing Objects . . . . .	95
4.3.4	Fusion and Fission . . . . .	95
4.3.5	Expert Feedback . . . . .	96

---

4.4	Conclusion . . . . .	97
<b>5</b>	<b>Space-Then-Time: Toward Selection Methods for Punctual Events in 3D Temporal Data through 3D Interaction</b>	<b>99</b>
5.1	Time-then-Space or Space-then-Time? . . . . .	100
5.2	Visualizing the Right Data . . . . .	100
5.3	Selecting 3D Information . . . . .	102
5.4	Disambiguation in Time . . . . .	103
5.5	Implementation Details . . . . .	105
5.6	Conclusion . . . . .	105
<b>6</b>	<b>Conclusion</b>	<b>107</b>
6.1	Contributions . . . . .	107
6.2	Perspectives . . . . .	109
6.2.1	Short-Term Perspectives . . . . .	109
6.2.2	Long-term Perspectives . . . . .	110
6.3	About Visualization in Bioinformatics . . . . .	111
6.4	Concluding word . . . . .	113
<b>A</b>	<b>Author's Publications</b>	<b>115</b>
<b>B</b>	<b>Résumé en Français</b>	<b>117</b>
	<b>Bibliography</b>	<b>137</b>





# INTRODUCTION

---

## 1.1 Why this thesis?

This thesis, entitled “Immersive and Interactive Visualization of Temporal 3D Data”, presents the research contributions we proposed to tackle issues around immersion, visualization, and interaction with data from other scientific domains. In this first section, we introduce the main parts of this thesis title, provides with elements of definition for each of those terms and illustrate the inspiration that led us to explore the topic.

**Why 3D temporal data?** Datasets are growing in size and dimensions, and more and more analysts have difficulties to handle their data. A whole research field, the Big Data, notably explores methods for the analysis of datasets composed of huge amounts of data entries. We chose to focus on the emerging issue of 3D temporal datasets. 3D temporal data is getting adopted in numerous fields, as biological microscopy imagery, medical imagery or macro scale geographical information. As the technology to handle 3D temporal data is maturing, the number of existing datasets of this type is increasing, and the interest toward this topic with it. The size of the datasets, measurable sometimes in terabytes, can now be acquired, stored, and displayed with hardware and software techniques developed for the past few decades. These datasets are rich in information and could give a new point of view in many subjects we thought were mastered already. Yet, the development of methods to properly analyze such data is still quite a challenge.

**Why Visualization?** Sight is the most important sense, providing more than 80% of information perceived, according to Rosemblum [1]. People always want to see, as it is the easiest way to understand objects, mechanisms, phenomenon, basically most things happening and existing around us. Indeed, seeing is actually a complex task, involving observation, extraction of elements of interest, analyzing them, their physical characteristics, their activity, and their link to the surrounding context. Many games are designed around the difficulty of this task, from “Where’s Waldo” to shooter games, or even when looking for a Lego piece in a huge box

(see Figure 1.1). Visualization is the domain that tries to formalize and tackle these everyday issues relying on vision, in the context of the analysis of data. As mentioned above, datasets are growing in size and complexity, so that analysts from various domains have trouble handling their data, ultimately creating new challenges in Visualization.



Figure 1.1 – The struggle of finding that one specific piece.

**Why interaction?** Interaction constitutes all the actions of moving, grabbing or pushing around items. Such actions can support the observation. For instance, to find that missing Lego piece, people rummage through the box, until that specific piece is not hidden, in a position and orientation that your eye can easily discern. Interactions allow developing strategies to find relevant elements in a large set of information. Yet, seeing an element of interest is only the first step. Interaction also helps to understand the nature of this particular element. Turning it around to discern its shape, making it move, applying pressure, feeling the surface, throwing it around... So many actions that a baby would do when discovering a new toy. Therefore, interacting with the data is crucial to support the various steps of visualization, as much as it is natural.

**Why Immersion?** Immersion is the ability to adapt to a different environment than usual, with different rules and references. Humans adapt very fast to new environments, and notably simulated ones. The notions of presence, i.e. the feeling of “being there”, and embodiment, i.e. perceiving an avatar as oneself, are thoroughly studied with virtual environments. In the context of data analysis, immersion can help us understanding models of objects of very different scales, from a planetary system to entities moving in a cell. Technologies supporting immersive

technologies also matured a lot in the recent years. Head Mounted Displays are now of high resolution, high frame rate and low cost. Such stereoscopic displays show two 2D images, one for each of our eyes, which simulates the same “3D” we are used to see. Tracking devices follow our head, hands, overall movements with high precision and low latency. Overall, immersion simulates visuals in a similar way than with our eyes, and also natural and supernatural interaction. This has potential to support visualization.

## 1.2 Context of the thesis

The fields of biology and medical imaging have been demonstrating significant improvements in the recent years, especially around issue of acquisition and curation of high dimensional and 3D temporal datasets. Ground-breaking live imaging techniques such as the Selective Plane Illumination Microscopy (*SPIM*) and Lattice Light Sheet Microscopy (*LLSM*) are now able to create 3D temporal images at a rate and resolution sufficient to observe and detect important temporal features, would it be general behaviors or punctual events. The automatic or semi-automatic analysis of the data got a lot of attention in the respective communities, and methods based on GPU computation or deep-learning algorithms emerged. These methods produce additional information, such as segmentation, tracking, or numerical and categorical information regarding the imaged entity, resulting in complex high dimensional 3D temporal datasets. Yet, there is a lack in the detection of regions of interest and visualization in these complex data, such that specialized scientists have difficulties exploring their images and can miss key information. This thesis was written in the context of the Inria Challenge Naviscope. This project aims at creating a comprehensive set of methods for the analysis of multidimensional and multi-valued images, especially in the context of biological and medical imagery. Such methods include techniques of navigation, manipulation and visualization of volumetric images, enable semi-automatic analysis, and put a particular focus on the investigation of temporal features in the data. A system implementing such techniques would be a tremendous support for scientists to better understand the massive amounts of information and extract most relevant elements.

Similar challenges appear in various research domains, as high dimensional, 3D or 3D temporal datasets are getting more and more common. The temporal dimension in the latter introduces even more difficulties, in representation, display and interaction with the data. The need for adapted tools helping analysts to understand and extract relevant information from these datasets is becoming crucial. Among the research domains trying to tackle these issues, the field of Visualization develops solutions to help users observe and explore the data. Such methods

rely on adapted visual representation, that emphasizing or filtering out some part of the data, compromising between the quantity of information to display and the capacity of the analyst to interpret it. Furthermore, the field of Visual Analytics attempts to complete Visualization methods using concepts from adjacent domains of data science. It includes techniques from data management to human-computer interaction, in order to give additional tools to analysts. Immersive Analytics, another research domain deriving from Visual Analytics, tries to tackle the same issues using immersive technologies. The methods from this field rely on stereoscopic displays and high degrees-of-freedom viewpoint and devices to exploit efficiently large 3D environments. Methods to enhance navigation in a 3D space, selection and manipulation of objects in various types of 3D environments can come efficient in solving classic visualization tasks. Regarding 3D temporal data, the size and number of dimensions, and the capacities of interaction of users become a center of interest to approach new visualization challenges. Therefore, Immersive Analytics can probably show its most potential.

### 1.3 Research issues

In order to approach the issues regarding the visualization of 3D temporal data introduced in the previous section, we address three main research questions:

**Research Question 1: How to represent 3D temporal data?** The first question focuses on the representation of 3D temporal data, and especially its fourth dimension, time. Both the representations of time in lower dimension data [2–4] and of 3D data [5–8] are a well-explored challenges in the visualization community. Yet, as 3D temporal datasets are getting more and more common, abstractions required to properly define 3D temporal features are lacking. An approach to characterize and formalize the various 3D temporal features is necessary to support adapted visualization and interaction methods.

**Research Question 2: How to visualize different types of 3D temporal regions of interest?** The visualization of 3D temporal datasets is limited first, by the number of dimensions available to display the whole data, second, by the capacity of the user to interpret large number of dimensions and information. 3D temporal data suffers from the issues of displaying both temporal information and 3D data. On one hand, 3D data suffers from occlusion issues, and the density and implied visual clutter further limits the human perception of the information. Such limitations call for solutions including adequate rendering or navigation features. On the other hand, temporal

information representation often involves obstacles in displaying of the information, as the mapping costs an additional dimension. Adapted visualizations for 3D temporal data need either to compensate for these drawbacks or to compromise in an optimal way to highlight the main features of the dataset.

**Research Question 3: How to interact with different types of 3D temporal regions of interest?** Interaction is often reported as a key element to support the limitations of visualization. Various methods were developed to enhance the interaction in 3D environments and notably to explore 3D data. Interactive navigation in time is also recommended to compromise between using an additional Euclidean axis and the cognitive workload of animations. The selection, manipulation and exploration of 3D temporal regions of interest involves both of these constraints. By analogy with the limitations of human perception for visualization, human capacity needs to be taken into account for interaction, both in terms of physical capacity and precision, and of cognitive ability. Consequently, interaction must be adapted either to map efficiently and naturally the input of the user to an action on the 3D temporal region of interest, in order to facilitate its analysis.

## 1.4 Scientific Challenges

The research questions presented before leads to several challenges. We identified four challenges that needs to be tackled to answer our research questions.

**Challenge 1: Approaching various types of regions of interest** Depending on the entity observed or represented, the methods for generation or acquisition, 3D temporal data will present varied characteristics, which can require a potentially different approach for representation and visualization. Variations in the nature of the data (e.g. volumetric, point clouds, etc.), density or visual clutter can add obstacles to the visualization. On the other hand, regions of interest can be of different nature (e.g. trajectory, objects evolving over time), or have sizes of different orders of magnitudes. These differences in size are relevant not only in space, i.e. small vs large objects, but also in time, punctual vs extended events.

These variations in context and regions of interest will have impact on the perception and exploration of the data by the user. The design of visualization and interaction methods must take into account this obstacle.

**Challenge 2: Navigating in time** Time is often represented either spatially or temporally. Representing time as a Euclidean axis increases the complexity of the visualization, and is especially difficult for spatial 3D data. Controlled animations reduce the number of dimensions, mapping the temporal information on a “rescaled” time axis, yet it collides with the slogan “Eyes beats Memory”, i.e. the difficulty of the user to interpret and compare data that are not directly visible. Using any of these approaches, navigating in time and exploring temporal information remains challenging. First, interactions need to map the input of the user, usually defined spatially, to coherent actions on temporal information. Second, navigation methods should optimize access to relevant information.

**Challenge 3: Managing the view for visualization and interaction in 3D and time** View management is a classic issue when exploring 3D environments, and therefore when visualizing 3D data as well. First, it includes managing occlusion [9] and visual clutter, which are caused or increased with the density of the data. Second, the work space needs to be organized correctly, notably when using multiple juxtaposed views. Occlusion issues can notably be compensated with adequate manipulation and navigation methods. Yet again, when confronted with 3D temporal data, such issues tend to be even more prominent, notably depending on the method used to visualize the time dimension. As such, occlusion management will need particular attention when designing visualizations and interactions.

**Challenge 4: Encoding large high dimensional dataset** As mentioned previously, 3D temporal datasets often also include numerical and categorical dimensions. They can be crucial for the exploration and analysis of the data observed, through means of filtering and comparison. Therefore, these dimensions also need to be displayed with the visualization of the 3D temporal data. Several channels can be used to display such information. More commonly, the information is encoded on the color channel through color maps. Depending on the nature of the information, it can also be encoded through sound, haptic feedback, with labels or juxtaposed views. The encoding of the information must take into account the analytical purpose, but it also should avoid cluttering the visualization or involve too much mental workload for the user.

## 1.5 Approach and Contributions

As mentioned through the scientific challenges, the temporal dimension is a strong constraint for both visualization and human-computer interaction. Exploiting recent progression in those

two research domains, the field of Immersive Analytics leverages the benefits of immersive technology to support visualization and interaction. Issues regarding navigation in the temporal data, observation of 3D data and overall view management could be facilitated by methods developed in this field. As such, we decided to involve immersive environments in our visualization and interaction approaches.

The strong variation in 3D temporal data highlighted in Challenge 1 led us to consider a global approach of our main research questions through different types of data. As such, the first step of our approach is the characterization of 3D temporal data and the features we will be confronted with. Furthermore, the constraints in the representation of time will call for more effort on either visualization or interaction. The remaining steps of our approach will try to tackle the main research questions in these different situations. The outline of this thesis is as follows:

**Chapter 2** presents literature report describing the objectives and methods developed in the main research domains surrounding the thesis subject. We present first the domains of Visualization, Visual Analytics and Immersive Analytics, and approach the question of representation of 3D temporal data in data analysis context, with illustrations from the field of biology imaging. Then, we focus on methods to represent and visualize the temporal dimension in general data, focusing on specific static visualization, namely the Space-Time Cube and Timelines. Finally, we present applications and methods from Immersive Analytics to approach visualization issues, notably regarding high dimension data, and conclude with an opening of collaborative visualization methods.

**Chapter 3** describes the Space-Time Hypercube representation, which extends the classic Space-Time Cube representation to 3D temporal data. We propose a method create visualizations from the Space-Time Hypercube, defining extraction operators based on a cutting plane defined by the user. The resulting visualization is a Space-Time Cube displaying the evolution of a cut-away view through time, highlighting major events in the dataset or the general evolution of shapes or values. Classic 3D interaction tools come to support the exploration and analysis of the complex 3D structure. We evaluated this method through a user-study on a biological imaging dataset, and also reported feedback from domain experts who experimented with the method.

Following these evaluations, we conclude that this visualization method helps emphasize 3D temporal features of significant spatial size and their evolution over large intervals of time.



**Chapter 4** presents a design space for the creation of 3D timelines visualization. This design space extends the classic visualization of timelines and explores ways to display them in a 3D environment. As such, 3D timelines can support the visualization of 3D temporal datasets. Leveraging the enhanced interaction and exploration of virtual environment, we developed interaction processes to exploit the 3D timeline. Using navigation, selection and filtering tools, the user can define and refine efficiently zones of interest in both space and time. A user-study was designed to assess the benefits of 3D timelines regarding usual visualization tasks using a procedurally generated dataset. We also report the feedback of biology experts, who tested the method on different types of biological imaging data.

The results of these evaluations led us to conclude that this visualization method, accompanied by the adequate interaction processes we proposed, helps define local regions of interest in both space and time, with short to medium temporal range.

**Chapter 5** explores a method of selection of events relying on a Space-Then-Time process. We focus on the selection of punctual events, that are challenging to access using traditional visualizations of temporal information. We propose that instead of exploring the temporal dimension, then the 3D space, to find and select a region of interest, an analyst could identify first the 3D location and then select the region of interest in time. We discuss an interaction process relying on three most important points: which information should be directly available to the user; how to select the region of interest in space; how to disambiguate the selection over time.

We suggest that an interaction method based on this concept could increase the efficiency of selection of 3D temporal features characterized by short temporal range.

**Chapter 6** concludes this manuscript, summarizing our contributions, as well as providing perspectives for future works on the methods we proposed, and on our propositions to the main research questions.

# RELATED WORKS

---

2.1	Definitions and Background . . . . .	17
2.1.1	Visualization and Visual Analytics . . . . .	18
2.1.2	Immersive Analytics: Virtual Reality and 3D Interaction . . . . .	21
2.1.3	3D Temporal Data: Towards the Notion of 4D Objects . . . . .	27
2.2	Visualization Techniques for Temporal Data . . . . .	32
2.2.1	High Dimensional Data Visualization . . . . .	32
2.2.2	Temporal Visualization: Dynamic vs Static Approaches . . . . .	33
2.2.3	Space-Time Cube Visualization . . . . .	35
2.2.4	Timeline Visualization . . . . .	37
2.3	Immersive Visualization for Temporal Data . . . . .	40
2.3.1	Immersion for Scientific Visualization . . . . .	40
2.3.2	Immersion for Information Visualization . . . . .	41
2.3.3	Collaborative Mixed Reality . . . . .	43
2.4	Conclusion . . . . .	48

---

This chapter presents a literature review of the research carried in the main domains surrounding our research questions. This study focuses first on defining these adjacent domains and highlighting the main challenges they approach, in order to contextualize our own contributions. The issues tackled in such domains as Visualization, Visual Analytics and Immersive Analytics and the general approach proposed in each of these domains, will be a starting point to answer our research questions. We will also focus on the characterization of 3D temporal data, as it is an emerging issue, notably relying on previous works tackling 3D data and temporal data.

As we identified the issue of navigation in time as one of our major challenges, we then report visualization approaches to handle temporal data. Techniques to tackle the general issue

of high dimensional data were proposed, and more specific approaches refined these techniques by exploiting time differently, as a dimension of unique nature. We compare those approaches and identify methods that attracted our attention as bases to our contributions.

Finally, we explore how Immersive Analytics in the literature leveraged the benefits of immersive technologies to answer visualization challenges. We present approaches of Immersive Analytics application in different datasets and use cases, and conclude with collaborative immersive applications, a main concern in the domain of Immersive Analytics.

## 2.1 Definitions and Background

In this section, we introduce the main domains related to our research questions. First, we present the domains of Visualization and Visual Analytics, which are the main fields of research regarding the issues of exploration and analysis of data through human perception and interaction. Then, we focus on the domain of Immersive Analytics, which approaches the same issues relying on virtual environments and related techniques. Finally, we focus on 3D temporal data, describing their main characteristics and proposing an approach to represent 3D temporal features, illustrating it with biological imagery examples.

### 2.1.1 Visualization and Visual Analytics

#### Definition of Visualization

Visualization is a research domain that has been developed for the few past decades to innovate in the creation of views to analyze data in various fields such as medicine [10], biology [11], CAD [12] or physics [13]. Visualization is usually classified into two categories: *Scientific Visualization* [14], in which the data observed is usually scalar or vectorial fields explicitly referenced in time and space, and *Information Visualization* [15], which aims at representing abstract data. Munzner [16] proposed a definition for visualization, as follows:

### Definition of Visualization

Computer-based **visualization** (*vis*) systems provide visual representation of datasets designed to help people carry out tasks more effectively.

Visualization is suitable when there is a need to augment human capabilities rather than replace people with computational decision-making methods. The design space of possible vis idioms is huge, and includes the considerations of both how to create and how to interact with visual representations. Vis design is full of trade-offs, and most possibilities in the design space are ineffective for a particular task, so validating the effectiveness of a design is both necessary and difficult. Vis designers must take into account three very different kinds of resource limitations: those of computers, of humans, and of displays. Vis usage can be analyzed in terms of why the user needs it, what data is shown, and how the idiom is designed.

This definition places the use of representation of the data as crucial for any analytical tasks and the human as a most important link in the decision-making process. It also introduces the main issues to compromise with when creating visualizations.

First, human limitations introduce an obstacle on representation. The first thing usually mentioned is the perceptual capacity. Ocular and cognitive characteristics require representations to emphasize patterns and features, as well as designing adapted color schemes, i.e. perceptually uniform, color maps [17–19]. The mental workload of the user is limited, thus the amount of information displayed must be limited accordingly. Physical characteristics also condition visualization. Human vision is stereoscopic, which directly induces issues on occlusion [9] and a need for depth cues. Furthermore, the precision, dexterity and sensation of the user's movement are key information to implement comfortable and efficient interaction on visualizations. Consequently, the second main limitations depend on the display, and more generally the Human-Machine Interface, characteristics. The most usual setup for visualization software is a screen, used with a mouse and a keyboard. This setup is very versatile and accessible to most users. Yet, screens confine the workspace to a 2D rectangle and the mouse is also restricted to 2D movements, which can be too restricting when visualizing large amounts of information or 3D data. Other interfaces explore different ways to display and interact with the data, notably with touchscreens or Mixed Reality (*MR*) setups. The latter allows the user to “see in 3D” through stereoscopic displays, and navigate and interact with the data through 3D interactions. Such technology, promising and scrutinized for visualization for decades now [20], leads to the last

main limitation: computing resources. Not only do algorithms must be adapted to the increasing size of datasets, but also to the increase in the standard quality of the rendering. Furthermore, Head-Mounted Displays (*HMD*) or CAVEs used in MR setup often require real time rendering and interaction, constituting a potentially high computational cost as well.

### Definition of Visual Analytics

Thomas and Cook [21] coined the term “visual analytics” and defined it as follows:

#### Definition of Visual Analytics

Visual analytics is the science of analytical reasoning facilitated by interactive visual interfaces. Visual analytics is a multidisciplinary field that includes the following focus areas:

- analytical reasoning techniques that let users obtain deep insights that directly support assessment, planning, and decision-making;
- visual representations and interaction techniques that exploit the human eye’s broad bandwidth pathway into the mind to let users see, explore, and understand large amounts of information simultaneously;
- data representations and transformations that convert all types of conflicting and dynamic data in ways that support visualization and analysis; and
- techniques to support production, presentation, and dissemination of analytical results to communicate information in the appropriate context to a variety of audiences.

Keim et al. [22] gave additional insight on the objectives and components of visual analytics. As depicted in Figure 2.1, Visual Analytics give an integral approach, incorporating elements of Data Management, Data Analysis Technology, perception, cognition and human computer interaction. Therefore, Keim et al. [23] proposed a mantra for Visual Analytics as follows: “*Analyse First - Show the Important - Zoom, Filter and Analyse Further - Details on Demand*”, in reference and extending the information seeking mantra presented by Shneiderman [24] (“*overview first, zoom/filter, details on demand*”). This ensemble needs to be supported by adapted infrastructures and reliable evaluation in order to tackle issues that can be out of reach for classic techniques of visualization.

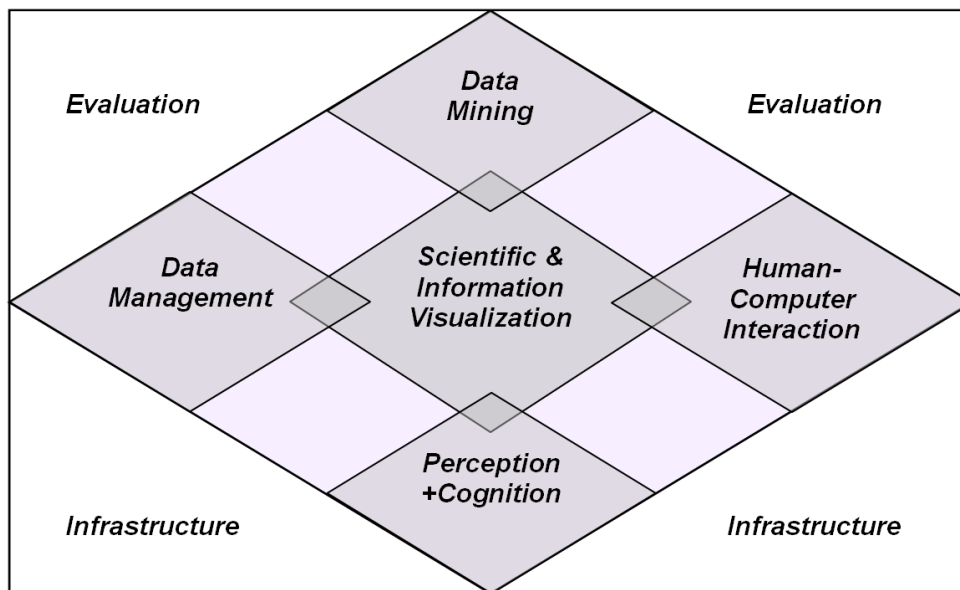


Figure 2.1 – Visual Analytics integrates Visualization and core adjacent disciplines, and depends on appropriate infrastructure and evaluation; *Keim et al.* [22]

As an illustration, we present a Visual Analytics system for analysis and visualization of biological imaging data, based around BioImageIT by Prigent et al. [25]. The system, as shown in Figure 2.2, integrates at its core tools for data management and data analysis. BioImageIT can be linked with multiple other existing systems of Data Management, such as OMERO [26], which proposes its own data formatting and hosting servers. Data Analysis plugins can be coded directly into the system, or added via Docker containers or Conda packages, allowing primarily easy communication between researchers, but also adaptability against the evolution in this field. Finally, the system uses visualization tools such as Napari [27] and ImageJ/Fiji [28, 29] to render the processed data. To summarize, the user can use BioImageIT system interface to manage their data, create a processing pipeline, and use their usual visualization tool to observe and interact with the resulting data.

Visual Analytics widen the scope of Visualization to attempt at improving the existing methods, in order to give more analytical tools to the user and ways to handle more diverse datasets. As such, Visual Analytics can also provide solutions for the main challenges and objectives of visualization. Kehrer and Hauser [30] notably reported the contribution of Visual Analytics to overcome the issue of scalability of systems with the increasing size, complexity and heterogeneity of data to handle, while maintaining possible interaction or acceptable processing time. Yet, as datasets still keep growing, the visualization of high dimensional data remains one of the main challenges of the research field.

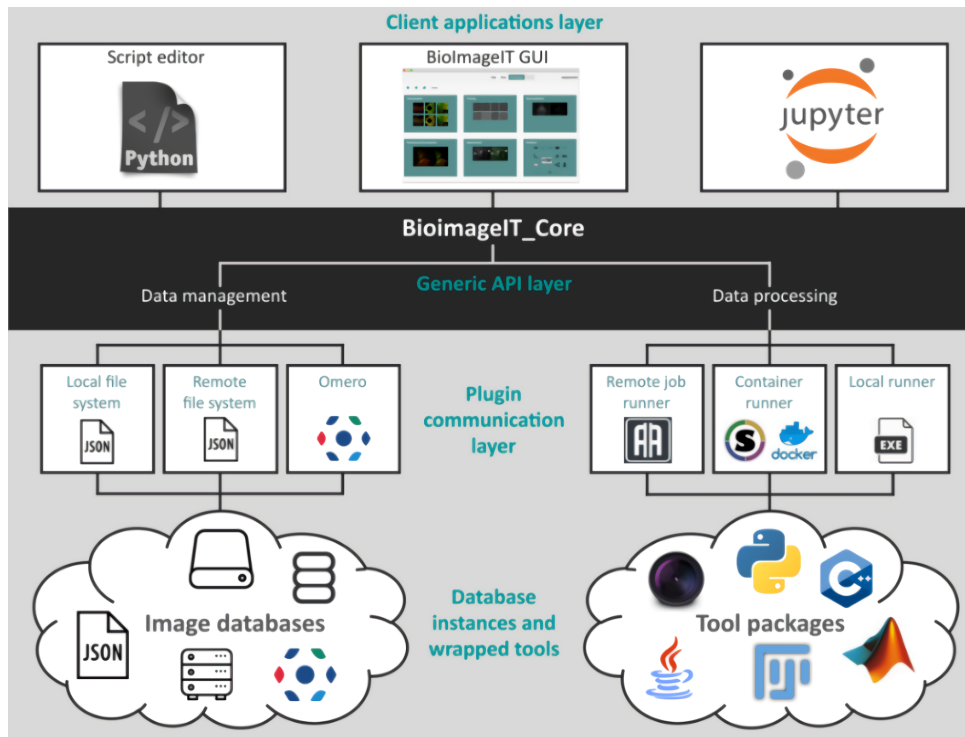


Figure 2.2 – Schematic view of BioImageIT architecture; *Prigent et al.* [25]

## 2.1.2 Immersive Analytics: Virtual Reality and 3D Interaction

### On Immersive Analytics

Mixed Reality technologies has already been used for visualization in several scientific fields for many years. It was used in archaeology [20, 31, 32], brain tumor analysis [33] or physics [34], giving mostly satisfying results. Experiments conducted by Bach et al. [35] made to evaluate the contribution of Virtual Reality in terms of interaction suggested that highly interactive tasks were achieved more intuitively in immersive environments. It was also noticed in other experiments at Carnegie Mellon University and the University of Virginia [20] that mistakes made in immersive environment, as distance evaluation and such, corresponded to real world mistakes, and that real world usual tasks such as rotating objects were achieved faster and with more precision [20]. Another study by Raja et al. [36] estimated that immersive environment and head tracking gave better results in terms of task performance for 3D scatter plots visualization.

The term of “Immersive Analytics” was defined in 2015 by Chandler et al. [37], as an emerging research topic stating as follows:

### Definition of Immersive Analytics

Immersive Analytics investigates how new interaction and display technologies can be used to support analytical reasoning and decision-making. The aim is to provide multi-sensory interfaces for analytics approaches that support collaboration and allow users to immerse themselves in their data. Immersive Analytics builds on technologies such as large touch surfaces, immersive virtual and augmented reality environments, haptic and audio displays and modern fabrication techniques.

As underlined out by the same author, Visual Analytics is agnostic of the interface used. As such, Immersive Analytics are a sub-domain of Visual Analytics, and share the same objectives and methods of enhancing visualization to support analytical tasks. The particularity of this recent domain is that it also integrates the methods developed around immersive interfaces. First, immersive interfaces usually provide with an additional visual channel through stereoscopic 3D rendering. This additional channel assists in the perception of various cues, notably for depth perception, which can help in visualizing 3D data rendering [38]. Second, immersive environments also provides with large work space, notably allowing the multiplication of juxtaposed views in an application. Finally, 3D user interaction allows efficient operations of manipulation, selection or application control [39], which could enhance an analytical workflow.

### Perceptual Benefits of Immersion

Most information received by human perception comes from the visual channel [1]. Humans are very good at identifying what they see, finding patterns or emergent properties. Stereoscopic displays, such as HMDs or CAVEs, usually provides a wider field of view than classic 2D displays ; the information in the peripheral vision provides further awareness and context of the VE to the user [20]. Experiments described by van Dam et al. [20] showed that most human-scaled problems, such as complex structures exploration, are more easily apprehended in immersive environment, where the body can move in the environment, rather than on a 2D interface where the environment rotates around the user. Non-human-scale problems are often not approached naturally by the user, yet they can be rescaled to correspond to a more usual viewpoint. For example, van Dam et al. [20] describe an arterial blood flow visualization represented as a pipe exploration, a more familiar macro scale object for the user. Furthermore, Andrews et al. introduced the notion of “Space to Think” [40, 41], referring to and demonstrating that interacting with large displays could support the cognitive process and reduce the mental workload, notably



by spatially organizing the information material through adapted interaction. This approach was later explored for 3D environments by Bandyopadhyay et al. [42], introducing the “Immersive Space to Think”. More works on this approach by Lisle et al. [43, 44] showing the benefits and proposing strategies to approach such environments to help understand large datasets.

As such, 3D displays have been used as general HCIs for 3D environments, for scientific visualization and for medical research. McIntire et al. [45] review 184 experiments based on 3D displays; they report that about 60% of the experiment they reviewed found positive effect - and 15% mitigated results - of the use of the display for usual analytical tasks such as manipulation, distance estimation or object identification. They observed that 3D display was beneficial in cases of either complex, difficult depth-related tasks, or when monocular depth cues were lacking. This statement is further supported by Marriott et al. [38], who discussed how various 3D displays from the literature was beneficial for depth perception of 3D environments. Figure 2.3 summarize the existing types of 3D displays against strong perceptual cues such as linear perspective, i.e. relative size of objects, occlusion or motion perspective. This was also confirmed in Laha et al. [46] study, which found a positive effect of head tracking and stereoscopic rendering for tasks involving visually and spatially complex search. This study also reports a significant effect of large fields of view when visualizing volumetric data, concurring with van Dam et al. [20] suggestion.

3D environments and stereoscopic technologies provide perceptual cues that help understanding of complex 3D shapes and achieving depth-related tasks, which is particularly relevant for the visualization of 3D data. To support analytical tasks, navigation and interaction methods were developed to exploit 3D environments more efficiently.

### **3D Interaction for Analytical Visualization**

3D interactions encompass the methods that allow users to interact with a 3D environment. A 3D interaction design can be approached using generic interaction techniques, easy to choose and implement thanks to widely available design spaces, evaluation results, by decomposing a task into canonical subtasks [39]. However, these approaches rarely take into account domain-specific knowledge. As such, the design of application-specific 3D interactions is a usual approach to improve the usability of an application [47]. Nonetheless, such approach implies an additional cost to design the interaction, based on a less well-defined design space and with little re-usability.

3D interaction techniques are usually separated into Selection, Manipulation, Navigation and Application Control [39]. Selection and manipulation are natural interactions in 3D environment, and the quality of these fundamental interactions have a tremendous impact on the quality of

	Linear Perspective	Aerial Perspective	Occlusion	Motion Perspective	Accommodation	Convergence	Binoc. Disparity and Stereopsis	User-controlled PoV	Subjective Motion	Interactive Content Manipulation
Regular photography or print	Y	Y	Y	N	N	N	N	N	N	N
Desktop Computer Virtual Reality	Y	P	Y	Y	N	D	D	Y	N	D
Fishtank Virtual Reality	Y	P	Y	Y	N	D	D	P	Y	D
Non-disparity monocular/binocular viewing	Y	P	P	P	N	N	N	P	P	D
Head-mounted Binocular Displays	Y	P	Y	Y	N	Y	Y	P	Y	D
Multi-display Environments, Large Displays	Y	P	Y	Y	N	N	N	P	P	D
Binocular CAVEs	Y	P	Y	Y	N	Y	Y	P	Y	D
Gazer (Simulation of Accommodation)	Y	P	P	P	D	P	P	P	P	D
Accommodation Optics VR Headset	Y	P	P	P	Y	Y	Y	P	Y	D
Multiview Autostereoscopic	Y	P	Y	Y	D	Y	Y	P	Y	D
Volumetric 3D Displays	Y	N	N	Y	Y	Y	Y	P	Y	D
Optical Holographic 3D Displays	Y	N	N	Y	Y	Y	Y	P	Y	D
Augmented Reality (AR)	Y	P	D	Y	D	D	Y	N	Y	D
AR Hybrids	Y	P	Y	Y	D	D	Y	D	P	D
Physical Visualisations (reality)	Y	P	Y	Y	Y	Y	Y	N	Y	Y

Figure 2.3 – Mapping 3D display technologies and depth cues (“Y”: yes; “P”: possible; “D”: depends, to some extent; “N”: no); *Marriott et al.* [38].

the whole 3D user interface. Selection techniques use different metaphors [48], such as a virtual hand, mostly for short-range or realistic interactions, or virtual pointing techniques for mid to long range interaction. The latter are notably differentiated by the number of degrees of freedom (*DoFs*) involved in the interaction, as illustrated in Figure 2.4. Lower *DoFs* usually makes for interactions that are easier to control [39, 48]. Volumetric pointers can be used to select small objects more easily, yet in dense environment, it can create an ambiguity on the selected object, which needs to be answered with adequate and usable disambiguation methods [49]. Vanacken et al. [50] evaluated other techniques supporting object selection in dense or occluded environment, notably advising for multimodal selection feedback. Manipulation tasks relate to the application of rigid transformations to 3D objects [51]. Direct manipulation approaches

involving one or two-handed interactions simulate natural interactions, with techniques as the Handlebar metaphor [52], or relying on widgets [53]. Indirect manipulation techniques allow the user to manipulate object at a distance, with straightforward approaches as HOMER [54], or with metaphors like the World-in-miniature approach [55]. For selection and manipulation techniques, the control-display ratio is sometimes altered, resulting in an anisomorphic control mapping, to compromise differently the strengths and weaknesses of the interactions. For example, the Go-Go selection [56] applies a gain to the distance between the user and their hand, increasing the range but decreasing precision; the PRISM technique [57] applies a gain to the hand speed to filter out noise and increase precision on slow movements. Finally, navigation techniques define how the user can move in space. These techniques are usually separated into Physical travel and Virtual travel. Physical travel involves movement directly from the users, such as simply walking, redirected walking or walking in place techniques. These methods require more or less physical space, and can be tiring for extensive use. However, they also provoke less motion sickness, as real movements from the user trigger the virtual movements. Virtual travel uses controller inputs, for example through steering techniques or teleportation. If these methods are less constraining in terms of physical space, they do not provide vestibular cues and can be perceived as less immersive.

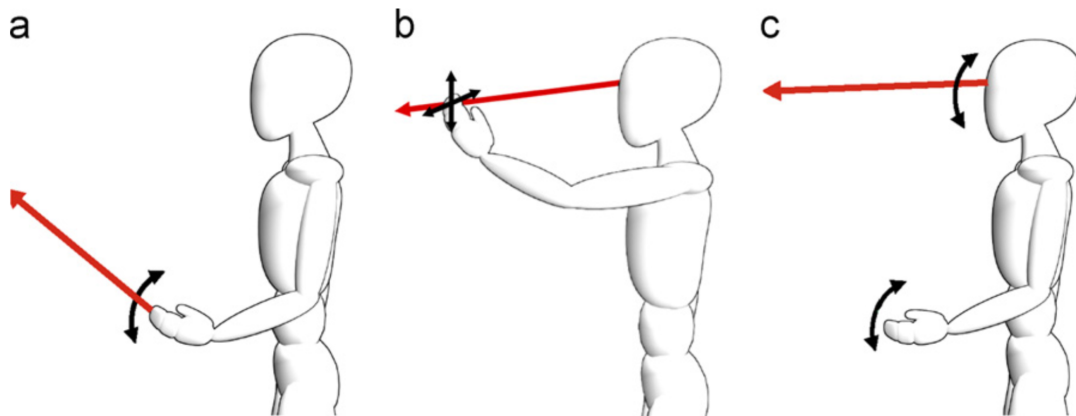


Figure 2.4 – Virtual pointing techniques: (a) raycasting, involving 2+3 DoFs, (b) occlusion selection, involving 3 DoFs and (c) raycasting from the eye involving only 2 DoFs; *Argelaguet and Andujar* [48].

Fonnet and Prié [58] report an overview of interaction tasks for Immersive Analytics. While still relying on Selection, Manipulation and Navigation general tasks, they notably separated the task of Application Control between several Visualization tasks. The main tasks explored in the literature are as follows:

**Details on Demand:** Interactions which goal is to display more complete or additional information about some data. This information is commonly displayed through a pop-up window upon selection [59, 60], yet also through labels appearing predictively depending on the application context [61], or using side screen that displays information [62, 63].

**Arrange:** This task consist in changing the spatial organization of data points, views or view components. This interaction relies either on manipulation of the mentioned elements, or through automatic methods, like force-directed placement [64].

**Change:** This regroups the interactions which goal is to modify the representation or visual encoding of data points or other view components, through ways of highlighting or changing attribute mapping.

**Filter:** This task, classic in visualization applications [16], consists in the determination of exclusion or inclusion criteria, in order to remove elements and simplify the view.

The remaining tasks concern Aggregation, Annotation, Import, Derive and Record, and are way less explored in the literature. Fonnet and Prié [58] argued that these overlooked tasks will nonetheless need to be developed in order to implement complete data-analysis systems.

### 2.1.3 3D Temporal Data: Towards the Notion of 4D Objects

Spatial 3D temporal data are more and more present in scientific visualization. These data are of various nature, notably point clouds [65, 66], more [67–70] or less [71, 72] large trajectory datasets, simulated flow data [73, 74] and surface or volumetric datasets [75]. Numerous methods have been developed to represent the time component and space-time relationships [3, 76]. Yet, the representation of spatial 3D temporal features remains challenging. In this section, we explore the main characteristics of 3D temporal data and discuss a representation of 3D temporal features, namely 4D objects, and provide with examples from the biology imagery domain.

#### 3D Temporal Features and 4D Objects

We approach the issue of representation of 3D temporal features as a way to partition logically the data. First, we consider 3D objects as represented in the 3D interaction literature. Overall, 3D objects in 3D environments are defined in a really transparent manner, i.e. with virtual objects that represent their real counterpart. The selection methods presented in the previous section highlighted different use cases related to the type of objects, yet also considered the characteristics of the 3D environment. Such factors as the density of objects in the environment,

the size of each object and their position compared to the user are determining in the choice of technique used. Manipulation methods will be also potentially constrained by the shape of the object.

We define 3D features in a context of data analysis by analogy of 3D objects. As such, like an actual object, a 3D feature must be a continuous volume, basically an independent semantic entity. As 3D objects, it will be notably characterized by its size, shape and position of data pieces represented in space. The encoding of the object, i.e. volumetric, vector-based, mesh-based, point clouds, or defined by functions, and the respective precision of the encoding (i.e. resolution, number of vertices, ...) is likewise a salient characteristic in the representation of the object. Moreover, additional categorical and numerical characteristics are usually attributed to 3D objects, such as a name, a color, a weight, or physical properties for example. Again, by analogy, such additional information, often present in high dimension datasets, can be attributed directly to a defined 3D feature. It can come from annotation,

Finally, we need to integrate the temporal dimension to these features. The first evident property is the lifespan of the feature, i.e. when it appears and disappears, and the duration in between. Corresponding to the matter of the encoding of the spatial 3D object, time can be defined as continuous or discrete, and the resolution in time is also an important property of this dimension. Furthermore, each of the characteristics evoked previously can evolve along time, constituting the dynamics of the objects.

Eventually, we introduce the notion of 4D objects to compile all the characteristics identified. To summarize, we attribute several features to qualify 4D objects:

- A 4D object is an independent semantic entity.
- A 4D object is defined over a continuous subset of the time dimension encoded in the dataset. Thus, it has a lifespan, a date of appearance, of disappearance and is defined either continuously in time or discretely with a temporal resolution.
- A 4D object contains a continuous subset of the 3D space encoded in the dataset, and thus has a shape, size and position. These characteristics can evolve over the temporal dimension.
- A 4D object can be attributed several categorical or numerical information, such as a name, color or weight. These characteristics can evolve over the temporal dimension.

This representation should support logic visualization and interaction while considering all the information of a 3D temporal feature. In the following, we illustrate how this representation can be integrated in concrete examples.

### Examples: 3D Temporal Bioimaging Datasets

In this section, we present several datasets from live microscopy, describing the context of their study and how our 4D object approach can be applied to the analysis of these data. These datasets will serve as examples in the contributions presented in this thesis.

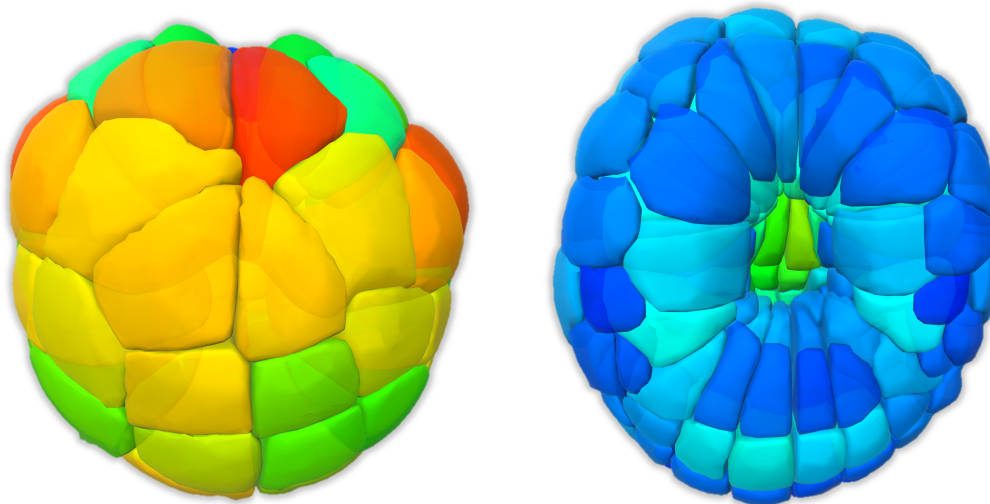


Figure 2.5 – Imaging of an embryo of *Phallusia Mammillata*, time points 1 and 75 i.e. nearly two hours of recording; *data from Guignard et al.* [77].

The first dataset, illustrated in Figure 2.5 is a live recording of the embryonic development of a *Phallusia Mammillata*, a marine invertebrate animal, more specifically a tunicate of the ascidian class. The ascidian embryos are characterized by their fast development and low number of cells (a few hundreds). The *Phallusia Mammillata* also presents particularly transparent membranes and a lack of apoptosis, i.e. programmed cell death, and cell migration in its early development. The main events happening during the development will be focused on asymmetric and/or asynchronous cell divisions. The acquisition of this dataset was made using confocal multiview light-sheet microscopy [77]. It generated 180 3D images, taken once every 89 seconds. The output data, a few terabytes and 4D with isotropic spatial resolution, was then segmented using the ASTEC pipeline (Adaptive Segmentation and Tracking of Embryonic Cells) [77] and meshed using the VTK library [78] and MeshLab [79]. It resulted in a surface-based spatio-temporal dataset of a few hundred megabytes. Additional categorical and numerical data are also available: the ANISEED database [80] provides us with information about the expression of various genes in the cells; the community of scientists added data such as cell volume; we were also able to compute locally information such as remaining lifespan before division. In addition to the 3D

segmentation and meshing, the ASTEC pipeline extracted the lineage of the cells.

In this dataset, we represent each cell as a 4D object, represented by a mesh, identified by a name and related to categorical and numerical information, with tracking over time. It is to be noted that temporal relationships exist between the 4D objects, as cell division creates two new cells.

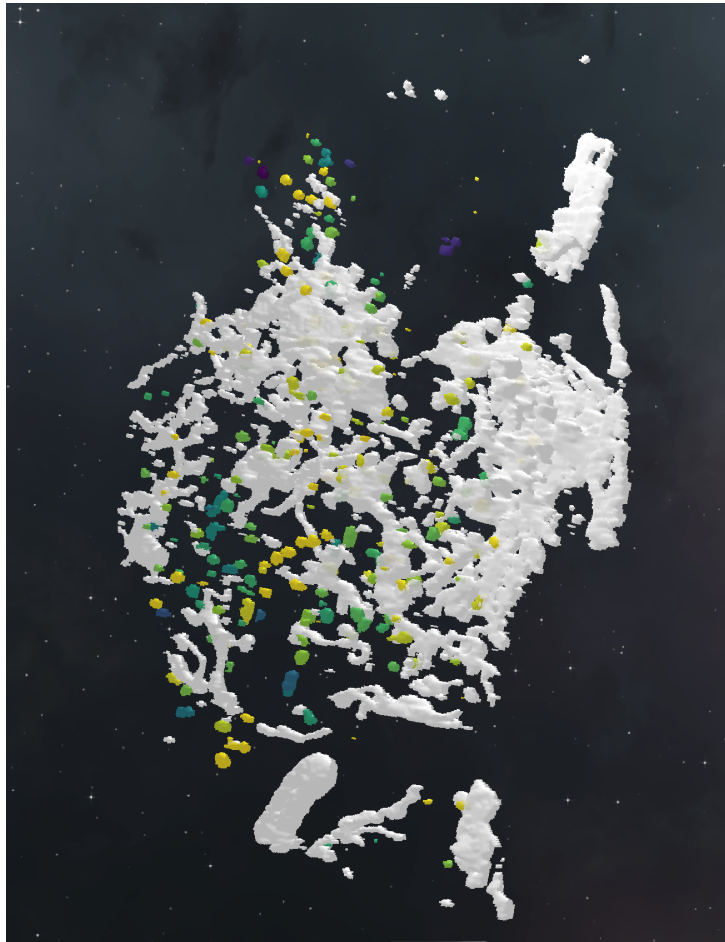


Figure 2.6 – Imaging of a cell with tracking of mitochondria and cd63 endosomes; *data from Valades et al.* [81].

The second dataset we study is a recording of a live cell with marking of mitochondria and CD63-positive late endosomes [81], illustrated in Figure 2.6. CD63 is a protein usually associated to the surface of the cell membrane or present in late endosomes. It is notably involved in cell activation, adhesion and differentiation, and its activity seems to have inverse correlation with late stages of cancer development [82]. This STED microscopy recording was

acquired using a Lattice Light Sheet Microscope [83] (*LLSM*), using CD63-Turquoise.2 labeling late-multivesicular endosomes and PKMOrange [84] labeling mitochondria. A hundred 3D images were acquired, one per second, with a spatial resolution of 104 x 104 x 325 nm per pixel, resulting in 495 x 500 x 60 pixels volumetric images. They were then segmented using the software Imaris [85], retaining endosomes and mitochondria information. The endosome tracking was computed with Trackmate [86]. Some additional information could be computed, such as the volume of the endosomes and the distance between the endosomes and the mitochondria.

In this dataset, we represent endosomes as 4D objects, as they are segmented, tracked in time and have additional information directly related to them individually. Mitochondria are too difficult to track because of the resolution of the data, so they are kept as background contextual information.

The third dataset we focus on, illustrated in Figure 2.7, is a simulation of astrocytic calcium dynamics. Astrocytes regulate neuronal information processing through a variety of spatio-temporal calcium signals [87]. This dataset simulates calcium signals over a real 3D temporal LLSM recording of an astrocyte. These signals are classified into blips, of short duration and low amplitude, puffs, of higher amplitude and duration, or waves, similar to puffs but moving in space. Nonetheless, calcium signals of all classes appear over only a few time points at most. The dataset is constituted of a hundred volumetric images of resolution 170 x 512 x 48. The calcium signals are generated separately, and thus are directly segmented and tracked in time. Consequently, we can represent the calcium signals as 4D objects.

These datasets all encode spatial 3D temporal information, completed with categorical and numerical dimensions. The features represented are of different nature and size, both in time and space. Yet, the 4D objects representation generalizes these different features, allowing us to consider them as equivalent for visualization or interaction purposes.

## 2.2 Visualization Techniques for Temporal Data

The representation of temporal information is an issue that goes way further than just scientific visualization. Visual storytelling, from caveman paintings to comics and other artistic domains, or visual explanations, like manuals or music sheets, required to encode time. Classic methods used juxtaposition of multiple scenes, canvases or symbols, relying on the usual reading direction of the targeted audience. Movements are particularly difficult to represent, using techniques such



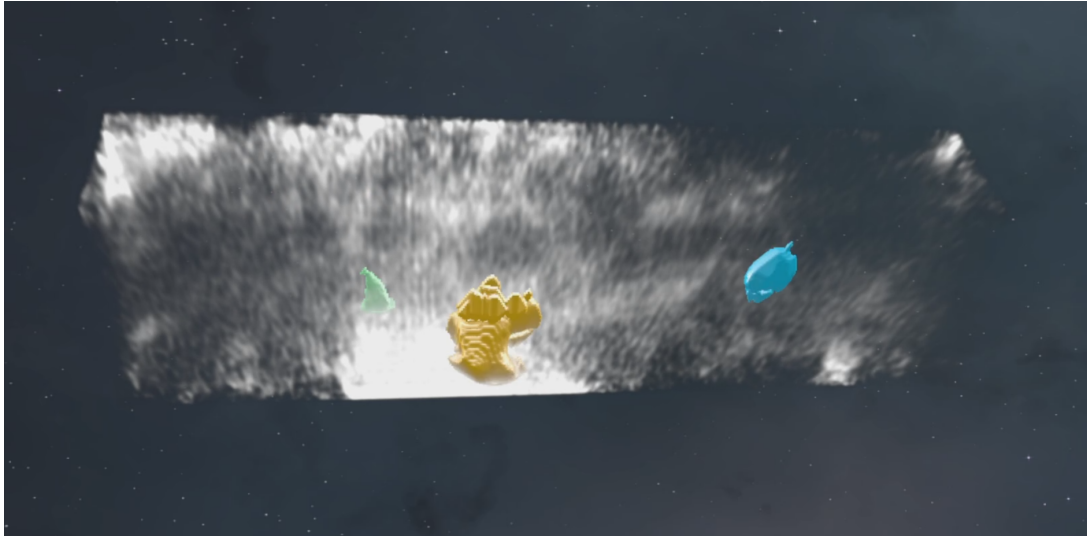


Figure 2.7 – Imaging of an astrocyte, with simulated calcium signals (in color, different for each signal); *data from Badoual et al. [87]*.

as motion lines in comics, or overlaying multiple steps of the movement.

Nonetheless, temporal data visualization is one of the main challenges of Visualization and Visual Analytics. In this section, we present the approaches taken to visualize high dimension data, then focus on methods to visualize temporal information. Finally, we detail specific examples of temporal visualization techniques that drew our attention according to our main research issues, namely the Space-Time Cube and the Timeline visualizations.

### 2.2.1 High Dimensional Data Visualization

High dimensional data poses a challenging visualization problem not only due to the raw data size but also due to the heterogeneity of the different dimensions constituting these datasets. These dimensions are spatially and temporally referenced, represent numerical or categorical information, and come from various sources, such as imaging, simulations or annotation processes. Therefore, there is a large diversity in datasets characteristics and topology; ensues a visualization challenge both to represent and display such amount of information. Andrienko et al. [2] presented various approaches to handle this challenge: data aggregation and more generally dimensionality reduction; semi or fully automatic feature extraction; and juxtaposition.

First, dimensionality reduction approaches focus on extracting and displaying the most relevant information with a lower-dimensional representation in order to make it easier to apprehend or to help in classification tasks. For example, Demšar and Virrantaus [88] visualize

vessels trajectory sets by aggregating and summarizing the data as a volume by computing the density of movement, as shown in Figure 2.8. The result is thus less cluttered and more legible. Woodring and Shen [89] proposed a general visualization scheme allowing the projection of several variables, combined with different volume operations into a 3D volume. Dimensionality reduction can also rely on linear transformations. Principal component analysis is a classic example in the analysis of multidimensional points clouds. Derived algorithms [90, 91] further improved the method, better conserving the variance of the original data. Other methods use non-linear transformations to reduce dimensions, such as methods based on Fisher Linear Discriminant Analysis [92] or the locally linear embedding [93].

The second approach consists in extracting specific features or patterns from the data. This can result in abstract representations that may complete the analysis on a direct depiction of the data. For example, TransGraph [94] extracts transitions in features or data items in time-varying volumetric data to produce a graph in addition to the 3D rendering. Finally, juxtaposition helps represent and explore high dimensional data by displaying different views and projection of the data separately. Regarding this topic, Munzner [16] proposed four design choices for coordinated juxtaposed views. The different models were characterized by whether the encoding used is different or not, and whether the data displayed in each view is complete, a sub-set or a partition. For example, Duran et al. [95] proposed a system to visualize a 3D molecule simulation, juxtaposing the 3D rendering with linear information on several objects. Al-maneea and Roberts [96] notably reported that more than half visualization systems, among the 491 reviewed, had 2 to 5 views respectively in accordance with the rules of Diversity and Consistency proposed by Baldonado et al. [97], juxtaposing and coordinating several dimensionality-reduced views is a reliable option to visualize high dimensional data.

High dimensional data are diverse and their visualization face many issues. Nonetheless, higher dimensional data also includes temporal data, and as such, the visualization methods adapted to the latter can be analog.

### 2.2.2 Temporal Visualization: Dynamic vs Static Approaches

Time-oriented data is a subset of high dimensional data, yet the temporal dimension needs to be modeled particularly, according to the understanding and perception of time by the user in the context of the dataset visualized. Two main categories of approaches exist to visualize time-varying data: dynamic methods, i.e. animation and interaction, and static visualizations, of either the full data or extracted lower-dimension data.

**Dynamic Visualizations.** Animation is an intuitive method to explore time evolution in

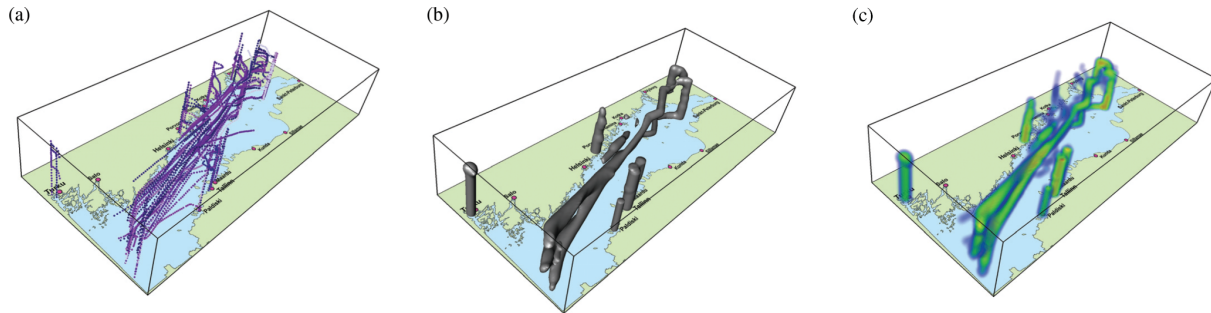


Figure 2.8 – Trajectories of tankers represented in a space-time cube; *Demšar et al.* [88]. Representation through (a) direct rendering; (b) density with isosurface; (c) density with volume rendering.

3D temporal datasets. In designs using animation, time increases automatically, showing the evolution of the data through time. The work of Coffey et al. [98] showed that animated and interactive design choices for time exploration can decrease the amount of error in analysis tasks. They also suggested that hybrid methods that would implement interactive, animated and/or static time exploration designs could compensate for the flaws of other methods. For instance, Akiba et al. [99] proposed an interactive animation interface. Using their tool Aniviz, the user was able to explore time-varying volumetric data by editing a time-dependent transfer function, specifying the evolution of parameters and how the data should overall be displayed and animated. However, animation can be less adequate for comparison tasks [75] or the analysis of space-time-value relationships [89]. There is a higher cognitive load for the user who has to remember the state of the data between different moments, which can limit the observation of details, as the slogan “*Eyes Beat Memory*” suggests. Finally, Solteszova et al. [100] proposed to use time-warping in animations to cope with this issue. Their method allows the user to manipulate time evolution of a video or a selected point of interest in the video, to allow longer and more precise observation of an event. Yet, a more intuitive solution for the fore-mentioned issue lies in static visualizations.

**Static Visualizations.** Static visualizations aim at including the temporal information directly into the visualization. This additional dimension can make direct rendering difficult, non-intuitive or even impossible, yet it can make the information reachable by the user. The approaches to solve this issue are mostly analog to the methods described for high dimensional data. Woodring and Shen [89], mentioned previously, proposed a solution for static temporal visualization for time-varying volumetric data relying on dimension reduction. Set and numerical operations, such as the definition of a time window, unions or intersections, were used to determine which data to display in the volume. Such operations aimed to reduce occlusion and focus on the points of interest. In addition, a color mapping can be applied to overlay chronological information [89].

With this method, the temporal evolution is visualized by merging the spatio-temporal data into a volume. Although, there is a compromise to make between occlusion and the amount of displayed data, it is less suited for dense spatio-temporal data. Alternatively, in order to reduce the data to display, regions of interest can be defined either manually or automatically. For example, Lu and Shen [66] used a dissimilarity measure to extract single time steps in the volumetric temporal data. The final layout displays snapshots of the data at time steps estimated as most important for understanding the data evolution. Those time steps are then linked with color mapped timeline, keeping temporal information. MotionRugs [101] is another dimension reduction based method, producing a 2D visualization by ordering objects moving in a 2D space on a 1-dimension vector using a space filling Curve. The rendered image makes patterns appear that matches trends in the movement of the objects. TransGraph, a tool developed by Gu and Wang [94], takes the approach of feature extraction, creating a graph of points of interest extracted from blocks of volumetric data. The resulting graph is juxtaposed with the 3D rendered volumetric data. Correspondences between nodes and volume regions are handled by a brushing and linking method. This allows the user to apprehend the evolution of 3D temporal data over time through a 2D interactive graph representation.

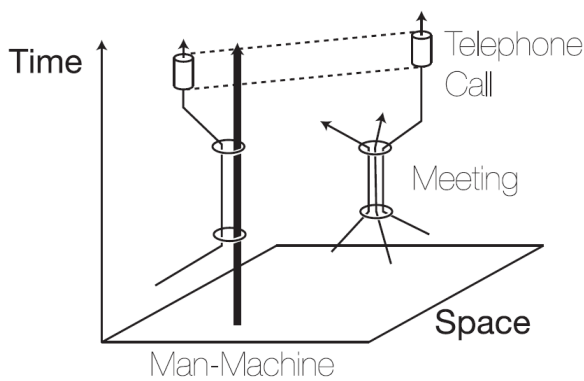
Overall, these two categories balance differently the user's capacity in terms of memory, perception and interaction with the data they will be presented. As we expected the memory workload to be too high in the case of high dimensional and temporal data, we focused on static visualizations.

### 2.2.3 Space-Time Cube Visualization

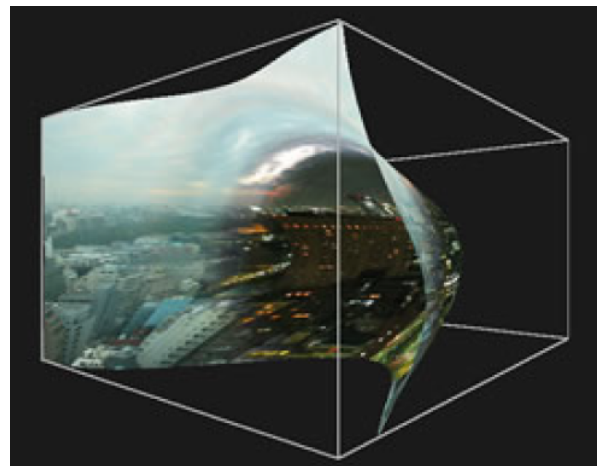
First introduced by Hägerstrand [102] as time-space volume and paths in a context of socio-economic study, the Space-Time Cube (*STC*) is a representation using two axes for data and a third axis for time, as shown in Figure 2.9-a. It is used for numerous representations of time-varying data, would it be for geometrical illustration, geographic data [103, 104], trajectories[105] or videos [106]; the latter is illustrated in Figure 2.9-b. Bach et al. [107] summarized, in their review of temporal visualizations based on the *STC*, different types of operations that can be applied to visualize data in a *STC*. Cutting operations allow the extraction of an image at a particular moment in time, as short exposure photography, or a particular plane in the data space, a slice of the cube. On contrary, flattening operations collapse the *STC* along an axis to obtain a 2D representation, when the time is collapsed, it can be depicted as a long exposure photograph. In addition, depending on the data and the visualization design, 3D rendering, interpolation, volume extraction, non-orthogonal or non-planar operations can also be used. Later work by the

same authors [108] generalized the notion of STC visualization, modelling various visualization methods as associations of operations on a STC.

Among the topics emerging from STC visualizations, two kept our attention. First, **higher dimensions** in the data, such as 3D temporal data, can be visualized as a higher dimension Space-Time Hypercube. In the case of spatio-temporal data, operations of cutting, corresponding to a projection of the 4D data, could yield a visualizable 3D image. If the idea of a higher dimension STC was evoked in Bach et al. [107, 108] reviews, this lead has not been thoroughly explored. Among the works that are the closest to it, the Woodring and Shen's [89] method described previously already evoked a time flattening operation on a STH; in this direction, Woodring et al. [109] proposed a method to generate and render 3D slices based on an arbitrary hyperplane equation. In the latter contribution, the authors gave a few guidelines to interpret the output visualization with particular value of the hyperplane equation. However, the intuitiveness of the equation parameterization and concrete interpretation of the visualization have not been formally evaluated. Finally, another method was proposed by Krone et al. [110] in which the focus was on the evolution of the surface of molecular membranes. In this scenario, surface data for each time step was projected into a plane, enabling the visualization of the evolution of the membrane in a STC.



(a) Hägerstrand [102]



(b) Cassinelli and Ishikawa [106]

Figure 2.9 – Examples of STCs from the literature. Figure (a) is STC representation of social interactions by Hägerstrand [102]; Figure (b) illustrates the Khronos Projector [106], here representing a video of a scene transitioning from day to night into a STC.

The second emerging topic from STC visualizations is **interactivity**. If Bach et al. [108] advice against operations of 3D rendering of STCs, it seems that interaction and navigation

methods, notably with immersive technologies [35] could help in solving some of the difficulties evoked [108], such as occlusion, depth ambiguity and perspective distortion. This would help take advantage of the general overview of the data that this operation can offer. STC visualization can also take advantage to direct interactions in immersive environments. For example, the GeoGate system [103] displays geographic trajectories (2D + time) in an augmented reality environment using a STC. A tabletop system displaying satellite information is coupled with the STC visualization to provide additional context information. Furthermore, the user can interact with the data through a tangible ring controller, providing natural interactions.

### 2.2.4 Timeline Visualization

Timelines are a classic visualization for temporal data, which are mainly used to represent series of events linearly or in form of a tree. Timelines have a wide range of design choices [111], and this range allows to create expressive representations. Hence, they are often used for summarizing events, storytelling or historical summaries, but also for planning, using calendars or Gantt charts for instance. Narrative visualizations are also often used to present data and information in an attractive yet understandable way, and timelines can be designed to balance perceptual and narrative effectiveness for this purpose. For example, TimelineJS [112] and TimelineSetter [113] are tools used in general media to generate slideshow timelines to describe long narratives, gathering numerous major events. In a context of data analysis, Lifeflow [114] and TimelineTrees [115] aggregate data using tree structures, and use timelines to explore the temporal aspect of these data.

Brehmer et al. [111] proposed a classification of timelines based on a review of 263 timeline designs, proposing a 3-dimension design space, illustrated in Figure 2.10. The first dimension is the *Representation* of the timeline, i.e. its “most visually salient aspect, its guiding visual metaphor”. The most common and versatile representation of a timeline is linear, yet radial or spiral representations can be more adapted to show periodic data. Other representations can rely on grids, as for calendars, or on arbitrary curves designed to support a narrative. The second dimension is the *Scale*, which determines the link between temporal and displayed distance; it is characterized notably by its reference point and the function mapping the temporal dimension (e.g. linear or logarithmic). The third dimension is the *Layout*, which describes if the display shows one timeline or multiple faceted ones, if the timelines are segmented or not. Following this work, Di Bartolomeo et al. [116] evaluated different representations on classic visualization tasks and proposed additional design recommendations. As the design space includes some non-intuitive possible designs, Brehmer et al. [111] proposed 20 most “viable” designs that were

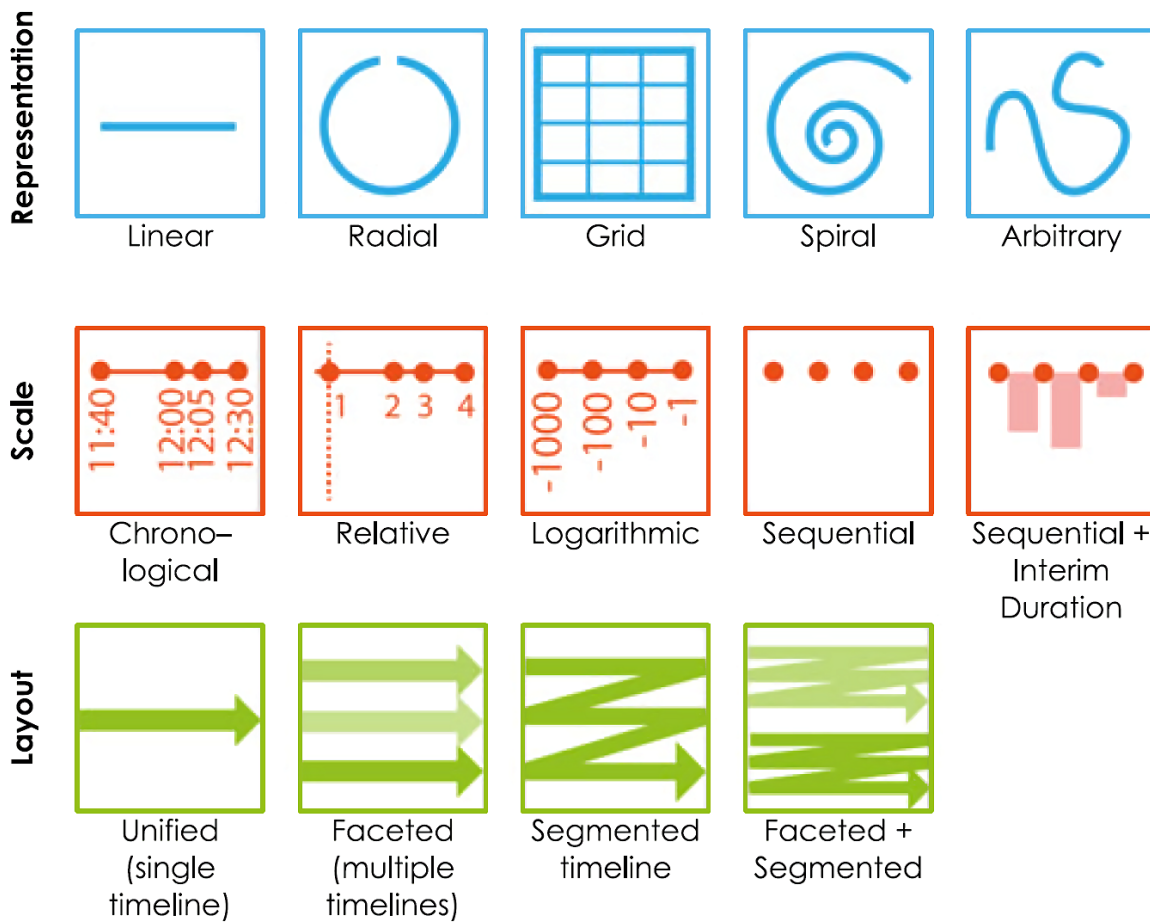


Figure 2.10 – The three dimensions of our design space for expressive storytelling with timelines: representation, scale, and layout; *Brehmer et al.*[111].

emphasized in their study. Notably, they pointed out that about half of the studied timelines follow linear chronological unified or linear chronological faceted designs. Nonetheless, 3D timeline designs are not approached in this design space, and are actually lightly explored in the literature. The few examples include Beedocs [117], a timeline authoring tool using 3D animations to explore a 2D timeline, HeloVis [118] which displays radar signal data on an helical visualization or works by Kullberg et al. [119], who use the horizontal space of a 3D environment to display time.

Nonetheless, the creation of timelines, and infographics in general, can be very time-consuming, whether it is for the extraction of information or the visual design. Several methods exist to generate timelines from different types of information. For example, a lot of temporally annotated information can be found from blogs, Twitter or Facebook content; tools like Story-

Graph [120], EvenTweet [121] or similar methods [122, 123] allows the extraction of relevant summarizing information and the generation of timelines to represent series of events. Time-LineCurator [124] extracts automatically temporal information from unstructured texts, such as journal articles, and also provides controls for curating and editing the events on a timeline. Charles et al. [125] proposed a method to generate timelines from 3D interactive narratives, which could be used to support more intuitive exploration and edition. To tackle the issue of visual designs of timelines, Chen et al. [126] proposed a deep-learning based tool to extract extensible templates from existing infographics, to use with other types of information.

To help the exploration of timelines, interaction methods adapted to the visualization have been developed. The most common interaction is based on scrolling or sliders to move in time, which is notably recommended by Blascheck et al. [127], for the familiarity with which the user will approach it. For example, works by Charles et al. [125] or Card et al. [128] use timelines to give an overview of events while using sliders to explore data in time, that is displayed in a juxtaposed view. TimeZoom [129] also relies on horizontal scrolling to move in time, yet also base several other interactions on *regions of focus*. The interaction set notably include scrolling in time by dragging the region, zooming on the region or the whole timeline in order to variate levels of detail, and finally means of creation, deletion and edition of such regions. Such classic methods as sliders or pan and zoom were evaluated by Schwab et al. [130], to give creators more guidance to adapt the navigation on their visualizations. Yet, the need for enhanced interactivity led to the use of various user interfaces for timelines. As such, Morawa et al. [131] proposed Time Beads to interact with the timeline using a touch user interface to support intuitive manipulation of time points, and Drossis et al. [132] proposed to explore the temporal information through a *time-tunnel*, displayed in an immersive 3D environment.

However, S4D data is rarely considered on timeline visualizations. A few examples can be found in contexts of 3D model editors, as proposed by Denning et al. [133] or Doboš et al. [134], that use timelines to display the step-by-step construction of the model. Although, S4D visualization tools sometimes use timelines as sliders, juxtaposing 1-dimension additional information with the 3D spatial data, as in Duran et al. [95] work or RubberSlider [59], which uses a VR adjustable slider to explore a timeline and display 3D data.

The two static temporal visualization methods presented in this section provide static views of temporal information, with very general and versatile approaches. On both cases, the visualization can be dense, introduce clutter or be overall difficult to access information precisely. As



such, interactive designs are often proposed to extend the capacity of the user to exploit these visualizations. Although, visualizing spatial 3D temporal data in such context introduces further obstacles, notably in terms of displayable dimension, workspace and user perception of 3D and temporal information. Nonetheless, the field of Immersive Analytics explores the usage of immersive interfaces and displays for visualization. Such system and associated methods could provide solutions to tackle the issues aforementioned.

## **2.3 Immersive Visualization for Temporal Data**

As reported in LaViola et al. [39], technologies that support 3D user interfaces, such as stereoscopic displays, 3D tracking or pointing device, are becoming mature and are proliferating. Notably, the release of affordable high-quality HMDs since 2016, notably with the Oculus Rift and HTC Vive, replaced the CAVE system [135] that got popular in the late 1990s. Applications are getting more and more common, in fields as art, education and formation, architecture or gaming. Concurrently, the number of immersive visualization applications publications increased, as reported by Fonnet and Prié [58]. These applications rely on various characteristics of 3D virtual environments (VEs) that match the related tasks: the feeling of presence provided by VEs can enhance gaming and simulation; 3D interactions simulate natural skills and thus support training applications.

In this section, we report Immersive Analytics applications for scientific visualization, information visualization, and finally we consider solutions proposed to tackle the major issue of comparison of 2D and 3D temporal data.

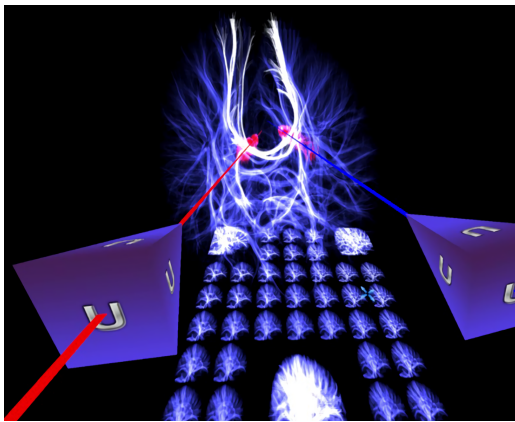
### **2.3.1 Immersion for Scientific Visualization**

As mentioned in Section 2.1.2, scientific visualization can take advantage of the perceptual benefits of virtual environment for the representation and display of 3D data. Natural interaction completes this display, helping efficient exploration of the data. As such, many Immersive Analytics systems were developed for scientific visualization, for various use cases.

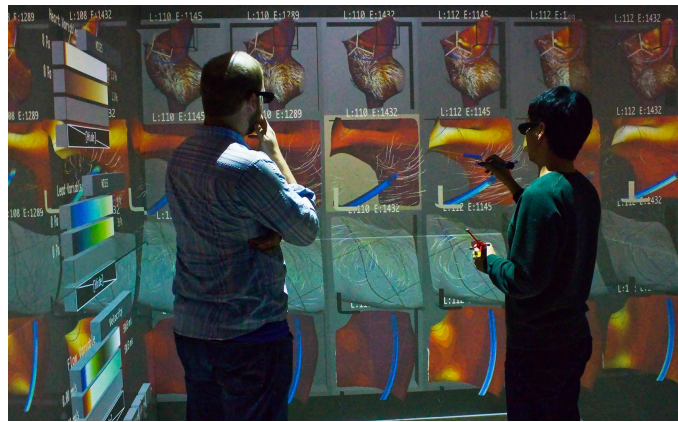
In the context of biology imaging, El Beheiry et al. [136] proposed DIVA, a Virtual Reality system supporting the exploration of high-resolution microscopy 3D images. The system renders images with up to 4 channels of information, with customizable transfer function for each channel, and includes basic manipulation and annotation features. Another VR system, Genuage [137], handles point cloud data, notably generated through biological microscopy. It

proposes methods to select a group of points in the cloud by defining a convex mesh, placing the vertices through direct 3D interaction. In the domain of archeology, several immersive applications exist to either explore archeological sites or interact with fragile artifacts, as reported by Gaigne et al. [138]. For example, ArtifactVis2 [32] renders 3D environments generated through datasets of GIS data, 3D artifact scans and digital photography, recreating and allowing users to explore complete archaeological sites excavation. Lécuyer et al. [139] proposed the software INSIDE to visualize and manipulate artifacts, relying on the stereoscopic and interactive screen zSpace. Likewise, Immersive Analytics systems approach geographical and trajectory datasets. Hurter et al. [140] propose FiberClay, depicted in Figure 2.11, a system that renders large 3D trajectory sets, which includes a bimanual intersection brushing technique to efficiently select trajectories, and refine that selection by adding or subtracting trajectories from the selection set. Moreover, Filho et al. [105] propose to display trajectory datasets using a Space-Time Cube in immersive environment, as shown in Figure 2.11-c. Providing with a basic interaction toolset, they notably report that it helps in usability and partially addresses the issue of the steep learning curve of Space-Time Cubes.

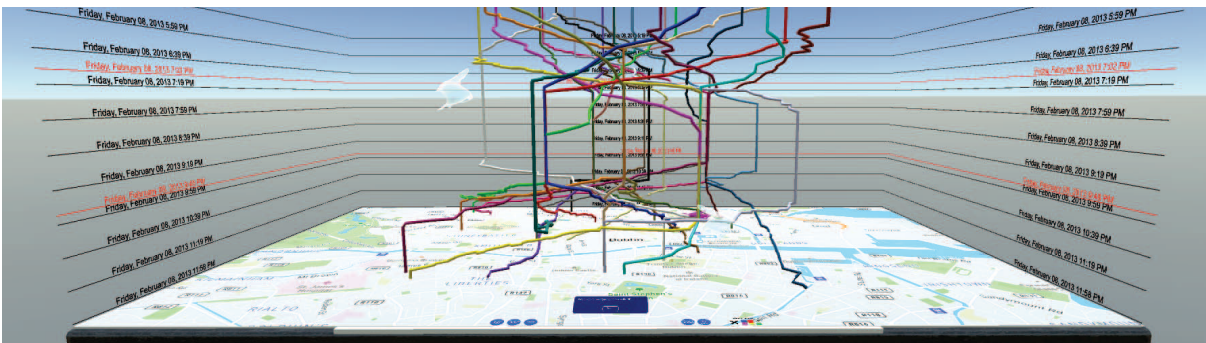
A specific issue often mentioned in visualization, and especially in scientific visualization, regards comparison. Such task is often a very important step in the analytical process, through the comparison of a simulation or a model to an observed ground truth, or else of multiple acquisitions of a same entity. Yet, it basically adds a dimension to the data, making visualization and interaction challenging, as highlighted by Kim et al. [75] survey. The latter also notably mention that juxtaposition is a natural approach for comparison tasks, and therefore the large workspace available in 3D environments can come especially useful. Hence, immersive analytics systems were designed around comparison tasks. For example, Johnson et al. [141] proposed BentoBox, a Virtual Reality data visualization interface for simulated 3D temporal data, illustrated in Figure 2.11-b. BentoBox disposes of a range of tools focused on the comparison of datasets and manipulation of parameters, using animations, color mapping and 3D bimanual interactions. Following a small multiple approach, it juxtaposes the same simulated volumetric dataset under different parameters, related either to the display options or to the simulation, in an array allowing direct comparison of up to twenty to thirty instances. The small multiple approach was further developed by Liu et al. [142], who proposed a design space to arrange small multiples in a 3D environment, notably to improve comparison.



(a) FiberClay, Hurter et al. [140]



(b) BentoBox, Johnson et al. [141]



(c) Wagner Filho et al. [105]

Figure 2.11 – Examples of Immersive Analytics user interfaces from the literature. Figure (a) is Fiberclay [140], which features a bimanual interaction for selection tasks in a large trajectory dataset; Figure (b) is BentoBox [141], showing simulations of blood flow in a heart. Each column has different simulation parameter, each row shows a different view of the data; Figure (c) is a VR implementation of a STC representing trajectories by Wagner Filho et al. [105].

### 2.3.2 Immersion for Information Visualization

An additional challenge comes with information visualization, regarding how to use the 3D environment to display non-spatialized data. To create efficient and natural interactive exploration and visualization of such data, several toolkits were developed for immersive environment, such as DXR [143] or IATK [144]. Both use a visualization and interaction grammar inspired by Vega-Lite [145]. Vega-Lite, itself based on the Vega language [146], proposes high-level specification for interactive data visualization, combining a grammar of graphics and a grammar of interaction. The grammar of graphics defines *units* to describe one set of data, its transforms, filters, type of display and other visualization parameters. Units can be used to create more complex views,

called *layers*. Several operators are then available, to merge shared axis, apply concatenations, create different views. The grammar of interaction is based on *selections*. It is designed to select points corresponding to a predicate when an event occurs, and then apply transforms on the data, such as addition or removing from selection, translation, zoom.

DXR [143] is a toolkit for Unity to design immersive data visualizations. It relies on a Vega-Lite inspired graphics grammar. It defines an analog to the Vega-Lite *unit*, but simplified, named *dxrvis*, composed of the data, the graphical object, a description on how the data is mapped. The graphical object is represented by a Unity prefab, representing each data as a recognizable object. With this grammar, DXR proposes a high-level GUI and a panel of object templates, easy to learn and efficient to prototype quickly visualization, as illustrated in Figure 2.12. The interaction part is though limited to scaling, rotating and details on demand when pointing any of the data item visualized, and performances decrease after an order of magnitude of a thousand objects. IATK [144] is, similarly to DXR, a Unity package for immersive visualization. It is a high-level interface based on a composable grammar capable of rendering millions of data items and offers a large interaction panel. The graphic grammar defines several elements:

- view-frames to choose the type of representation of the data, such as scatterplots or matrices,
- geometric objects to represent the data item, as spheres, cubes or quads, named *glyphs*,
- data mapping,
- visual linking across multiple visualization.

This allows the user to create a wide range of visualization. Some commonly used, such as scatterplots, line graphs or trajectories, are preconfigured in the IATK package, yet the expressive API also allows the creation of novel immersive visualizations, as shown in Figure 2.13. Representing the data through glyphs optimizes the rendering, such that the system can displays several million data points at usable frame rate. The interaction model is also designed to support large datasets. It includes functionalities of filtering, i.e. removing outliers or defining ranges on the axes, details on demand, animated transitions and a *brushing and linking* tool to outline corresponding data on several visualizations, using GPU computation to maintain performances.

These approaches compromise differently the spatialization and quality of representation of the data, the interaction and the amount of data available to the user. These different characteristics are adapted to different use cases, notably depending on the amount of data, the type of feature to observe or the profile of the user.

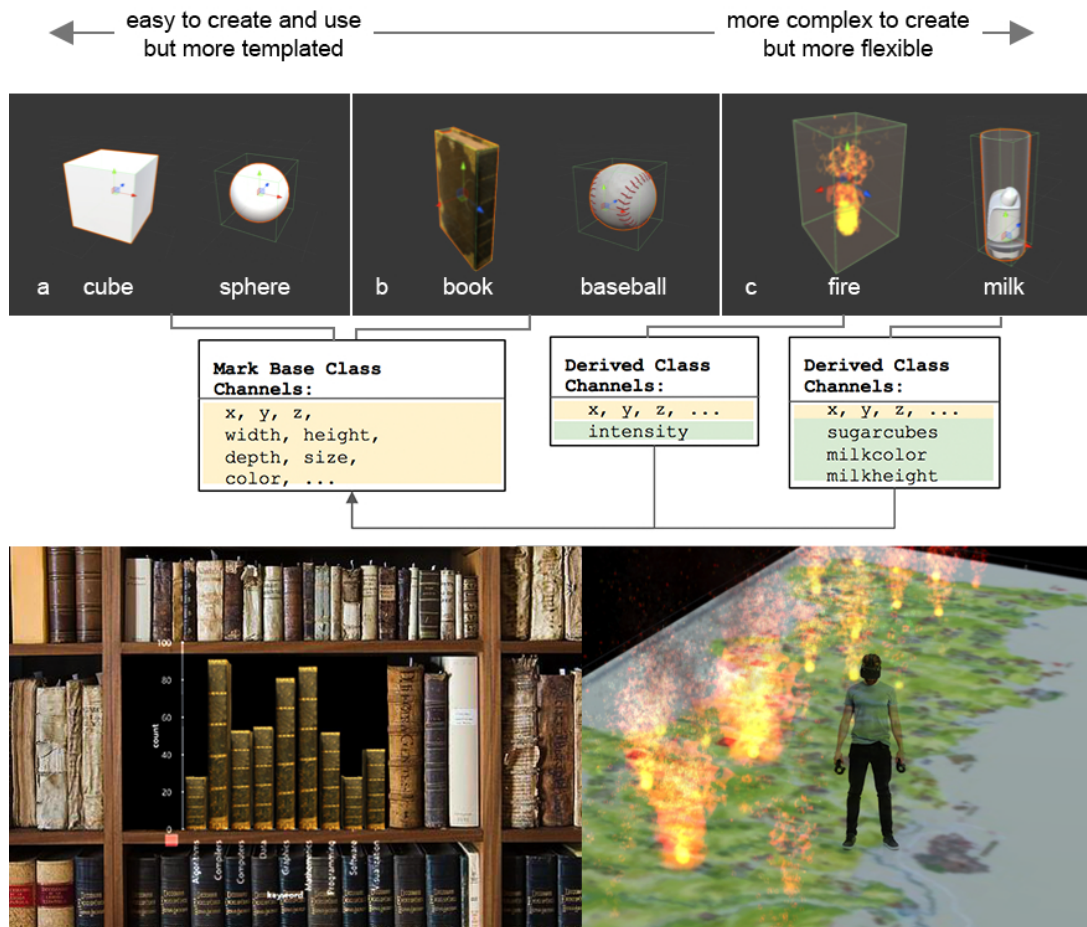


Figure 2.12 – Visualization prototypes using DXR, on different use cases and using different types of graphical representation of the data points; *Sicat et al.* [143]

### 2.3.3 Collaborative Mixed Reality

The question of collaboration in Immersive Analytics is often raised in the community [31, 147]. Ens et al. [147] discuss related challenges, in terms of hardware and communication between users, and also suggest cross platform collaboration for specific use cases requiring different perspectives or users with different roles. We discuss in this section the main solutions existing for multi-user MR applications, and then potential of asymmetrical collaboration setups.

#### Multi-user Applications in Virtual Environments

Margery et al. [148] proposed a general framework for cooperation in VEs, based on three levels of cooperation. The first level, basic cooperation level common to all multi-user systems,

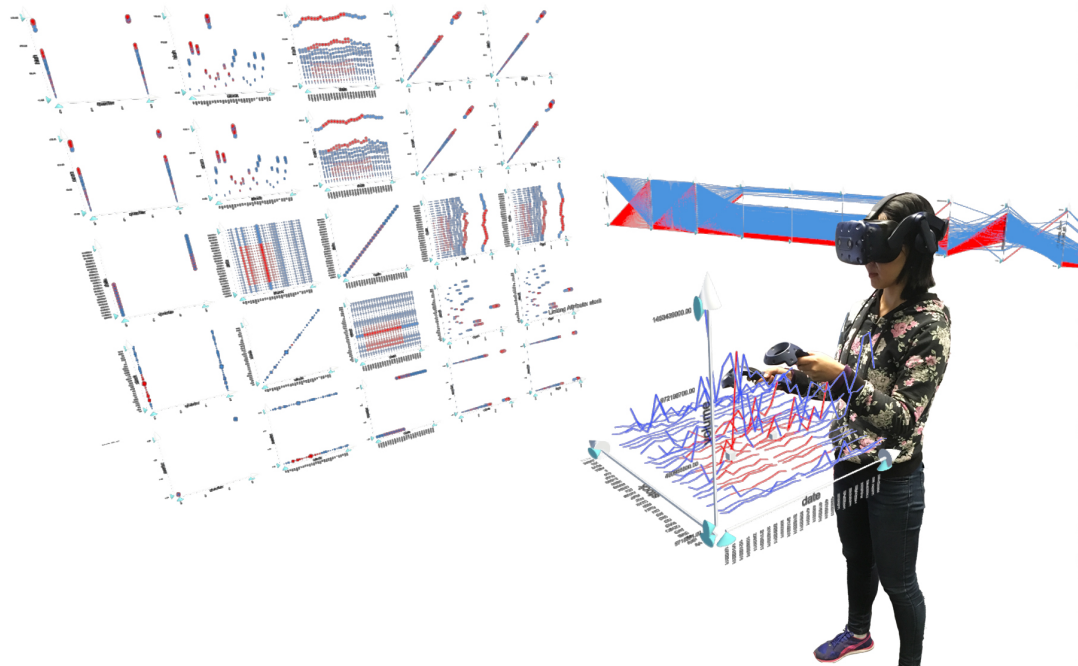


Figure 2.13 – VR visualization of multidimensional data (Dow Jones dataset) using IATK. The user brushes a 3D trendline, and the selection is colored similarly on the other visualizations; *Cordeil et al.* [144]

is done by enabling perception of the other users through avatars, and providing communication means between them. The second level is defined by the action the user can execute on the scene. This level can be subdivided, depending whether the interactions are constrained by the scene or if the users have freedom of actions. The third level is attained if multiple users can interact in cooperation on one object. This level can be subdivided as well, first if the cooperation is done on independent properties of the object, or if the properties can be modified through a combination of the input of the users cooperating.

These levels of collaboration must be supported with adapted hardware and infrastructure to share one same virtual environment between multiple users. The most usual solutions rely on see through AR HMDs, VR HMDs or CAVEs. Although, the latter implies important cost and infrastructure, whereas VR HMDs get similar or even better results on classic analytical tasks, according to Cordeil et al. [149], so CAVEs system are now less considered for such application. Network software architecture has to be adapted as well to ensure information and application state consistency between the users. For example, Fleury et al. [150] compared multiple models of network architecture for data distribution and communication between nodes.

The authors also proposed a dynamic adaptive model implementing three data distribution modes, in order to answer to constraints of network capacity, consistency and responsiveness of various environments.

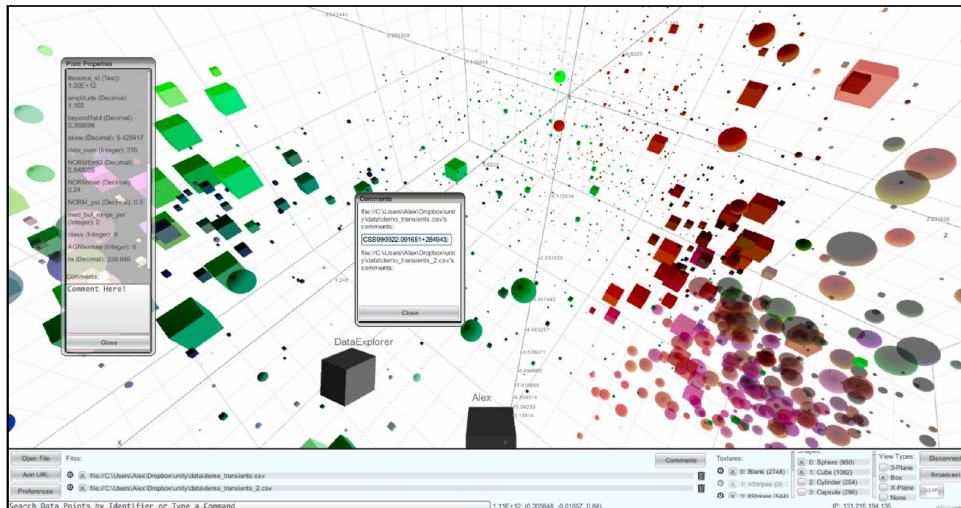


Figure 2.14 – Interactive user interface of the data visualizer iViz; *Donalek et al.* [151]

Multi-user applications for Immersive Analytics are explored a little, with systems as Telearch [152], a virtual reality system for archeology or Shvil [153], an augmented reality system for land navigation, which both proposed distributed collaborative features. Donalek et al. [151] presented a progress report on VR systems directed toward information visualization, and presented iViz, illustrated in Figure 2.14. iViz is a system based on Unity for information visualization, multi-platform and notably supported on web-browser, allowing multiple users to share a view with one user navigating through the data.

Although, as evoked previously, immersive applications are beneficial for certain complex 3D and depth-related tasks, yet some tasks are more suited to 2D setups. One of the solutions proposed in the literature, notably by Isenberg [154], relies on asymmetric collaboration.

### Hybrid Systems and Asymmetrical Collaboration

The development of hybrid systems, i.e. systems that are based on several different interfaces, is closely related to asymmetrical types of collaboration. Hybrid systems allow to implement techniques using multiple displays, and especially using both immersive and 2D setups, in order to cover more efficiently visualization tasks and to display data of different nature [155]. In this dynamic, several systems were proposed, such as the CyberCommons [156] and CAVE2 [157] systems, that propose stereoscopic screens, more adapted to 3D data for example, adjacent to

2D high-definition screens, to display graphs or 2D images. The DataSpace system proposed by Cavallo et al. [158] is a room-sized environment designed for high adaptability of heterogeneous devices. It is composed of 15 high-resolution displays controlled by robotic arms to modify the configuration of the room and screens, depending on the analytical need; it also includes table projectors, AR and VR headsets, and delivers the content through web-based technology to connect easily to smartphones or laptops. With such diverse interfaces, multi-platform compatibility, 3D and 2D visualization capabilities, the authors introduce the term of “Hybrid Analytics” to design such environments.



Figure 2.15 – DataSpace environment, with 15 high-resolution displays attached to robotic arms, 2 table projectors, AR and VR headsets; Cavallo et al. [158]

Nonetheless, some simpler systems involve two users in a AR/VR setups or even desktop/VR setups, and can focus on specific scenarios. For example, Vishnu [159] proposes a teacher-student type of collaboration: an expert is equipped with an AR headset and is working on real material, while the student is equipped with a VR setup and interacts with a virtual environment. Usually in collaborative analytical scenarios, the tasks and the information are, at least partially, separated and the nature of the visualizations on both displays are different. Consequently, the issue of communication comes up to synchronize the information and interaction to achieve the analytical task. Reski et al. [160, 161] experimented on the communication between users collaborating through different interfaces. Figure 2.16 illustrates one of the experiments [161], with the two user interfaces, one on desktop, the other in VR. The experiment consisted in finding correlation between climate information, help by the desktop user, and plant information, held by the VR user. The participants then answered a questionnaire proposed by the authors and based on Snowdon et al. [162] characterization of key features of collaborative virtual environments:

- Transition between shared and individual activities;



- Negotiation and communication, through verbal and non-verbal exchange of information;
- Sharing context, i.e. the characteristics and features of ones part of the interface and information;
- Awareness of others, of the activities of the peer.

The results of this experiment reflected good awareness of the peer’s activities independently of the interface, frequent verbal communication and a shared understanding of the overall data. Not only the separation of the interfaces and information is not that much of an obstacle to analytical tasks, the users also were enthusiastic about working together in a balanced way, yet through different interfaces.

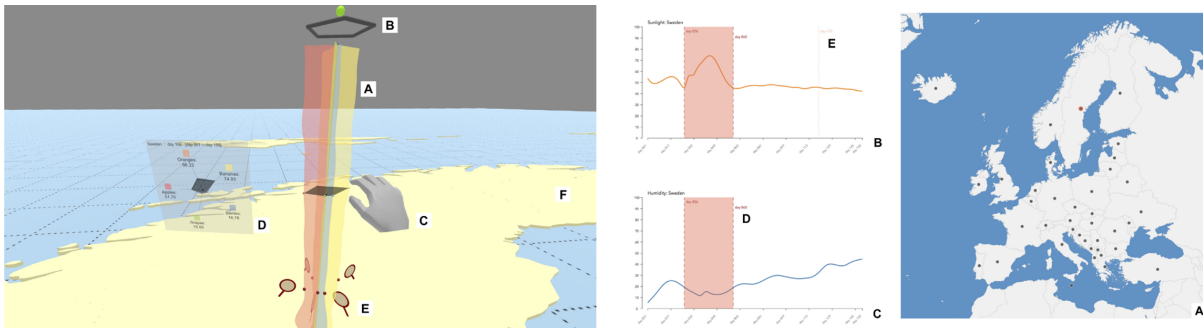


Figure 2.16 – Two user interfaces from Reski et al. [161] experiment. The left image shows the immersive interface, with a 3D Radar Chart visualization [163]; the right image shows the desktop interface, with views of a map and graphs. The desktop interface shows, through a red dot on the map, the position of the immersed user.

## 2.4 Conclusion

In this chapter, we gave the definitions and described the main research questions and objectives of the domains, in order to contextualize our approaches. We notably introduced the notion of 4D object as a representation of 3D temporal features in order to support the interaction and the visualization of the main characteristics of these features. Then, we summarized the main techniques of visualization of temporal data and 3D temporal data, focusing on static visualizations and especially Space-Time Cubes and Timelines. Finally, we reported solutions developed in the field of Immersive Analytics to approach scientific and information visualization, and eventually for collaborative Immersive Analytics. We also presented examples of 3D temporal datasets taken from biological imagery, that we will use to illustrate our contributions presented in the following chapters.

# IMMERSIVE AND INTERACTIVE VISUALIZATION OF 3D SPATIO-TEMPORAL DATA USING A SPACE TIME HYPERCUBE APPLIED TO BIOLOGICAL IMAGING DATA

---



---

3.1	Space-Time Hypercube Visualization . . . . .	51
3.1.1	Generalizing the STC in 4D . . . . .	51
3.1.2	Extracting a 3D STC from a 4D STH . . . . .	52
3.1.3	Visualization: 3D Rendering and Quantitative Data . . . . .	53
3.1.4	Interacting with the STH and STC . . . . .	55
3.1.5	Generation and Interaction Performance . . . . .	59
3.2	Use Case: Application for Morphogenesis . . . . .	59
3.2.1	VR Visualization Application . . . . .	59
3.2.2	Use Cases . . . . .	60
3.3	Evaluation . . . . .	62
3.3.1	Tasks and Hypotheses . . . . .	63
3.3.2	Apparatus and Participants . . . . .	64
3.3.3	Experiment . . . . .	65
3.3.4	Results . . . . .	66
3.3.5	Discussion . . . . .	67
3.4	Expert Feedback . . . . .	68
3.5	Additional examples . . . . .	70
3.6	Conclusion . . . . .	70

---

Our first approach regards the visualization of 3D temporal regions of interest with large temporal components. Such region describes the continuous evolution of values or shape of objects, which is essential to analyze an object and can potentially give insight on the global evolution of the dataset.

In this chapter, we propose an extension of the Space-Time Cube (STC) visualization technique [107] adapted to 4D spatio-temporal data, named hereinafter Space-Time Hypercube (STH). Conceptually, the STH is a representation of the 3D temporal data which consists laying the data in a 4D hypercube with three spatial dimensions and one temporal dimension. To enable the direct visualization of the 4D hypercube, we extended the classical operations of the STC to generate varied meaningful 3D visualizations, that are juxtaposed to obtain a compact overview of spatio-temporal data. Precisely, we propose a projection operation on the hypercube, independent of the type of spatial representation (e.g. mesh, volumetric), which projects the hypercube into a 3D volume that can be directly visualized. The projection operation relies on a user-defined cross-section on the spatial dimension. This cross-section is then computed along the temporal dimension and stacked together into a 3D volume, which can be enriched with numerical and categorical data (see Figure. 3.1).

In order to explore efficiently the complex 3D structure generated, we use the STH in an immersive environment and propose a set of interactive tools to explore and analyze the dataset. The enhanced depth perception of the virtual environment should improve the visual extraction of meaningful structures of the STH. and the use of 3D user interfaces would allow users to explore naturally the STC from different perspectives. The set of interaction proposed includes methods to explore naturally the complex structure, yet also selection methods that use the notion of 4D objects defined previously, supporting further analytical tasks. Furthermore, the enlarged interaction space of VR allows the juxtaposition of the STH and snapshots of the original spatio-temporal data. This juxtaposition enables the synchronized exploration and manipulation of the two visualizations. Finally, the chapter presents a use-case illustrating the usages of the STH for the visualization of spatio-temporal data in embryo developmental studies, as well as an evaluation of this visualization method both with non-expert and domain expert users. The illustrations used and use cases explored in this chapter are based on the recordings of embryonic development of a *Phallusia Mammillata*, the first dataset presented in Chapter 2, Section 2.1.3.

In summary, the main contributions of the chapter are:

- A novel visualization method for spatial 3D temporal data based on the Space-Time Cube method, with a generation algorithm independent of the spatial data encoding.
- Description of VR system for the visualization of the STC including specific 3D interaction

methods for the exploration and manipulation of the juxtaposed views.

- A formal evaluation of the proposed method on embryology use cases by non-expert users and domain experts.

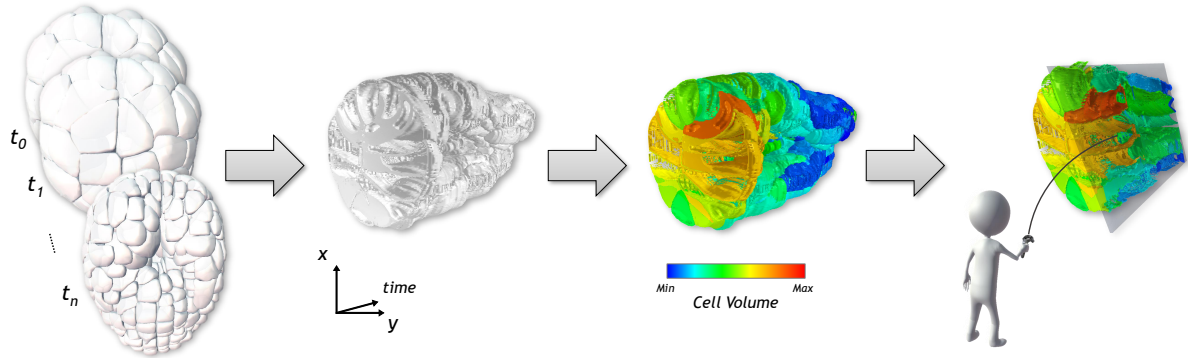


Figure 3.1 – From a cross-section on the 3D surface-based temporal data shown on the first figure, we generate a Space-Time Cube visualization, displayed in the second image, showing the evolution over time of the spatial data of the cross-section displayed on the x and y axes. The third picture shows how the visualization can be enriched with quantitative and qualitative data using different color coding. A set of interaction tools help the user to explore the generated visualization, as seen in the last image.

### 3.1 Space-Time Hypercube Visualization

This section presents our main visualization method, based on the Space-Time Cube. First, we present a generalization of the STC in 4 dimensions, the STH, then we detail the design choices for the generation and visualization, as well as the interaction methods available.

As a support example for this section, we will use a dataset of a time-varying 3D spatial data, a 6-hour-long live recording of an embryo development. In this work, we use 100 of the 180 time points recorded, from a 65 to 383 cells embryo. Figure 3.1 shows some of the time steps of the embryo that were used. The dataset is composed of surface meshes, for each cell at each time step. The temporal links between cells, notably after division, are also present, as well as quantitative and qualitative information. The dataset will be described more thoroughly in Section 3.2.

### **3.1.1 Generalizing the STC in 4D**

In a classic 3D STC, the data visualized is composed of 2 spatial dimensions as well as a temporal dimension  $(x, y, t)$ . In contrast, a STH can contain 3 spatial dimensions and a temporal component  $(x, y, z, t)$ . With this abstraction, any elementary operations applicable on a STC, notably described by Bach et al. [107, 108], should be extendable and applicable to the STH. Geometry and content transformations now modify a 4D volume, filling operations now includes 4D interpolation, extraction operations can render 4D volumes and flattening operations can compress 4D data into a 3D volume. Complex operations for a STH can be designed based on this extended set of operations. One of the main objectives of such operations is to provide meaningful visualizations of the data, but with varied points of view and dimensionality.

In practice, while a STC can be directly rendered, a STH cannot be directly rendered as is. To enable a direct visualization, a projection operator on the STH has to be defined either by using an extraction or a flattening operation that would result on a 3D volume, yielding a 3D visualization. However, using such method on denser data can result in a volume which would potentially be prone to occlusion issues, because of the increased density due to data aggregation. In contrast, a volume extraction operator would enable the reduction of the data dimension without the increased data density. Thus, we opt for a volume extraction operating by defining a hyperplane laying in a 4D space. Nevertheless, two major issues remains:

- An extraction operation implies a loss of data during the creation of the visualization. Thus, the user must have control over which data is selected.
- The concept of a 4D hypercube is not easy to comprehend; the extraction of a volume along a hyperplane is even more difficult. The complexity of the model will be a constraint during the extraction operation, as well as any other interactive operation based on the 4D data.

These two constraints will influence our design choices, especially the generation process for our 3D STC visualization.

### **3.1.2 Extracting a 3D STC from a 4D STH**

The proposed projection method relies on the use of a 4D hyperplane, manually defined by the user, to extract the 3D visualization. However, the definition of a hyperplane of this nature is an abstract task which cannot be directly visualized. A simple example would be to define a hyperplane perpendicular to the time axis which would result on the extraction of the spatial

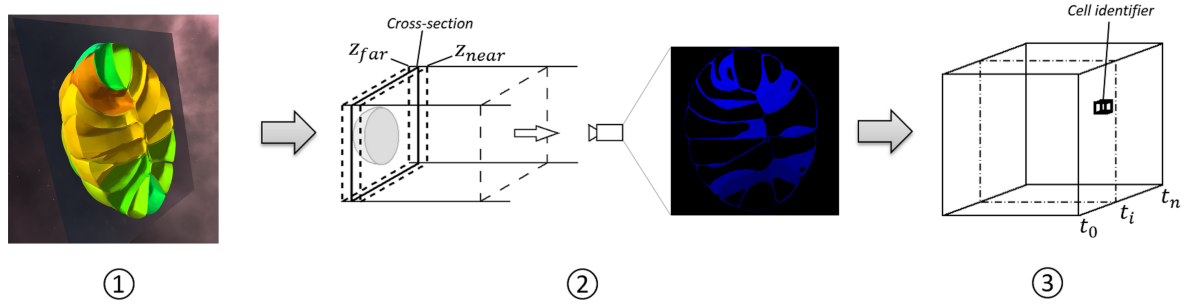


Figure 3.2 – Flow diagram of the STC generation. In step ①, the user places the interactive clipping plane to get the desired cross-section. In step ②, camera parameters are automatically set in order to render the cross section at each time point. The image presents the output of the rendering operation, using the RGB channels to save cell identifiers. Stacking the rendered images yields a 3d volume, as shown in step ③. Each voxel contains a cell identifier, and its position in terms of depth indicates a time point  $t_i$ .

data at a given time point. In order to ease the process and obtain a hyperplane yielding more informative STCs, we propose a user defined approach based on the cross-section, a commonly used tool in scientific visualization to explore spatial 3D data, extracting a 2D view from 3D data.

Precisely, the user can place an interactive clipping plane, that will act as a cutting plane, as they would do to get a cut-away view of 3D spatial data. With the same analogy that we used to consider our spatio-temporal data as a 4D volume, the plane, as a time-varying object in the 3D space, can be considered as a hyperplane in the 4D space. The operation thus corresponds to a projection such as  $(x, y, z, t) \rightarrow (x', y', t)$ , with  $x', y'$  the projected coordinates on the cutting plane. Such projection avoids any spatial distortion that could impair the interpretation of the output shape. Considering the whole dataset as a 4D Space-Time Hypercube, it sums up as a space cutting [107] by a hyperplane, extracting a 3D space-time cube.

The proposed generation method is data agnostic (either mesh-based or volumetric) and its three main steps are illustrated in Figure 3.2, and summarized in Algorithm 1. ① The user places a clipping plane on the model at any time point in order to define the “hyperplane” which will determine the projection. ② For each time step, a 2D image of the cross-section of the 3D model is computed. The rendering is achieved by setting an orthogonal camera perpendicular to the clipping plane and setting the near and far planes at a distance of  $\varepsilon = (z_{near} - z_{far})/2$  towards the clipping plane. The field of view of the virtual camera is minimized according to the maximum size of the cross-section over time. The color channel of the rendered image encodes objects (cells in our examples) identifiers, which allows indexing numerical or categorical data during

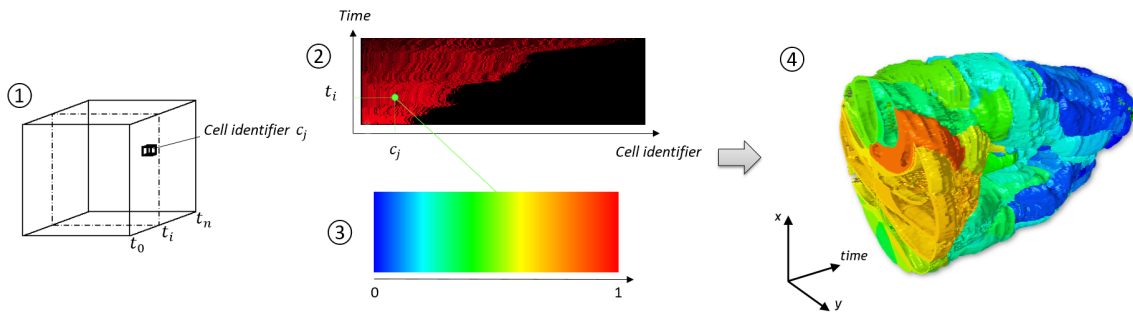


Figure 3.3 – Visualization process. Figure ① corresponds to the output of the STC generation. Each voxel contains the cell identifier  $c_j$  and a time point  $t_i$  can be found. Figure ② is a texture containing quantitative information - here the volume of each cell at each instant - normalized between 0 and 1. The value at  $(c_j, t_i)$  points to a 1D color gradient, shown in figure ③. Figure ④ is the resulting visualization after shading and color mapping. Smaller cells can thus be identified by a colder color, bigger cells by a hotter color.

visualization. ③ The output images are stacked into a 3D texture in which the RGB channel is used to keep track of the object identifier. The depth coordinate for each pixel encodes the time step. The use of object identifiers is considered for convenience when the spatio-temporal data has this information. In case that this information is not available, other information could be stored, such as density values from a CT or fMRI volumetric dataset.

---

**Algorithm 1** Generation of the Space-Time Cube. First, the camera parameters are initialized and the identifiers of the cells are encoded into colors. Then, for each time point, the camera renders the cross-section and the result is added into the 3D texture.

---

```

1: procedure GENERATESTC(ray, start, end) : Texture3D
2:   Texture3D texture3D
3:   InitCameraParameters()
4:   for each cell  $\in$  Cells do
5:     cell.color  $\leftarrow$  encodeIdAsColor()
6:   for each  $t \in \llbracket t_0, t_n \rrbracket$  do
7:     tempTexture2D  $\leftarrow$  camera.Render()
8:     texture3D.AddTexture2DAAt(tempTexture2D, t)
9:   return texture3D

```

---

### 3.1.3 Visualization: 3D Rendering and Quantitative Data

The projection operator generates a 3D texture which can be directly rendered using Direct Volume Rendering methods [164]. Due to the nature of our datasets, we consider an opaque

rendering avoiding semi-transparency, in order to limit color distortion when using color to encode information. Thus, once a hit is found, the final color for the ray can be computed. In order to compute the color of the ray, two indexations are required so that we can properly use the cell identifier and annotate the objects accordingly. First, using the cell identifier ( $c_i$ ) and the time step ( $t_j$ ), encoded in the RGB channels of the 3D texture and the depth ( $z$ ) position of the voxel respectively, we can obtain the attribute value of the cell at the given time step ( $a_{i,j}$ ). This information is encoded in a 2D texture (see Figure 3.3 ②) Second, the attribute value allows to index a 1D texture, which encodes the color (Figure 3.3 ③). Thanks to this method, switching either the information displayed on the visualization or the colormap used only consists in switching a small texture. Finally, we apply a Blinn-Phong illumination model on the cube to enhance depth cues and get a better understanding of the shape of the volumetric data. To reduce the rendering time, normals are pre-computed during the generation of the STC and stored in an additional 3D texture. Normals are computed using 3D Sobel-Feldman gradient operators on each direction:

$$\vec{n} = \left( \frac{\partial S}{\partial x} \quad \frac{\partial S}{\partial y} \quad \frac{\partial S}{\partial z} \right)^T \quad (3.1)$$

with  $S(x,y,z)$  representing the surface,  $\vec{n}$  normal to the surface. The result of the 3D rendered color mapped STC is shown in Figure 3.3 ④. The full adapted raycasting algorithm is described at Algorithm 2. Depending on the numerical or categorical information that has to be rendered, a number of attributes and color textures can be pre-computed. As discussed in the previous section, when object identifiers are not available, the information stored at each voxel could be used to directly index a color palette.

However, the rendered STC could still contain a lot of information and could present a complex layout. The following section details manipulation techniques proposed in order to improve the exploration of the STC.

### 3.1.4 Interacting with the STH and STC

Interaction will be a key concept to compensate for issues implied by direct rendering, such as occlusion. Bach et al.[107, 108] described several generic operations that could be applied to a STC, and mentioned dynamic uses of those operations. In addition, by displaying the STC in a VR environment, additional depth cues will be available, such as binocular cues and motion parallax cues [165], which will increase the identification of the intricate structures in the STC.

In the first place, as previously mentioned, the STC is interactively generated, since the user



can choose the base cross-section, and thus the hyperplane, and start the generation process at run time, doing a space-cutting operation of the 4D data. Taking advantage of immersive environment in terms of interaction, we considered and designed a number of interactions adapted to our data structure and the benefits it would imply for data visualization. All the techniques described in the following sections assume that the user is wearing a head mounted display (HMD) and holding by the hands two 6DoF hand-held controllers. As such, the user will be able to explore the STC by just naturally walking in the virtual environment and use both hands to use the different tools. We refer the reader to the accompanying video which showcases the different interaction tools.

### Exploration tools

The tools described in this section are meant to help the user to explore the potentially dense and occluded volumetric representation.

**Selection operator:** This tool is a pointer that displays summarized information of the hovered object, such as its identifier. More detailed information can be accessed upon clicking on

---

**Algorithm 2** Simplified Ray Casting Algorithm. The method considers a *ray* generated from the virtual camera position and *start* and *end* define the first and last intersections points with the 3D volume. Four major textures are used: 3D texture containing the cell identifiers (*textureCell*), the 2D texture containing the quantitative data for each cell (*textureData*), the gradient (1D) used to encode the quantitative data (*texturePalette*), and the normal 3D texture (*textureNormal*). As we are considering and full opaque rendering pipeline, once the first intersection is found the RayCasting is terminated.

---

```
1: procedure RAYCAST(ray, start, end) : RGBColor
2:   current  $\leftarrow$  start
3:   while current < end do
4:     voxel  $\leftarrow$  computeVoxel(ray, current)
5:     cellId  $\leftarrow$  fetchCellId(textureCell, voxel)
6:     if cellId  $\neq$  -1 then ▷ Check for an intersection
7:       timeStep  $\leftarrow$  voxel.z
8:       value  $\leftarrow$  fetchData(textureData, cellId, timeStep)
9:       color  $\leftarrow$  fetchColor(texturePalette, value)
10:      normal  $\leftarrow$  fetchNormal(textureNormal, voxel)
11:      color  $\leftarrow$  computeLighting(color, normal)
12:      return color
13:      current  $\leftarrow$  current + samplingDistance
14:   return (0,0,0)
```

---

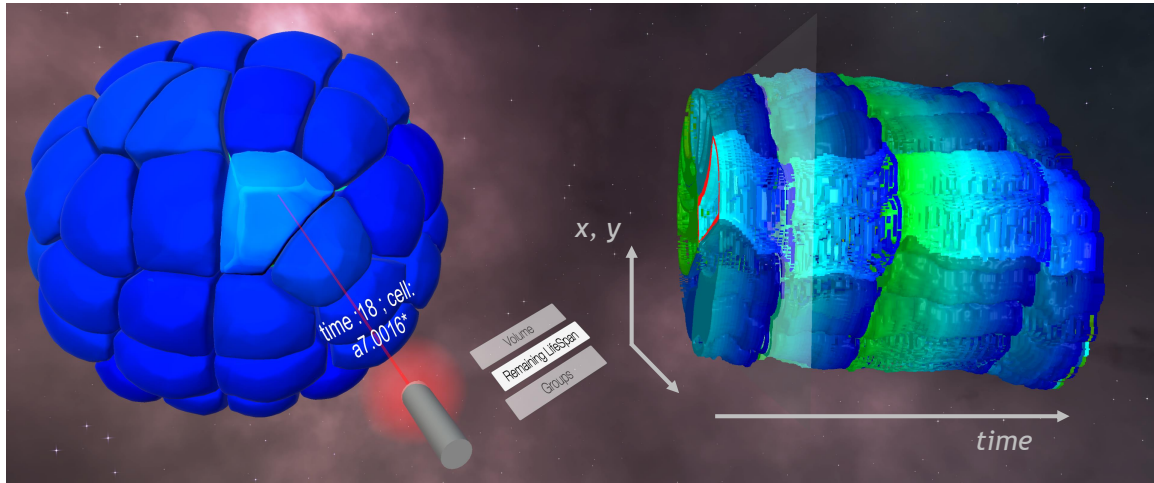


Figure 3.4 – STC (right) and meshed model (left) visualizations in the VR framework. On the laser selector, a list of available information allowed the user to color map the remaining lifespan of cells on the visualizations. A cell is selected on the meshed model. The name of the cell is displayed on the pointer, and feedback appears on the STC, highlighting the lineage of the cell.

the trigger. This is overall a detail-on-demand operator, making the whole data accessible at any time. It appears as a red arrow object, so that the user can put the pointer precisely on the desired object. The interaction is supported by a highlight feedback upon hovering and selection.

**Switching the color mapped information:** When various numerical or categorical information are present in the dataset, the user can scroll through the list of information displayable (see Figure 3.4). As shown in Figure 3.3, the underlying operation corresponds to switching the texture containing the information. This is thus a light operation allowing interactive use.

**Clipping Plane:** An interactive clipping plane generate cut-away views of the STC. The user can directly grab the clipping plane and manipulate it using direct hand translations and rotations. Yet, some orientations are easier to interpret:

- Time cutting, i.e. putting the plane perpendicularly to the Z-axis, corresponds to going through the original cross-section at given instants.
- Linear space cutting, i.e. putting the plane along the Z-axis, corresponds to the evolution of a segment of the spatial data over time, giving for instance information of the evolution of the spatial structure.
- In case of moving objects, slightly oblique cutting can help track the object over time.

This type of cut was used to generate the cut in Figure 3.6.

**Light:** Taking advantage of the Blinn-Phong illumination model, an interactive light helps the user to reveal shape, reliefs and details of the STC, using this tool as a point light. This helps understand the shape of the volumetric data by adding depth cues. The user could directly grab the light source (yellow sphere) and manipulate it using direct hand translation.

### **Filtering Operations**

As occlusion remains an issue in dense volumetric data, reducing the amount of data displayed becomes necessary.

**Value Filter:** This tool allows the user to filter the range of continuous data displayed on the STC. Filtering on value can help identify groups of objects sharing same characteristics, complementing the color mapping by removing the occluding other objects. The parameters of the filter are adjustable through a user interface which allows to define the range of values that are displayed.

**Time Filter:** This filtering operation lets the user define a temporal window to constraint the data rendered in the STC within two time steps. Events ongoing during this specific temporal window can then be more easily pinpointed. The parameters of the filter are adjustable through a graphical user interface which allows to define the range of values that are displayed.

**Object Filter and Tracking:** Focusing on objects, two issues came up. First, we need to keep track of objects in the temporal dimension. Second, the presence of numerous objects can occlude the visualization. The user can solve these issues respectively by highlighting or hiding the objects. It can be done either by pointing the object using the same tool that gives details on demand, described in 3.1.4, or by selecting an object in a list of identifiers. The selected object thus changes state —from normal to highlighted to masked— upon clicking the trigger of the controller. Note that if the objects follow a tree hierarchy in time, such as the cells with their children cells in our example dataset, the operation is applied to the children objects. Figure 3.4 shows an example of object tracking.

### **Linking Multiple Visualizations**

We also took advantage of the large workspace offered by virtual environments to display the meshed model in addition to the STC. We followed advice from Munzner [16] for the

design choices implied by this juxtaposition: multiple views should be coordinated, and even interactively coordinated. Conceptually, the operations we described above are applied to the complete dataset. Feedback of these operations is given through the visualizations displayed - the STC and the meshed representation of the 3D spatial data. Links can then be set up between the visualization by applying a shared encoding of the effect of the operations.

**Linking the time exploration:** In addition to the time filtering sliders evoked previously, a middle cursor controls the current time displayed on the meshed model. Feedback of this cursor appears as a transparent plane orthogonal to the temporal axis of the STC, as shown in Figure 3.4.

**Linking the spatial exploration tools:** The same color mapping is applied to the STC and meshed model, notably after switching the color mapped information interactively, as shown in Figure 3.4. The clipping plane used on the meshed model to generate the STC can go back on click to a default position, which is the one of the displayed STC's base cross-section. A marker line on this cross-section gives context information about the position of the clipping plane applied to the STC. This line corresponds to the intersection between the STC's clipping plane and the temporal feedback plane.

**Linking the filters:** Any filtering operation done on the STC is also applied to the meshed model, and vice versa. The same objects are highlighted, hidden or filtered out by time or value.

These operations were designed to help users to explore temporal evolution with the static visualization offered by the STC, and correlate the multidimensional data or pinpoint events by combining the two visualizations and the interactive tools available, as illustrated with the following use case.

### 3.1.5 Generation and Interaction Performance

The VR application runs on Unity 2018.2.21 and is supported by a PC with Windows 10, an Intel Xeon W-2104 CPU (4 cores, 3.2 Ghz base frequency) and a RTX 2080 GPU. All interaction methods described previously are designed in order to maintain a framerate above 45 fps.

In terms of performance and texture resolution, the STC used in the figures has a resolution of 256x256x100. The full generation process takes about 5 seconds. This process is GPU-friendly, which enables the generation of the STC during runtime. Normals are for instance generated and saved instantly using compute shaders. However, the bottleneck of the current implementation

of the generation algorithm is the CPU - GPU transfer, provoking a framerate drop. Hence, we chose to forbid completely other interactions during the generation time.

## 3.2 Use Case: Application for Morphogenesis

This section presents an application of the STH to the visualization and analysis of spatio-temporal data from the recordings of embryonic development of a *Phallusia Mammillata*, the first dataset presented in Chapter 2, Section 2.1.3. First, we detail a VR application in which the STH has been integrated. Then, we describe two use cases illustrating the potential benefits of the STH.

### 3.2.1 VR Visualization Application



Figure 3.5 – Examples of tool uses: the first one allows the creation of a scatter view ①, with green lines representing adjacency links. The cube ② is a two-handed control allowing rotation and rescaling of the embryo. The clipping plan ③ is remotely controlled by the user’s hand.

Taking advantage of the large workspace offered by immersive environments, we developed a VR framework for the user to interact with the meshed model, in addition to the STC visualization, as illustrated in Figure 3.5. We based our environment on the framework *MorphoNet* [166], an online interactive browser for the exploration of morphological data. The development of the application was done using Unity 3D and the HTC Vive was the main visualization and interaction system.

Our framework displays the dataset described above using meshed model of the embryo at each time point, as well as a STC based on a cross-section placed close to the median plan of the embryo, as shown in Figure 3.7. The color mapped on the visualizations here corresponds to the volume of the cells.

Regarding the user interface, it was displayed as a virtual desk containing all the available tools. In order to enable a tool, the user just had to grab it using the trigger button of the HTC Vive controller. Once the tool was grabbed, the trigger could also be used to enable and disable it. Tools that enabled the control of a continuous value (e.g. the time), or the scrolling of a list require the user to perform circular motions on the circular touch pad of the HTC Vive controller. The user could grab a tool in each hand.

The transformation applied by these tools, i.e. selection, clipping or rotation, can also be applied to the STC. In addition, the rotation can be enabled at any time, even while using a tool, by holding the trigger button on both controllers. This set of tools, as well as the ones dedicated to the STC described in section 3.1.4, provides the user primary controls to explore the dataset.

### 3.2.2 Use Cases

In the way to study functional organization and arrangement of the tissue, embryo developmental studies remain essential to access cellular functions inside a self-organized isolated system.

With a fast development, a few hundreds of cells, ascidian embryo is the perfect choice to analyze the link between cells or tissue geometries and differentiation. In the case of *Phallusia mammillata*, the cell membranes are very transparent, which makes for an easier imaging of the membranes or endosomes of the cell through light sheet microscopy. Without any apoptosis, i.e. programmed cell death, or cell migration in early ascidian development, embryo topological complexity can be summarized in the result of unequal divisions of cells, resulting in two different volumes for each daughter cell, and/or asynchronous divisions, i.e. two daughter cells having different cell cycle duration. Each of these events correlates with cell fate decision of the cells. This way, with the exploration of cell architecture and adjacency in a dynamical view in embryos, we have access on a major part of the story and decisions taken by each cell.

We will illustrate in the following examples of use of the STC to observe events and behaviors with a strong temporal component related to the exploration issues described above. For this purpose, we generated a STC from the embryo cross-section shown in Figure 3.7.

#### Cellular Deformation

One of the main steps of the embryonic development for most animals is gastrulation. It is characterized by morphogenetic movements that form a cavity in the embryo. These movements set the base of the determination of the morphology of the future individual. The actual source

of these movements and deformations of the cells is still unsure, and no formal measure of deformation exists. Visualization of this deformation over time is necessary for the analysis of the embryonic development.

The STC shows the deformation of the embryo over time, as shown in Figure 3.6. A cross-section allows the exploration of the main cells involved in the movements and provides a view of the global and local deformation. The user can then identify the cell to visualize by selecting them on the STC and continue the exploration on the 3D representation.

### **Waves of Cell Divisions**

During the early stages of the embryonic development, cells tend to divide approximately simultaneously. This phenomenon results in “waves” of division, during which numerous cells divides within a short time.

By sliding through the time component, one can notice this kind of event on the surface-based representation through several aspects. First, the characteristic dynamics of the membranes of a cell can be observed on a large number of cells: on the surface of the embryo, and inside by using a clipping plane. Second, as cells divide, they reduce their volume. Thus, the color mapped on the embryo will change a lot during such event.

Keeping this last property in mind while exploring the STC, color clusters become distinguishable thanks to the volume information displayed. This observation can thus be done directly, without having to do a time-sliding operation, as shown in Figure 3.7. Up to four color clusters, hence three waves of division, can be identified.

### **Asynchronous Behavior in Cell Divisions**

Regarding cell determination, cells with different fates will not result in the same number of cells, and embryonic development has to be controlled. Thus, at specific moments, some cells will not divide at the same time as the other ones and skip a wave of division.

Exploring the surface-based representation in order to find cells presenting this behavior, the user has to slide back and forth in the time window corresponding to the wave of division and observe which cell will not divide.

The STC can give a more global view of this time window, with a part of the context of the embryo. In Figure 3.8, membranes of a cell are highlighted in red. Only one division can be observed for each of these cells during the time window represented. Up to three were to be expected here, according to the waves of division identified before, which confirms an

asynchronous behavior for these cells. With the feedback of the cell selection tools on the STC, the user can find quickly the related cell on the 3D model of the embryo.

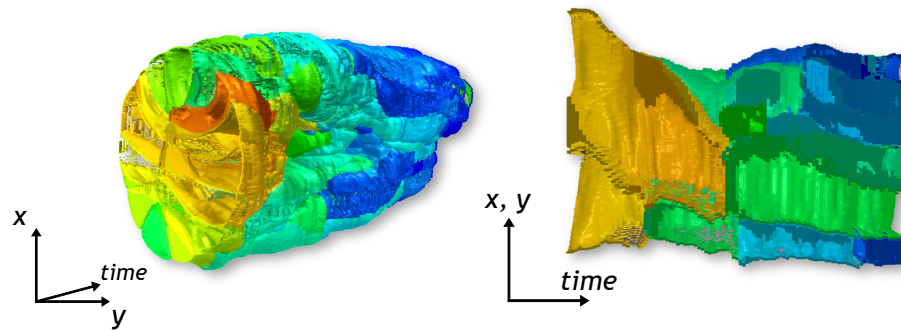


Figure 3.6 – The STC at the left presents the cavity formed by gastrulation. The cross-section at the right shows the deformation of cells involved in this particular morphogenetic movement.

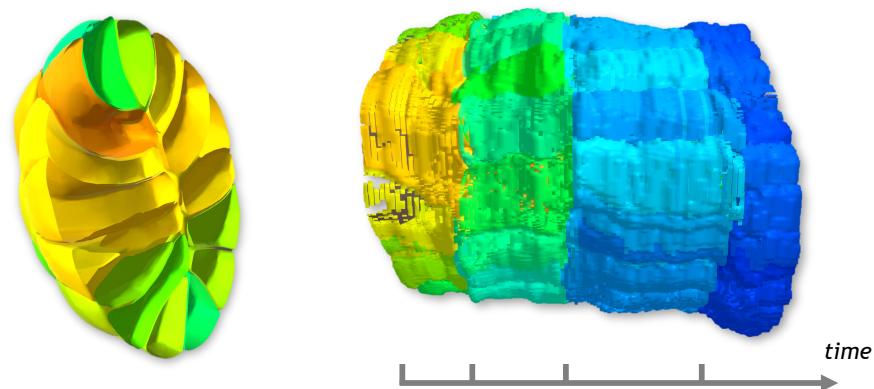


Figure 3.7 – Cross-section and related STC generated. The color displayed on the STC corresponds to the volume of cells, and helps distinguish 4 parts.

### 3.3 Evaluation

In this section, we present and discuss a user evaluation aiming to assess the benefits and limitations of the proposed method using the previously defined use cases. The evaluation was motivated due to the complex and intricate 3D visualizations that are generated by the proposed projection, which could be difficult to interpret. Thus, the main goal of the evaluation was to



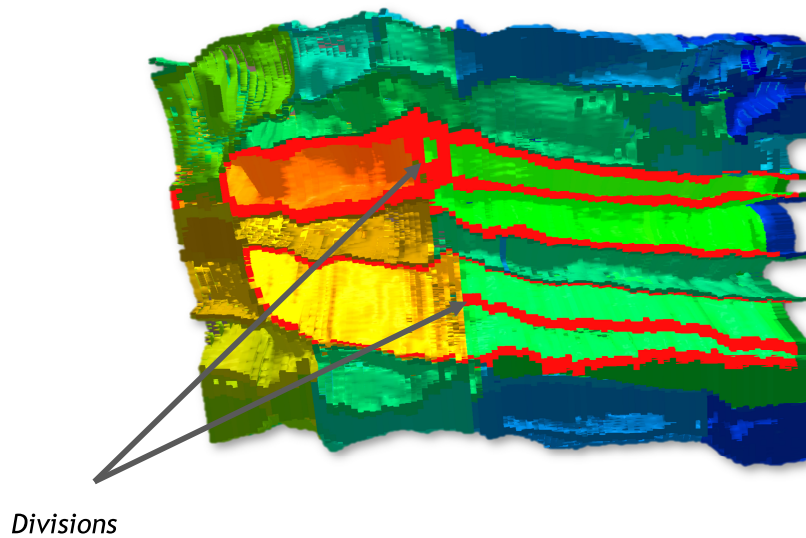


Figure 3.8 – Cross-section of the STC. Two divisions are indicated. The membrane of the original cells and their respective daughter cells are highlighted in red.

provide a first assessment on whether and how users could take advantage of the generated STC visualizations when punctual and continuous events have to be located. Although other use cases could be envisioned, we decided to focus on the biological use cases, as they were our first motivation for proposing the STH approach. In this context, as biologists mainly explore this dataset by exploring one time point at a time, as a baseline condition, we considered the mesh visualization on which users can navigate in time (e.g. using a slider); hereinafter referred to as the meshed model alone condition. In the meshed model & STC condition, the mesh data was also juxtaposed to the STC visualization.

### 3.3.1 Tasks and Hypotheses

We focused our evaluation on the efficiency and accuracy provided by the STC through tasks of identification of cell divisions, waves of divisions and asynchronous behavior, as described in 3.2.2. Such events and behaviors have temporal and spatial components, thus can be considered as 3D temporal objects. Using the same abstraction as described in section 3.1, they qualify as 4D objects. As such, we suggest that one of the visualizations will render more information depending on the characteristics of the event. We discern two types of events. First, punctual events can be identified by comparing the state between 2 time points. To detect such events, the user requires more complete spatial contextual information over a very local temporal context,

i.e. a few time points. For this reason, we hypothesize that the meshed model visualization will be more helpful in the detection of punctual events. The second type of events evolves over time, and is thus mostly characterized by a temporal component extended in numerous time points. As the generated STC provides complete temporal information over a reduced spatial context, we hypothesize that the use of the STC will be more relevant to detect such events.

For this study, we considered the complexity of the tasks and the fact that our participants were not domain experts. Consequently, we chose to focus our evaluation on the accuracy of the analysis and not on efficiency, which could be more biased, notably by the approach taken by the participant. Based on our previous rationale, our main hypotheses were:

- H1:** Punctual events in time will not be pointed more accurately using the STC than on the meshed model only;
- H2:** Events or behaviors with a larger temporal component will be identified more accurately using the STC than on the meshed model only.

### 3.3.2 Apparatus and Participants

The PC configuration is the same as described in 3.1.5. The virtual environment was displayed in an HTC Vive Pro HMD, with a resolution of 1440 x 1600 per eye. Two Vive Pro controllers were available, including 3 buttons and a touchpad. The HMD and the controllers were tracked in an empty space of a 2.5m x 2.5m surface.

12 participants, 10 men and 2 women, were recruited from the local laboratory for this experiment, aged from 22 to 32. They all had medium to high experience in VR environments, but had no expertise on the dataset nor in embryology.

### 3.3.3 Experiment

#### Task Design

In order to keep the morphogenetic analysis context, we designed tasks of annotation of the dataset that were still accessible to non-expert users. From the use cases presented in section 3.2.2, tasks of pinpointing waves of cell divisions or identifying asynchronous behavior in cell divisions, respectively section 3.2.2 and 3.2.2 corresponded to events with large temporal component.

As a task of pinpointing punctual events, we considered cell divisions. They are common events yet essential for the analysis of the embryonic development. The temporal resolution of

the dataset allows us to consider the divisions as punctual events.

The spatial deformation occasioned by a division can be easily noticed on the 3D representation of the embryo by sliding through time. An additional hint would be the abrupt change in the color displayed, which can be used to pinpoint this event on the STC. As described in 3.1.4, the hierarchy, corresponding here to the cell lineage, is highlighted. Upon selection, finding the change of color in the highlighted selection thus corresponds to finding a cell division.

## **Experimental Protocol**

At the beginning of the experiment, participants signed an information consent form and were briefed regarding the equipment used, the data recorded and the experimental tasks. In order for the participant to understand the context of the tasks, we explained the nature of the dataset, specifying the methods of recording and the purpose of analyzing such data. Emphasizing on the temporal component of the data, we then presented the STC visualization, its generation process and its purpose in terms of temporal visualization. Since the participants were non-experts, we explained for each task the characteristics of the events to pinpoint, the scientific purpose in embryology analysis as well a few methods to identify those events in each visualization. Finally, we presented the virtual environment and the available tools to the participant for about 8 minutes, before having themselves equip the HMD and get familiar with the framework, for about 8 minutes as well.

Participants were then asked to perform the three exploratory tasks:

- Discern the number of waves of cell divisions, providing an approximate estimate of the time for each wave of divisions; duration of the task: 2 minutes
- Identify cell divisions and give corresponding instant and cell identifier; duration of the task: 4 minutes
- Identify cell with asynchronous division behavior and give corresponding cell identifier; duration of the task: 4 minutes

For the tasks of identifying divisions and asynchronous behaviors, the events were present abundantly enough not for anyone to finish the task early. The experiment was divided in two blocks. Depending on the visualization method available, the participant performed the tasks first with the meshed model alone and then with meshed model & STC, or vice-versa. The order of the visualization method was counter-balanced to minimize ordering effects.

As the main goal of the experiment was to evaluate how users will take advantage of the generated STC visualizations, we decided to provide an initial STC visualization. In addition,

having the participants work on the same dataset and the same STC view generates smaller variability and enables better comparison of results between participants. Second, considering the potential learning curve in STC based visualizations, we assumed that the level of comprehension of the STH would be very different from user to user. Such differences could induce an important bias in the experiment, especially since the users are not familiar with the datasets observed. We thus generated a STC arbitrarily, though following one objective criterion: the plane would be placed in order to capture the gastrulation movement, as described in part 3.2.2. We expected this to act as a point of reference to help participants locate themselves in the data. Nonetheless, we left the opportunity for the participants to generate another STC from a different cross-section, but none of them did.

For each condition, we recorded the answers of the participant for each task, the total time use of each tool, and the total time watching either visualization. At the end of the experiment, participants had to fill a short questionnaire in order to gather subjective impressions of the overall app and demographic data (age, gender, and VR experience).

### 3.3.4 Results

Eventually, we get a total of 24 paired observations, characterized by 2 two-level factors, the **order** of the observation and the **condition** - i.e. whether or not the STC is present. Since we focus the study on accuracy, we computed the precision for each task:

$$precision = \frac{true\ positives}{total\ selected\ elements} \quad (3.2)$$

Repeated measures two-way ANOVA was used to analyze the results, considering the order as a between-subjects factor and the technique as a within-subjects factor. When the normality assumption was not met (Shapiro–Wilk normality test), the Aligned Rank Transform (ART) was used before performing the ANOVA analysis. When necessary, Tukey HSD post-hoc tests were performed. The statistical analysis was done using R language.

#### Waves of Cell Division Counting Task

The two-way ART ANOVA order and condition vs precision showed a significant effect of the condition ( $F(1,10) = 18.10$ ;  $p < 0.01$ ;  $\eta_p^2 = 0.64$ ), and no significant order nor interaction effect. Post-hoc tests showed a significantly ( $p < 0.05$ ) better performance in terms of accuracy using meshed model & STC ( $M = 0.94$ ;  $SD = 0.16$ ) rather than the meshed model alone ( $M = 0.72$ ;

$SD=0.16$ ). This **supports H2**.

### Asynchronous Behavior Identification Task

The two-way ANOVA order and condition vs precision showed a significant effect of the condition ( $F(1,10) = 5.61$ ;  $p < 0.05$ ;  $\eta_p^2=0.36$ ), and no significant order nor interaction effect. Post-hoc tests showed a significantly ( $p < 0.05$ ) better performance in terms of accuracy using meshed model & STC ( $M=0.87$ ;  $SD=0.14$ ) rather than the meshed model alone ( $M=0.64$ ;  $SD=0.27$ ), **supporting H2**.

### Cell Division Identification Task

The two-way ANOVA order and condition vs precision showed no significant result on any factor nor interaction, so we can give **no conclusion about H1**. The box plot of the precision of the participants on this task (see Figure 3.9) does not show important difference either.

## 3.3.5 Discussion

The results from the *waves of divisions* and *asynchronous behaviors* tasks, considered as objects with large temporal component as explained in 3.3.3, showed that the use of the STC provided higher accuracy in those identification tasks, **supporting H2**. However, these tasks were designed with numerous known targets but unknown location in space and time. Placing the user in more diverse situations would help to estimate more thoroughly the added value of the STC in general exploration tasks. The results from the cell division task gave no significant results, allowing **no conclusion on hypothesis H1**.

As evoked by our hypotheses, we focused this study on accuracy. For various reasons, the protocol as it is could not allow a significant efficiency evaluation. Participants were given the same advice on how to approach the tasks, described in 3.2.2 and 3.3.3. However, the numerous tools available made it difficult for them to choose an optimized strategy. Users usually chose a strategy at the beginning of a task and followed it until the end, even if it felt suboptimal. Such phenomenon creates subgroups. To counter this effect, we would require either more participants, or ones that are trained with the system. Furthermore, we focused our study on only one dataset, since it was the most complete one at our disposal. Considering our task design, we could expect an important order effect for our efficiency measurements, since users would remember what they did on the same task in the other condition.

Despite all these constraints, we could output a result on the efficiency of the system. On the *waves of division task*, some users could finish at least 20 seconds before the 2 minutes time limit. In the meshed model only condition, only 1 out of 12 finished the task early (0 on the first part, 1 on the second part). In the meshed model & STC condition, 8 out of 12 finished the task early (4 on the first part, 4 on the second part). The two-way ANOVA order and condition vs the boolean value "finished the task early" showed a significant effect of the condition ( $F(1,10) = 14.41$ ;  $p < 0.01$ ;  $\eta_p^2 = 0.59$ ), and no significant order nor interaction effect.

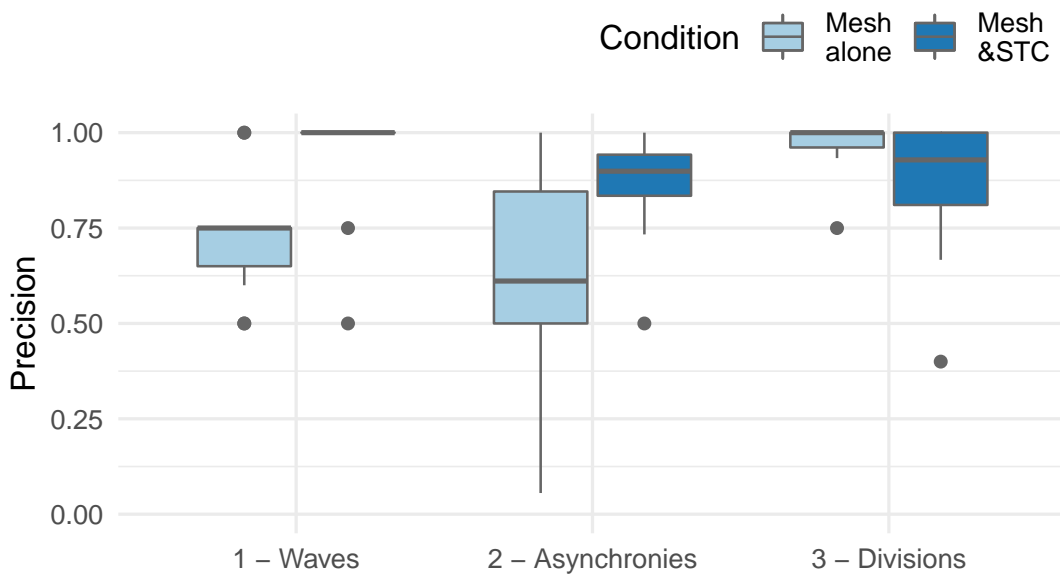


Figure 3.9 – Box plots of the precision of the participant in each of the 3 tasks and for each condition, i.e. with or without STC. Each plot corresponds to 12 observations.

### 3.4 Expert Feedback

During the design and development of our method, five domain experts helped us by providing recommendations and testing the application. In addition to the informal discussions during the design of the system, the domain experts tested the application in two different sessions at different stages of the development of the prototype. Each session lasted one hour for each domain expert. The domain experts had no previous experience with Virtual Reality, three of them had experience with the *MorphoNet* framework and the dataset. The two others had no experience with either.

In the first session, most filtering operations and interactions on the STC were not implemented yet, so the main focus was on the overall usability of the system, their first impressions on the STC visualization and the potential integration of a VR system in their workflow. In the second session, the domain experts were confronted with the same tasks that were considered for the non-expert evaluation. However, mainly expecting subjective feedback, there was no time limit for the tasks. These tasks were proposed as exercises to introduce the STC as an interactive visualization tool, but they did not completely corroborate with usual tasks achieved by the analysts.

During the first session, the application was overall appreciated. Despite the low experience with VR or virtual environments, the users quickly handled the tools at their disposal, deemed quite user-friendly. Nonetheless, the large variety of tools in the environment inevitably creates a consequent mental load, that requires more experience with the system to get used to. The STC visualization felt more difficult to approach due to the higher level of abstraction of the data. However, the handling was quite fast. At the end of the test, all users were able to interpret the visualization and have a good intuition on how to use it, especially regarding temporal behaviors in the data. A user notably expressed the necessity to be actually confronted to the visualization to understand it. The format of the test answered this need, introducing the visualization with an analysis exercise.

During the second session, opinions were mitigated on the asynchrony and division detection tasks, depending on the strategy applied by each user, *i.e.* their choice of tool and ease to use them. They were although unanimous on its utility for the wave detection task. The STC was deemed equivalent to a cell lineage tree [167]; although, the visible neighborhood relations give a supplementary dimension in analysis. This, aided with adequate color mapping, could be relevant in cases of analysis of signals or communications between cells for example.

Few other improvements were suggested during these tests, most of them regarding the addition of further information in the environment, or enhancing some controls. The need of comparing and linking different datasets was also especially pointed out, echoing with Kim et al. [75] observations.

### **3.5 Additional examples**

In this section, we present two additional examples of datasets, also taken from the MorphoNet database, for which we generated STCs with the method previously described. The cutting plane capture resolution on these examples is 512x512. For each of the two datasets, we

generated STCs based on three orthogonal cutting planes.

The first dataset shown in Figure 3.10, left side, is a simulation in 42 time points of an abstract oryzalin-treated organ. The appearing outgrowth is obtained by locally softening the membrane of a shoot-apical meristem filled with uniform and steady turgor pressure. The stress magnitude on each cell, notably implied by this outgrowth, is colormapped on the STCs. The second dataset, shown in Figure 3.10, right side, is part of a 3D temporal imaging atlas of cell morphology for the *C. elegans* embryo. The recording includes 150 time points, from the 4 to 350 cells stages. The STCs displayed show the remaining lifespan of each cell as a colormap.

More details about the datasets and related publications are given on the Morphonet website (<https://morphonet.org/dataset>), respectively under the names “Shoot-apical meristem (Simulated, oryzalin-treated organ formation)” and “Sample 04 (Wild type *C. elegans* , Live Confocal Imaging)”.

## 3.6 Conclusion

In this chapter, we have proposed a novel spatio-temporal visualization based on the Space-Time Cube visualization. The proposed visualization, the Space-Time Hypercube, extends the STC visualization to consider a third spatial dimension in the data. However, the interaction and manipulation of 4D remains unpractical. Thus, to enable a direct visualization, we proposed a projection operator on based on a user-driven cross-section defined in 3D space. The projection of the hypercube, consequently a STC, contains only a partial spatial information of the dataset, but creates a view containing temporal information. Numerical and categorical information could be displayed as well on the visualization. We juxtaposed and linked the STC and original dataset visualizations in a VR application, taking advantage of immersive environments benefits in terms of visualization and interaction in 3D. Various tools for exploration, filtering or tracking objects apply transformations on both visualization and come to assist in the analysis of the dataset. Moreover, we illustrated the potential usages of the STC in several use cases in the context of morphogenesis. The evaluation of the STH in a context of embryology with non-experts and domain experts showed that the STC visualization presents a number of benefits with respect to traditional visualizations, especially for the detection of events for which the identification required information for all or most of the temporal range. The STH approach could pave the way to new types of visualization and interaction methods for 3D spatio-temporal data, and we believe that such tools will help the adoption of VR technologies for data visualization.



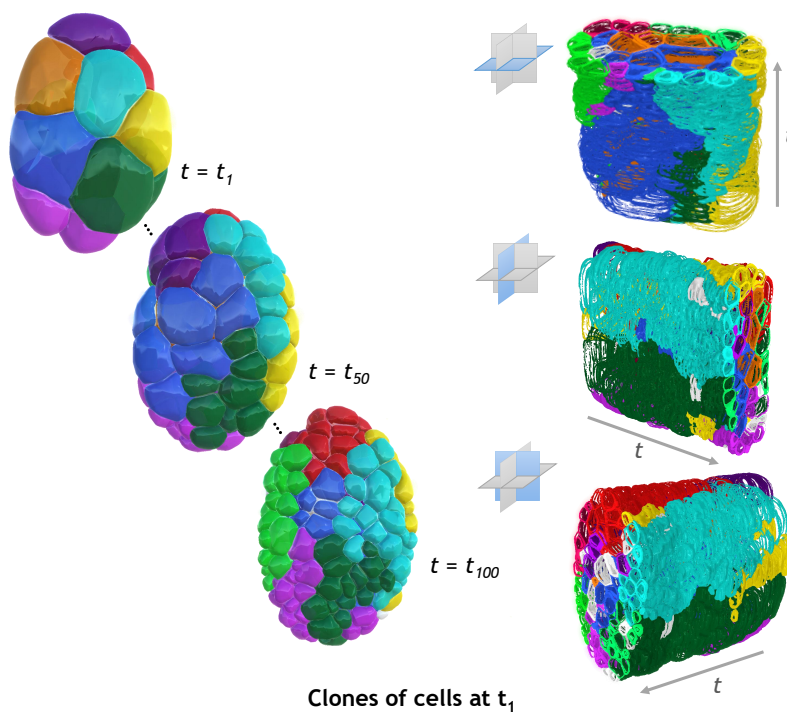
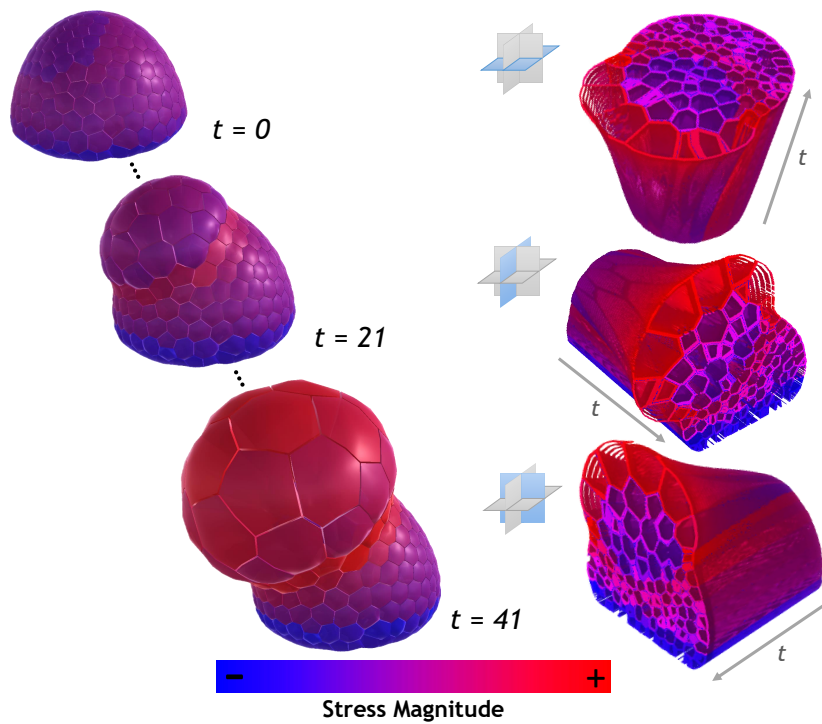


Figure 3.10 – Examples of STCs based on 3 different base planes for the capture, on each example dataset presented in part 3.5. The top image is extracted from the shoot-apical meristem dataset, colormapped with numerical values of stress magnitude. The bottom images are extracted from the *C. elegans* embryo dataset. Each color represents the successive divisions of the cells present at  $t = t_1$ .

# TIMELINE DESIGN SPACE FOR IMMERSIVE EXPLORATION OF SPATIAL 3D TEMPORAL DATA

---



---

4.1	A Timeline in a 3D Environment . . . . .	74
4.1.1	Extending the 2D Timeline Design Space . . . . .	75
4.1.2	Interacting with 3D Timelines . . . . .	81
4.1.3	Choosing a Timeline Design . . . . .	83
4.2	Evaluation . . . . .	84
4.2.1	Dataset and Task Design . . . . .	84
4.2.2	Hypotheses . . . . .	85
4.2.3	Apparatus and Participants . . . . .	86
4.2.4	Independent and Dependent Variables . . . . .	86
4.2.5	Experimental Protocol . . . . .	87
4.2.6	Results . . . . .	87
4.2.7	Discussion . . . . .	91
4.3	3D Timelines to Explore 3D Temporal Imaging . . . . .	91
4.3.1	Application and Timeline Design . . . . .	92
4.3.2	Finding Regions of Interests in Large Datasets . . . . .	93
4.3.3	Comparing Objects . . . . .	95
4.3.4	Fusion and Fission . . . . .	95
4.3.5	Expert Feedback . . . . .	96
4.4	Conclusion . . . . .	97

---

This chapter approaches the issue of visualizing 3D temporal regions of interest. The objective is to be able to define a zone of the 3D temporal data, bounded both spatially and temporally, with a range adapted to a direct observation by the analyst.

To tackle this issue, we describe in this chapter an extended timeline design space for 3D environment, adapted to the visualization of 3D temporal data. This design space is inspired from the design space for 2D timelines described by Brehmer et al. [111]. Our design space extends the original one, adapting the related design choices to the additional workspace dimension. We describe how 3D timelines can partition and structure 3D temporal data, represented as 4D objects, in the 3D environment.

Moreover, due to the specific characteristics of interaction of immersive contexts and in order to take full advantage of 3D timelines, we discuss the basic set of interaction techniques to explore and manipulate them. We also propose additional interaction processes to tackle specific tasks of exploration and analysis more efficiently.

In order to explore the potential benefits of 3D timelines, we conducted two evaluations. The first evaluation, was a formal summative evaluation, which explored how 3D timelines could improve data exploration tasks. For this evaluation, mainly VR experts were considered, and we mainly focused on performance and usability. The second evaluation, was a qualitative evaluation conducted in collaboration with experts in biology. The objective was to gather feedback on how 3D timelines could be included in their analysis workflow, precisely, on how they could take advantage of 3D timelines to ease the exploration and validation process on their 3D temporal imaging data.

In summary, the main contributions of this chapter are as follow:

- A design space for 3D timelines, displayable in 3D environments and adapted for the visualization of 3D temporal data
- 3D interaction and exploration processes supporting complex analytical tasks in such visualization
- A formal evaluation of the benefits of 3D timelines in general visualization tasks, as well as feedback from biology experts giving insights on concrete use of the method.

## **4.1 A Timeline in a 3D Environment**

This section introduces our design space for 3D timelines, which extends the 2D timeline design space [111] for 3D environments, and notably immersive environments. The extension

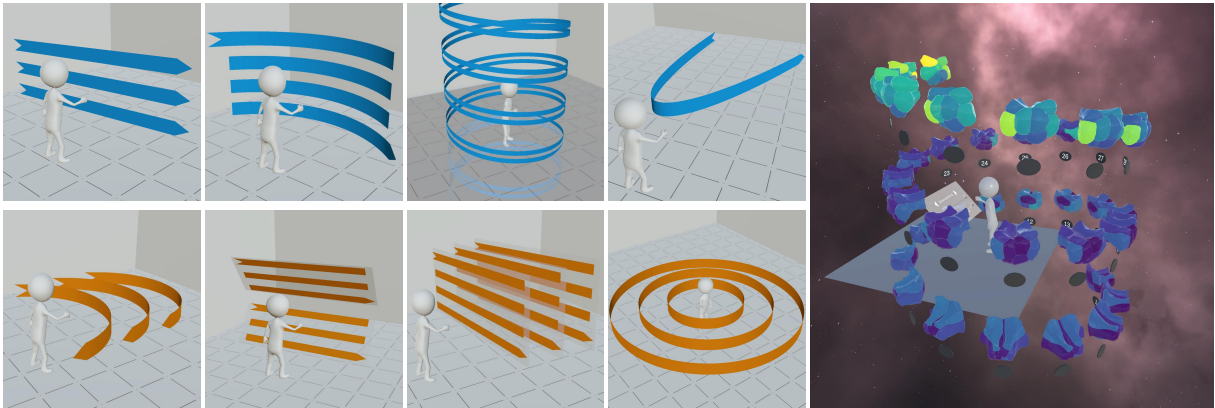


Figure 4.1 – Illustration of the proposed 3D timeline design space for immersive exploration of time-varying spatial 3D data. The first row showcases different timeline representations, i.e. guiding curve of the timeline; while the second row showcases different support configurations. The rightmost image illustrates the use of an helicoid representation for the exploration of an time-varying embryo imaging dataset. The viridis colormap is used to encode the elongation ratio of cells involved in morphogenetic movements.

considers the additional spatial dimension in which data can be laid enabling the direct display of the temporal dimension of the data.

As mentioned in the introduction, we focus on S4D datasets. We assume that the temporal component of such dataset is discrete, or at least it can be discretized. As such, we can construct a timeline in which every time point is populated by a **3D snapshot**, i.e. the state of the 3D temporal dataset at an instant. We consider that some datasets are composed of a set of objects, i.e. shapes with the own semantic value, and define, assuming sufficient tracking information, **4D objects** that span along multiple time points. These objects can be defined by segmentation process for imaging data [77], or by construction in a surface-based 3D model [133, 134].

Finally, in order to exploit the interaction capabilities provided by IVR systems and to take advantage of the 3D timelines, we detail the set of interaction tasks needed for their exploration.

#### 4.1.1 Extending the 2D Timeline Design Space

As presented in Section 2.2.4, Brehmer et al. [111] proposed a design space for 2D timelines with the three following dimensions: *scale*, *layout* and *representation*. In this part, we adapt the design space to 3D timelines. The two first characteristics are mainly similar for 2D and 3D timelines, we added those parts for completeness of the design space, also adding a discussion for 3D temporal data. Then, we extended the design space by adapting the *representation* dimension choices, yet also proposing other types of guiding curves adapted to a 3D environment. Finally,

we introduce a fourth dimension to this design space, as a result of using a 3D display, which describes the supporting plane on which timeline branches are laid: the *support* dimension.

### **Scale: Displaying Time**

The *scale* dimension represents the relation between the displayed distance and the temporal distance. Although events will be laid in 3D space, this relation will remain. Therefore, the *scale* dimension remains characterized as defined by Brehmer et al. [111]:

- A **chronological** scale spaces time points according to the actual temporal distance, either **linearly** or **logarithmically**, depending on the distribution of the events.
- A **relative** scale arranges the time points according to a baseline event. It can notably be used to compare multiple timelines regarding this event.
- With a **sequential** scale, the distance between time points is fixed and does not correspond to the temporal distance. A similar approach consists in encoding the duration between time points on the timeline as well.

### **Layout: Arranging Time Points**

The layout dimension corresponds to how the timeline is partitioned in the display. Brehmer [111] describes several characteristics of a 2D timeline layout. A first main characteristic of a layout is whether it is **segmented** or not. Segmentation is used to cope with spatial organization issues, such as the limitation in size of a 2D display, but also for analytic purposes, for example to separate the timeline to make some periodic events more salient. The timeline layout can also be qualified as **unified** or **faceted**, i.e. showing a timeline with one or several lines; the latter can be useful for comparing data from different sources over time. Whether derived from segmentation or faceting, we refer to timeline parts as *branches*.

These two characteristics can be used to describe 3D timelines as well. Similar factors are taken into account for the choice in layout. Segmentation helps in solving issues of juxtaposition of visualization and optimization of the large workspace offered by 3D environments. Its analytical purpose is notably relevant in case of periodic data. On the other hand, the choice between faceted or unified layout relies on the nature of the data and use case. A unified timeline design is more suited to focus on the dynamic features of one region of interest or group of objects, while a faceted layout allows the comparison of several ones. Faceted layouts are also adapted to compare of multiple datasets, as in such cases, the most common task is comparison. In any case, faceting or segmenting the layout tends to clutter the workspace. Attention should

be given to properly indicate the origin and characteristics of each facet or segment as not to overwhelm the user.

### **Representation: Shaping the Timeline**

The representation of a timeline corresponds to the shape, the guiding curve along which are placed the time points. This curve is therefore an equivalent of a time axis. In most cases, timelines are represented linearly [111], as for history timelines. This type of representation maintains a single orientation, often horizontal and following reading direction, and make for a good timeline readability [116]. Other designs use radial representation, to emphasize cyclic repetitions, or spirals, often used to get compact visualizations. Depending on the goal of the author of the timeline, some other types of representation can be designed for aesthetic, density or pedagogic purposes. From these representations used in 2D designs, we propose representations that take advantage of the 3D environment. First, the linear representation could be extended to a **3D curve**. Three main possibilities emerge:

**Flat curve.** The most direct extension of the linear representation in 2D would be to use a simple flat curve, as seen in Figure 4.2-A. In terms of representation, there is no limit to the amount of time points displayable in the environment. The main drawback is that the further the curve goes, the harder it is to reach or interact with the time points.

**Convex curve.** This representation displays the time points around the user. Several types of curves could be considered. An arc of a circle centered on the user would place all time points at the same distance, enabling the same capacity of interaction and observation for each time point. Such curve is shown in Figure 4.2-B. This counters the primary issue of the flat curve representation, yet the radius of the circle will increase with the amount of time points, limiting the proximity required for interaction. To compromise between proximity and amount of time points, the user could be brought closer from a part of the arc of circle. Another approach would be to use a parabolic curve, as in Figure 4.2-C. In both those cases, a local temporal context is brought very close from the user for interaction and observation, yet the other time points remain at a reasonable distance.

**Concave curve.** As opposed to the previous ones, a concave curve can be used to display close from the user a few time points, and sending the other ones that are further in time, even further in the environment. This representation emphasizes a local temporal context, frees some radial

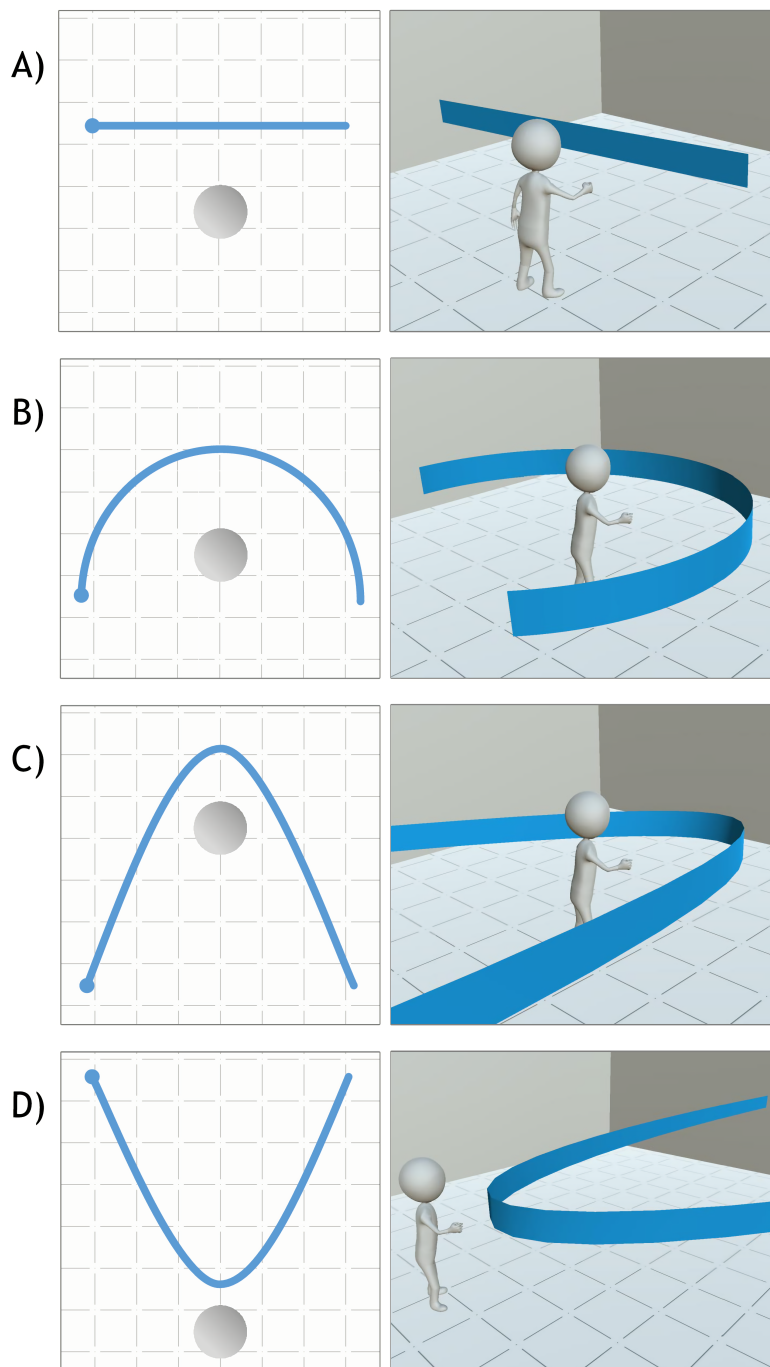


Figure 4.2 – Third person and top views of options for the representation dimension of the 3D timeline design space. These illustrations show **A)** linear, **B)** convex arc of circle, **C)** convex parabola, **D)** concave parabola, **E)** helicoid and **F)** spherical representations.

space around the user and decreases the density of information in their field of view. In this sense, the amount of time points displayed is potentially unlimited, yet harder to access. In a similar way to convex curves, concave curves could rely on parabolas, as in Figure 4.2-D, or arc of circles, depending on the amount of time points that need to be close to the user.

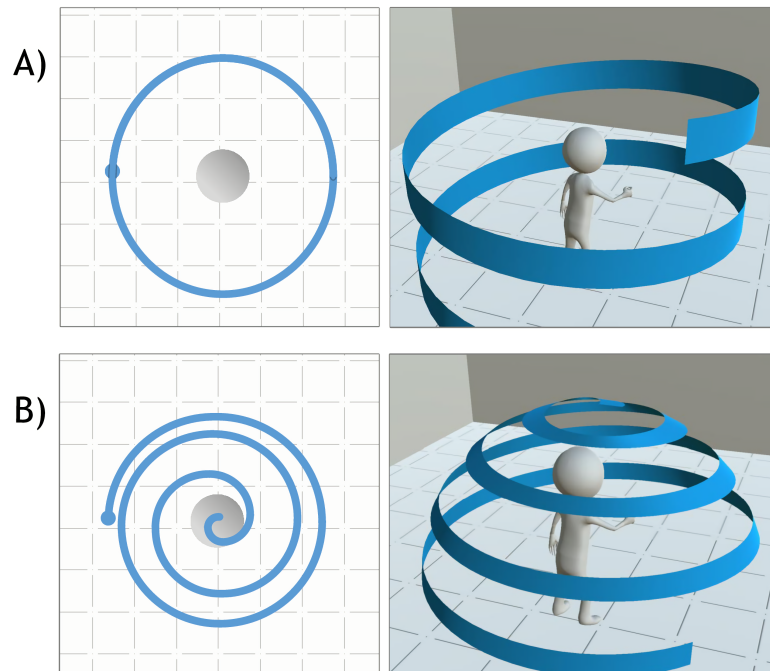


Figure 4.3 – Third person and top views of options for the representation dimension of the 3D timeline design space. These illustrations show **A)** helicoid and **B)** spherical representations.

Other designs for 2D timelines rely on circular or spiral representation. These representations are particularly adapted to provide an insightful representation of periodicity in time. For example, a spiral layout can be used to represent several occurrences of a same periodic event, as demonstrated in Weber et al. work [168]. However, because of the varying radius of a spiral loop, the number of periods has to be limited. Nonetheless, spirals are also intrinsically space-filling, thus producing dense representations, and can be engaging or even playful. Consequently, we propose two additional representations adapted to the design of a 3D timeline:

**Helicoid.** This representation coils the time points around a cylinder base. It can be centered on the user, displaying every time point close from the user, as shown in Figure 4.3-A. In a similar way to the 2D spiral representation, this shape invites the display of several occurrences



of periodic data, without the drawback of a varying radius between each period. For example, manipulating the scale dimension of the design, the circular periods of the helicoid could be aligned according to the occurrence of a particular event, for comparison purpose.

**Spherical.** Similarly, a spherical representation, as shown in Figure 4.3-B, coils around a sphere base. The time points are thus displayed around the user at the exact same distance, reducing distortions, in size of orientation for instance, implied by distance or perspective. This representation shares very similar advantages and drawbacks with the 2D spiral. It is aesthetically interesting, but the varying radius between two circular periods restrains its use for periodic data.

These two representations share several other characteristics. The exploration of the timeline is no longer horizontal as in the curve representation, but rather radial and vertical, allowing fast jumps in time. It is compact and takes full advantage of the 3D work space. However, due to the use of the spatial upward axis, it can limit the use of faceted layouts, as it could lead to confusion between the timeline branches juxtaposed and the next circle of the helicoid. Other representations using either different curves or volume could be used, that may be tailored for specific analysis use cases, for an aesthetic purpose or to create mnemonic designs. Changing the orientation in either axis can also be a way to explore original representations.

### **Support: Exploiting the 3D Environment**

In usual displays, timeline branches are most usually laid out on the display plane. As mentioned in part 2.2.4, a few works explored displaying timelines in 3D environments. Beedocs [117] includes 3D perspective to animate and display the timeline at a different orientation for aesthetic purpose, while Kullberg et al. [119] even lays the timeline on the horizontal plane of a 3D environment, using the vertical plane to display the content of the time points.

As we propose to display 3D timelines in VR, we introduce an additional dimension, the *support*, to refer to the 3D shape that supports the timeline branches in such 3D environment. We describe here the main choices that will mostly influence the timeline design. This includes shape, size, position, and also count of supports on which the timeline branches are displayed. We propose the following choices for this dimension:

**Vertical plane.** The branches are laid on a plane vertically in front of the user, like a classic 2D display.

**Horizontal plane.** The branches are laid on a plane parallel to the floor. Horizontal head movements and field of view are usually preferred over vertical ones, thus this design choice could be beneficial compared to a vertical plane support in some cases, such as for comparison at one time point of multiple branches. The main drawback is occlusion, since branches are displayed one in front of the others.

**Multiple Planes.** As opposed to the previous design choices involving a single plane, here the branches are displayed on several ones. This can be useful to optimize application design, or separate clearly facets and segments.

**Cubic.** The branches are laid along multiple vertical or horizontal planes. Such layouts can be useful to organize branches along 2 parameters, much like a 2-dimensional array. While very meaningful in this purpose, this design is quite dense, which can be overwhelming for a user and cause difficulties in the exploration.

**Concentric cylinders.** The branches are displayed on multiple isoradial planes centered on the user. In terms of exploration, it is quite similar to horizontal planes, yet fills the space around the user, which can serve aesthetic purpose.

Each of these dimension choices are illustrated in Figure 4.1, second line, in order. While this dimension is unnecessary for timelines with a unified layout, these design choices can be useful for some specific use cases, for application design, notably in terms of workspace usage, or for aesthetics. Yet, some of these designs can also involve significant occlusion issues. Adapted navigation and application controls might be required when using these design choices.

## 4.1.2 Interacting with 3D Timelines

This section discusses the interaction methods required for the exploration and manipulation of a 3D timeline. First, we consider methods enabling the free exploration of the timeline, supporting consume and search tasks. Then, we consider tasks that allow the manipulation of the timeline, in order to modify the arrangement of the timeline. The discussed interactions consider that the user is using an immersive virtual reality setup (e.g. head-mounted display), in which the user can move physically to explore the virtual environment and that additional input capabilities are provided by hand-held devices (e.g. controller). For the sake of generalization, we will not

discuss how the interactions can be implemented, but which parameters (e.g. distance among time points) could be modified.

The timeline is arranged in the environment in such a way as to have one time point, that we will call from now on *central time point* of the timeline, that is the closest from the user, as shown in Figure 4.6. Time points are identified by an indicator beneath the objects represented.

### **Exploring the Timeline**

First, the user can physically move (e.g. walk) in order to approach the time point of interest. However, the range of time points that can be explored will be dependent on the shape of the timeline and the workspace of the virtual reality setup. Some timeline designs covering an important part of the work space around the user, for example when using convex curves or spherical representation, will enable the direct exploration of all time points without requiring a large physical workspace. In contrast, linear or parabolic representations can spread far away for the user, and faceted or segmented layouts might display data too high, limiting the number of time points that the user can access. To overcome this limitation, one solution is to consider virtual navigation methods [39], that enable the user to virtually (without physically moving) navigate. Potential good candidates are scene-in-hand methods [169] or virtual steering [170] which will allow users to reach time points arbitrarily far away from them. Yet, the choice in the virtual navigation method will depend on the implementation of the timeline, the data represented and the end user profile.

Finally, another alternative to enable a full exploration of the timeline is to move the timeline along its time axis, thus changing the *central time point*. This can be done continuously by scrolling the time points (e.g. using a temporal slider), or directly by selecting a time point from afar (e.g. using a ray-based selection method [48]). These methods will minimize the user's physical motion.

### **Manipulating the Timeline**

There are numerous continuous parameters involved in the display of the timeline, such as the space between time points, the center and radius of curvature for curved representations, the height for helicoid representations or the distance between timeline branches for faceted and segmented layouts. These values can strongly vary, notably depending on the amount time points displayed in the timeline. For this reason, the user could be able to choose among pre-defined configurations of timeline designs. Nonetheless, to increase the flexibility of the visualization,

the user should be able to adjust the parameters of the timeline display in order to better fit their use-case requirements. The modification of these values can be done using graphical user interfaces or specific 3D widgets [171]. Moreover, in order to control the information contained in the environment level-of-detail options are also relevant. The user should be able to choose to display only a proportion of the time points selected regularly along the timeline, and to directly choose time zones to collapse or extend via manual selection.

### **Manipulating the Content of the Time Points**

The final interaction category relies on how the content of the time points could be modified. First, the 3D objects at each time point can be rotated and scaled, in order to enable the user to explore them from different orientations. To ensure consistency, we advocate to link the rotations and scale for all time points, thus obtaining a consistent orientation for all time points. Such manipulation could be achieved using bi-manual manipulation methods [51].

Second, operations to reduce the information at each time point can also be considered. (A) Cut-away views defined by a clipping plane or a 3D volume (e.g. cube) operators. The user could define the position and orientation of the cutaway operator in the central time point, a corresponding cut-away view could be applied as well on each of the other object or group of objects, relatively to their barycenter. Standard 3D manipulation techniques can be used to control the cutaway operator [51]. (B) Object and value filtering operations. These operations will be highly dependent on the available data of the S3D. For example, if the data for each time point is composed by a set of 3D objects (e.g. different 3D meshes, segmented 3D volume), individual objects could be removed from the timeline by selecting them. Moreover, if the individual objects are linked with other objects at different time points (e.g. same object appearing at different time points), the selected objects and their linked objects could also be hidden. Finally, if additional categorical, ordinal or numerical attributes are available for each object (e.g. volume of a given object), filtering operations could also be defined (e.g. hide the objects with a volume lower than a threshold). These operations to reduce the displayed information could be of great relevance to reduce the amount of displayed information, reducing clutter. These interactions could be designed considering existing 3D selection methods [48] and 3D graphical user interfaces [171].

### **4.1.3 Choosing a Timeline Design**

In this part, we propose a set of design criteria that will drive the design choices of 3D timelines. Focusing on the constraints that can be introduced due to the attributes of the data

(topology, resolution, rendering method), application design constraints and more importantly the narration, storytelling and expressiveness purpose, we identified the following key criteria:

**Preferred exploration.** Designs will favor exploration of the timeline simply through head rotation, or through virtual navigation and manipulation of the timeline.

**Limit of time points.** The amount of time points displayable objects easily discernible can be limited, depending on how the design partitions the workspace.

**Workspace usage and visual clutter.** Designs occupy more or less radial and vertical space around the user, which can cause occlusion and application design issues.

**Periodicity in the data.** Periodicity and temporal patterns are often important characteristics in data analysis, and some design choices, such as segmentation or helicoids can emphasize such characteristic.

**Aesthetics, originality, playfulness.** The attractiveness of a visualization can be crucial when trying to convey information. The design can be adapted to the use case and the public for this purpose.

Innovative designs might create more adapted visualizations or more catchy aesthetics. Yet, it should be noted that exotic designs might also be more difficult to interpret, as stated by Brehmer et al. [111], it is thus recommended limit the unfamiliar choices in the design of the timeline. On the other hand, in some cases design choices are interlocked together between several dimensions. For example, a helicoid representation strongly implies the use of a cylinder support.

## 4.2 Evaluation

The previous section discussed a wide range of potential 3D timeline representations, yet, from the design on itself, it remains unclear how users will leverage the 3D timeline to explore S4D data. Thus, we conducted a user evaluation in order to assess the potential benefits of 3D timelines for the exploration of S4D data. Our objective was to assess representative 3D timeline designs to explore how users will perform exploration tasks.

### 4.2.1 Dataset and Task Design

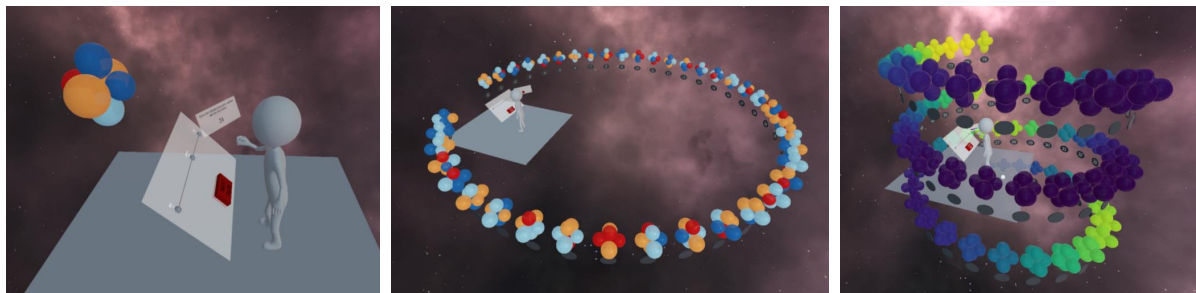


Figure 4.4 – Environment for the user experiment. The right image shows the **Locating time point** task in the *No timeline* condition; the middle one shows the **Counting occurrences** task in the *Curved* condition; the left one shows the **Finding a global maximum** task in the *Helicoid* condition, where the objects are colored using the *viridis* colormap.

The S4D dataset used in the evaluation was generated procedurally in order to keep the experiment accessible but also to limit the potential bias between users in the approach of complex S4D and in the manipulation of 3D models (see Figure 4.4). As such, we limited the number of time points and objects ensuring that users will be able to apprehend the dataset. The objects were represented by spheres, and their position did not change over time. The dataset was composed of 6 objects evolving over time, and depending on the task (see below) having either 40 or 80 time points. The size of the objects increased monotonously, so that users could keep points of reference when exploring over time. In order to enrich the dataset, objects were annotated with 2 types of information. First, a categorical information describing the affiliation of each object to one of 5 **groups**, which could change over time (see Figure 4.4, center), was encoded with different colors. We introduced randomly several occurrences of a specific pattern in the group information, on which we can evaluate success and error rates for the related task. Second, a continuous information (float **value**) evolving over time, encoded with the *viridis* color map (see Figure 4.4, right). This value was generated by adding 4 random Gaussian functions, one on each 20-time-point segment of the dataset.

During the experiment, the objective was to let participants to explore the dataset and perform different tasks. We defined four data exploration tasks that corresponded to common tasks for the exploration of time-varying data: locating a time point, counting occurrences of a particular event, finding temporal patterns or finding a global maximum. For the **location task**, a dataset of 80 time points was used. Participants had to find random defined time points between 0 and 79. They had to reach the indicated time point by using the time exploration technique available,

described below. For the **counting task**, a dataset of 40 time points, annotated with the group information was used. Participants had to count the number of objects of a given group in all time points. To limit the length of the task, it was limited to 3 minutes. For the **pattern task**, a dataset of 40 time points, annotated with the group information was used. Participants had to count the appearances of a specific 3-time-point-long temporal pattern that objects might follow in the 40 time points displayed. The task was limited to 3 minutes of exploration. Finally, for the **maximum task**, a dataset of 80 time points, annotated with the continuous information was used. Participants must find the time point exhibiting the maximum value. For simplicity, all objects from the same time point had the same value.

## 4.2.2 Hypotheses

The two first tasks (location and counting) did not require temporal context. Indeed, the information to find was punctual in time, thus any method allowing scrolling through time could be sufficient. Thus, we did not expect timelines to be particularly efficient for this type of task. Although having too much information can be overwhelming for the user, we argue that the added temporal context could still be beneficial. On the other hand, the two other tasks (pattern and maximum) required information from previous or following time points. As such, we expected better outcomes using timelines. The result could also be strongly dependent on the timeline design, as how the information is displayed and accessed. We expect that denser timeline designs would allow to access larger temporal context and could thus perform well when it is required, while also being useful to handle higher amounts of time points. Accordingly, we chose different timeline designs, which are detailed in Section 4.2.4. In summary, our hypotheses were:

- H1a** Tasks that did not require exploring the temporal context will be achieved at comparable performance with or without timeline.
- H1b** Tasks that did not require exploring the temporal context will be achieved more comfortably with a timeline.
- H2** Tasks that require exploring the temporal context will be achieved better using a timeline.
- H3** Denser timeline designs will more adequate for achieving the tasks.

## 4.2.3 Apparatus and Participants

The material used for the tests and experiences described throughout this chapter was as follow: a HTC Vive Pro HMD with 2 Vive controllers, a PC with Windows 10, an Intel Xeon W-

2104 CPU (4 cores, 3.2 GHz base frequency) and a Nvidia RTX 2080 GPU. The VR application runs on Unity 2019.4.5f1.

This experiment included 21 participants, 5 women and 16 men, aged from 22 to 42, mostly recruited from the local laboratory. Two of them had low experience with VR, the others were expert VR users.

#### 4.2.4 Independent and Dependent Variables

The experiment followed a within-subject design in which participants had to perform the different tasks using 3 different visual conditions. The first one was the *No timeline* condition, in which only a snapshot of the dataset at an instant was displayed. The two others used timeline designs which took advantage of the 3D workspace, a helicoid unified and a circular convex unified timeline. They will be referred to as respectively *Helicoid* and *Curved* conditions.

For all tasks, we measured the time to complete the task, as well as the movements and the time using the different available VR interaction tools. For the locate task, we also computed the difference between the selected time point with the target time point. For the counting task, we also computed the error rate. For the pattern task, we further evaluated the precision and recall. Finally, for the maximum tasks, we evaluated the accuracy.

#### 4.2.5 Experimental Protocol

At the beginning of the experiment, participants signed a consent form and filled a demographic information questionnaire. Participants received an explanation of the VR system and the available interactions. We mainly considered interactions that allowed the users to achieve the designed tasks. As such, object selection and task validation were done using a virtual laser pointer, and object manipulation was done using a bi-manual control. Time exploration in the *No timeline* condition was done by scrolling on the controller touchpad or using a direct manipulation on a slider (see Figure 4.4, left). In the other conditions, scrolling made the timeline move along its directing curve, and a direct selection based on a gaze and click interaction was available, users had to orient their head towards the time point and press a controller button. We let them get used to the tools and application layout for 10 minutes. The participant then proceeds to the tasks in order, in which the display condition was counterbalanced using a Latin Square.

After each condition, participants were asked to fill the SUS [172] questionnaire to evaluate usability, and the CSQ-VR [173] and FMSS [174] questionnaires to assess cybersickness. Finally,



to subjectively assess the timelines, for each task and condition we asked the following questions: “What condition felt the most comfortable for this task?” and “What condition seemed the most efficient for this task?”.

## 4.2.6 Results

For each task, we obtained a total of 63 observations, characterized by the 3-level between-subjects factor **Order** and 3-level within-subjects factor **Condition**. We used repeated measures two-way ANOVA to analyze the results. When the normality assumption was violated (Shapiro-Wilk normality test) we transform the data using the Aligned Rank Transform (ART) [175] prior conducting the ANOVA analysis. Post-hoc pairwise tests with Bonferroni correction ( $\alpha = 0.05$ ) were used when needed.

### Main Effects for Condition

**Locate task.** This task was the first of each condition, thus we removed the two first trials of each participant, which might have induced too much variability, as users were still getting used to the method, and averaged the 8 other observations. The users made almost no errors ( $(M=0.018; SD=0.077)$ ), showing that participants were able to perform the task accurately. In addition, the ART ANOVA order and condition vs **average time** showed a significant effect of the condition ( $F(2,36) = 13.87; p < 0.001$ ). Post-hoc tests validated lower times during the *No timeline* condition ( $(M=7.12; SD=1.86)$ ) compared to the two others (*Curved* ( $M=8.75; SD=2.38; p < 0.001$ ), *Helicoid* ( $M=9.57; SD=4.13; p < 0.001$ )), yet no significant difference between the latter. This tend to **invalidate H1a**, since performance was lower using timelines.

**Counting Task.** While the task was limited in time, the limit was never reached. The ART ANOVA order and condition vs **time** showed a significant effect of the condition ( $F(2,36) = 11.99; p < 0.001$ ). Post-hoc tests validated that the *No timeline* condition ( $(M=106.8; SD=40.4)$ ) gave significantly higher times than the two others (*Curved* ( $M=76.8; SD=42.2; p < 0.01$ ), *Helicoid* ( $M=68.4; SD=32.7; p < 0.001$ )), yet no significant difference between the latter. This tends to **invalidate H1a**, since performance was higher with timelines. The ART ANOVA order and condition vs error rate gave no significant results.

**Pattern task.** Participants were able to achieve the task with almost no errors showing that all methods allowed to perform the task ( $(M=0.993; SD=0.025)$ ). Moreover, the ANOVA order and condition vs **recall** showed a significant condition effect ( $F(1.63,29.36) = 6.23; p < 0.01; \eta_p^2=0.26$ ). Post-hoc tests validated a significantly lower recall between the *No timeline* condition ( $(M=0.652;$

$SD=.201$ )) and the two others (*Curved* ( $M=0.798$ ;  $SD=0.15$ ;  $p < 0.05$ ), *Helicoid* ( $M=0.818$ ;  $SD=0.17$ ;  $p < 0.01$ )), yet no significant difference between the latter was found. This tends to **support H2**.

The ART ANOVA order and condition vs **time** showed a significant main effect on condition ( $F(2,36) = 12.5$ ;  $p < 0.001$ ). Post-hoc tests showed significantly lower times for the *Helicoid* condition ( $(M=157$ ;  $SD=38.8)$ ) against the *No timeline* condition ( $(M=192$ ;  $SD=20.9$ ;  $p < 0.001$ )), and also against the *Curved* condition ( $(M=180$ ;  $SD=28.5$ ;  $p < 0.05$ )), yet no significant difference between the latter. This tends to **support H3**.

**Maximum task.** We averaged the measured values of each of the 5 trials of each participant on each condition. The measured error rate was always close to 1 ( $M = 0.997$ ,  $\text{Min}=0.98$ ), participants were able to accurately perform the task with all conditions. Furthermore, the ANOVA order and condition vs **average time** showed a significant effect of the condition ( $F(1.69,30.43) = 8.27$ ;  $p < 0.01$ ;  $\eta_p^2=0.31$ ). Post-hoc validated significantly higher times for the *No timeline* condition ( $(M=32.5$ ;  $SD=10.54$ )) than the *Helicoid* condition ( $(M=26.1$ ;  $SD=9.12$ ;  $p < 0.05$ )) and the *Curved* condition ( $(M=22.8$ ;  $SD=9.19$ ;  $p < 0.001$ )). This tends to **support H2**.

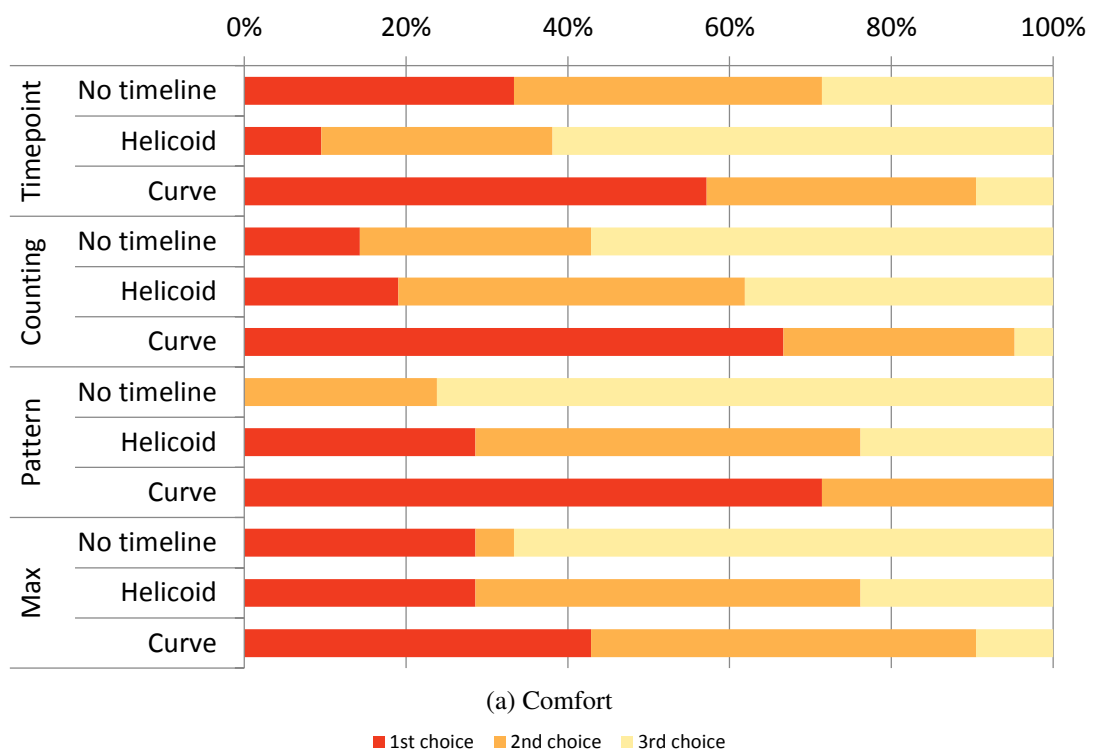


Figure 4.5 – Subjective results for each timeline design and task. (a) Ranking results for the question “What condition felt the most comfortable for this task?”.

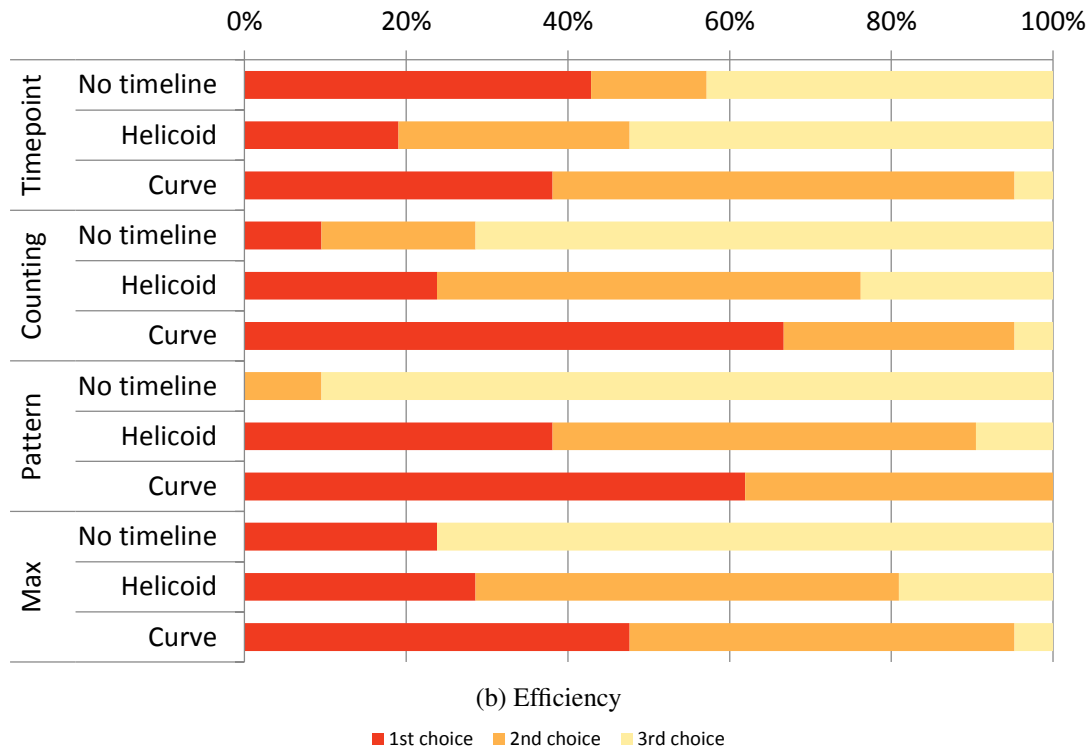


Figure 4.5 – Subjective results for each timeline design and task. (b) Ranking results for the question “What condition seemed the most efficient for this task?”

### Questionnaires.

According to the CSQ-VR and FMSS results (respectively ( $M=0.76/36$ ;  $SD=0.85$ ) and ( $M=1.7/20$ ;  $SD=1.5$ )), participants did not suffer a significant increase on cybersickness. The ANOVA order and condition for the SUS scores showed a significant effect of condition ( $p < 0.05$ ). Post-hoc tests only showed a significant effect for the *Curved* condition ( $(M=81.9$ ;  $SD=11.7)$ ) against the *No timeline* condition ( $(M=70.4$ ;  $SD=12.2$ ;  $p < 0.01$ )).

Figure 4.5 provides a summary for comfort ((a)) and efficiency ((b)) assessment for each condition. In terms of comfort, the users generally preferred the *Curved* condition for every task. The *No timeline* condition was second only in the Timepoint task, for the other tasks the *Helicoid* condition was preferred. About subjective estimation of efficiency, the *Curved* condition was still preferred in all tasks, except in the Finding Timepoint task, for which the *No timeline* condition was arguably even. However, the second place was more clearly attributed to the *Helicoid* condition for this criterion.

## Order and Interaction Effects

We analyzed potential order and interaction effects for each test. For most, the order effect was not significant, or could not be confirmed by post-hoc tests. However, we did find significant effects for some cases.

The ART ANOVA order and condition vs **average time** on the **Finding Timepoint** task showed a significant order effect ( $F(2,18) = 5.00; p < 0.05$ ), which was validated by a post-hoc test as a difference when the *Helicoid* was the first condition ( $(M=10.05; SD=4.26)$ ) and when it was the last ( $(M=7.1; SD=1.24)$ ),  $p < 0.05$ . Judging from the important standard deviation, we hypothesize that starting with the *Helicoid* might have been overwhelming to some users during their familiarization with the system, causing higher achieving times in this first task of the experiment. This interpretation is further supported as the *Helicoid* was judged the least comfortable condition for this task.

The ANOVA order and condition vs **average time** on the **maximum** task showed a significant interaction effect ( $F(1.69,30.43) = 8.27; p < 0.01; \eta_p^2=0.31$ ). Post-hoc tests confirmed that the results from the *No timeline* condition as first condition of a participant were significantly lower than any other case when the participant executes the task in the second timeline condition. This can be explained by a learning effect on the use of timelines, which becomes significant when achieving the task with a second design. Though, the condition effect showed that both *Curved* and *Helicoid* conditions obtained significantly lower times regardless of order, so this did not alter our conclusion on H2.

### 4.2.7 Discussion

The results from the two first tasks, that did not essentially require temporal context, were mitigated, so we must **reject H1a**. The results from the questionnaire however **support H1b**, as users did report preference for timelines for these tasks. Several results from the tasks of finding patterns and global maximum **support H2, that we can accept**. Finally, results from the task of finding patterns **supports H3**.

Overall, these results showed significant benefits of using timeline designs over classic visualization for temporal exploration tasks, in terms of time and quality of completion, yet also in user experience. Nonetheless, we expected a more significant difference between the two timeline designs, notably regarding the different number of time points between the tasks. We explain this lack of differences due to the choice of using a Latin Square ordering method: in two out of three orderings, the *Curved* condition was tested after the *Helicoid*. As learning effects did

disturb some results, we think that extending this study with the 6 other ordering possibilities might make such effect appear clearly, but would however require a large number of participants.

### 4.3 3D Timelines to Explore 3D Temporal Imaging

In order to illustrate the 3D timeline usage in a real application, we used our visualization method on the two first datasets described in Chapter 2, Section 2.1.3, respectively the recording of the embryonic development of the *Phallusia Mammilata*, and the intra-cellular Rab5 recording. Our goal was to gather domain users' feedback, on how 3D timelines could be used for the exploration of real datasets. A total of 20 biology experts participated, which were either experts in the topic relative to one of these datasets, or specialized in another adjacent biology domain, which allowed us to gather their feedback on the usage of 3D timelines for data analytic purposes. They all had low to no experience with VR.

The visualization of the post-processed dataset is an important part of the analytical process. Initially, as most of the image processing and annotations are automatic, users need to be able to validate, correct and add data manually, for instance to check for errors in segmentation which could lead to abnormal cell shapes. Then, the 3D nature of the data and high temporal resolution allows a general observation of the main dynamics involved in biological processes through different angles, giving insight and understanding of the evolution of the embryo. Specific regions of interest can be identified through the exploration of the cells, their surrounding and their evolution in time. Thus, information such as outliers or asymmetrical behaviors between sister cells can be extracted, as shown in Figure 4.8, to be ultimately compared either with a ground truth, a model, or other samples potentially acquired in different setups. We attempted to include as many tools as possible to support such analysis, in order to put analysts in situation and get more insightful feedback regarding the 3D timeline visualization.

#### 4.3.1 Application and Timeline Design

The application used in the experiment was extended in order to better support the analysis of the S4D datasets. First, the user could choose the annotated information displayed through a 3D GUI. Their choice will change the color-mapped information. Second, we also implemented an object filter operation to decrease the amount of information displayed on the timeline. User could select a cell or endosomes on the 3D snapshot to select the whole **4D object**, including parent and child cells, at each time point. For the meshed embryo dataset, only the cells were

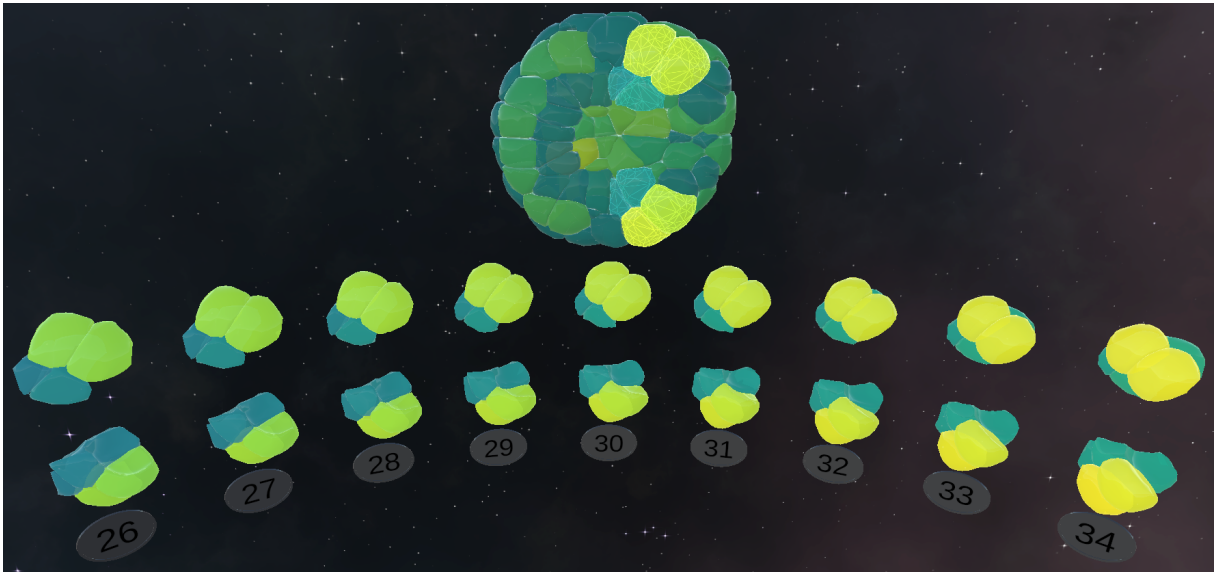


Figure 4.6 – Embryo at the 30th time point. The snapshot at the central time point shows 2 groups of are selected symmetrically as to compare their individual evolution. They are displayed on a **Circular Convex Faceted** timeline, **linear** scale, **vertical plane** support. The information color-mapped is the remaining lifespan before division (colormap *viridis*).

displayed (see Figure 4.6); for the volumetric intra-cellular data, a bounding box around the endosomes or the group of endosomes selected was displayed (see Figure 4.7).

From the datasets and the different use case analyzed, we proposed the following timeline design. As the datasets observed comes from imaging taken at regular time step, the scale dimension of our design is thus intrinsically **chronological and sequential**. Considering the tasks described in the previous section, we considered two layout choices, one that could allow comparison between 4D objects, and another for an analysis of the spatial context, respectively **faceted** and **unified** layout. The choice in representation is influenced by the amount of time points and the size at which the objects have to be displayed for a proper visualization. A helicoid representation could handle the amount of time points, yet it is not optimal to use with a faceted layout if the user wants to compare many objects, in which case we preferred a curved representation. Finally, we end up with two 3D timeline designs: (1) helicoid unified, chronological and sequential, cylinder support (Figure 4.6) and (2) curved faceted, chronological and sequential, vertical plane support (Figure 4.7, right).

Finally, taking advantage of the large work space offered by immersive environment, we juxtaposed the 3D timeline with the 3D snapshot at an instant or interest, as shown in Figure 4.6. The timeline provides with temporal context, and the 3D snapshot provides with spatial context,

giving a more complete point of view to the user. In the following, we will describe examples of processes for analysis relying on the timeline visualization. The accompanying video provides additional insights on the different examples.

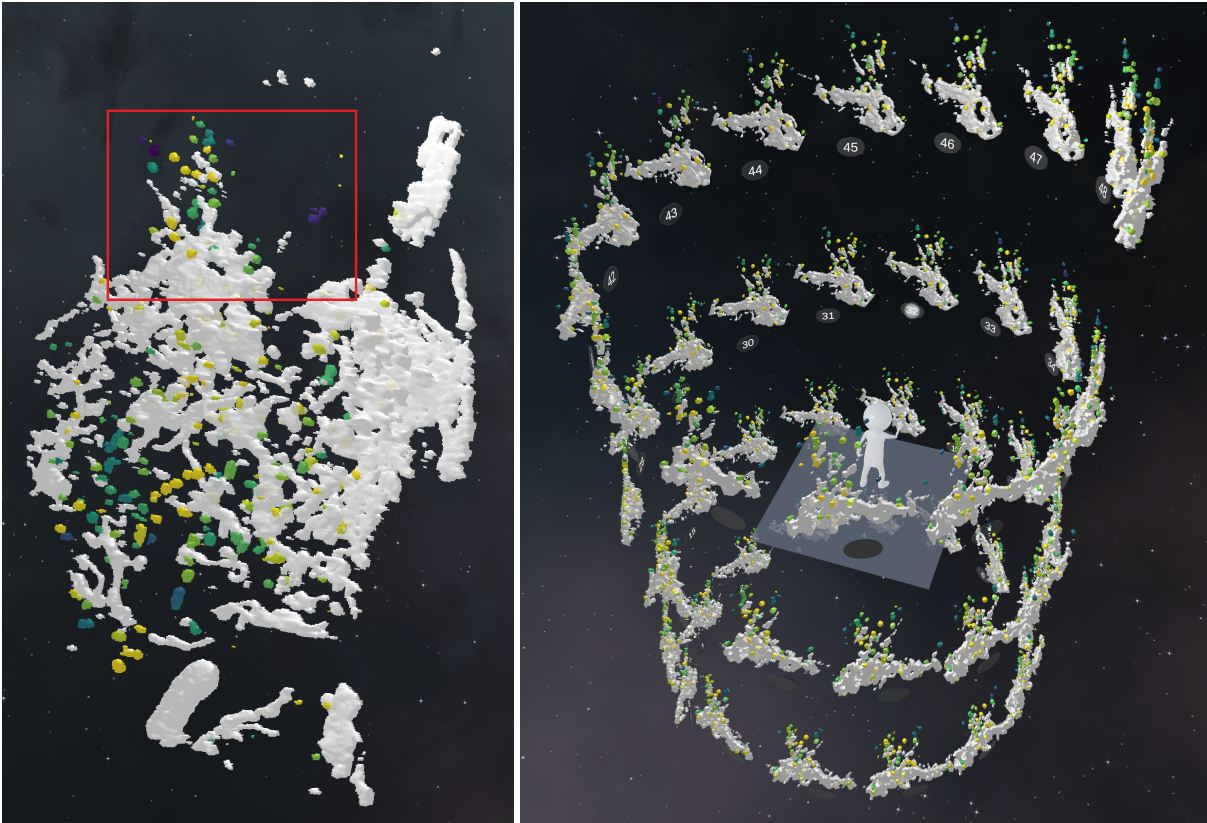


Figure 4.7 – A selection in the intra-cellular volumetric image (left) displayed in a **Helicoid Unified** timeline, **linear** scale, **cylinder** support (right). The information color-mapped is the distance to the mitochondria (colormap *viridis*).

### 4.3.2 Finding Regions of Interests in Large Datasets

Defining a region of interest is a classic visualization task, especially difficult when exploring large multidimensional datasets. On this use case, regions of interest were defined both in the 3D space and in time. We proposed an iterative interaction process to define and refine them, both in time and in space, using 3D timelines in VR.

Initially, the user selects a few objects via ray-based selection as well as an adapted layout for the 3D timeline. The first step of the exploration consists in a broad overview of the objects and color-mapped values displayed over the timeline, supported by the exploration techniques

detailed in Section 4.1.2. During this step, the 3D snapshot will follow the gaze of the user, in order to keep spatial context while exploring the global temporal context. Such global exploration can help eliminating some features, through value filtering or by collapsing the timeline at places nothing of interest happens, as described in Section 4.1.2, and identify some time points of interest. In the second step of this process, a time point can be brought in front of the user easily through a gaze and click interaction. The user is thus near a selected local temporal context, visible on the timeline, and the 3D snapshot is displayed in front of the user, allowing the refinement of the object selection, i.e. of the local spatial context. Further refinement of the spatio-temporal context can be done by repeating this process.

Overall, the timeline should give enough temporal context to find times of interest, and the 3D snapshot enough spatial context to find regions of interest. The juxtaposition and synchronization of interaction of the two visualizations, the timeline and the 3D snapshot, allows the search and definition of a spatio-temporal region of interest.

### 4.3.3 Comparing Objects

Comparison is also a usual analysis task in visualization, yet Kim et al. [75] report that this topic is quite underexplored in the case of S4D datasets. Timeline visualizations intrinsically juxtapose and allow a comparison between the selected objects or regions of interest at various time points. Depending on the temporal distance, such comparison can be supported by adequate 3D timeline designs, especially in the case of periodic data, as discussed in Section 4.1.3. Otherwise, interactive level-of-detail and timeline collapse methods described in Section 4.1.2 allow to choose specific time points to compare.

However, the task of comparing 4D objects is more complex, requiring to compare both temporal and spatial features that need to be identifiable in each of the compared objects. For example, using a faceted layout, the 3D timeline visualization allows the comparison of selected 4D objects or regions of interest, extracted from one or more datasets. The user can create a side-by-side view of the objects of interest, and manipulate them in coordination, according to methods described in Section 4.1.2. It enables a direct comparison of the 4D objects through several timeline branches, allowing to compare both the spatial information at each time point, and the evolution over time of the objects.



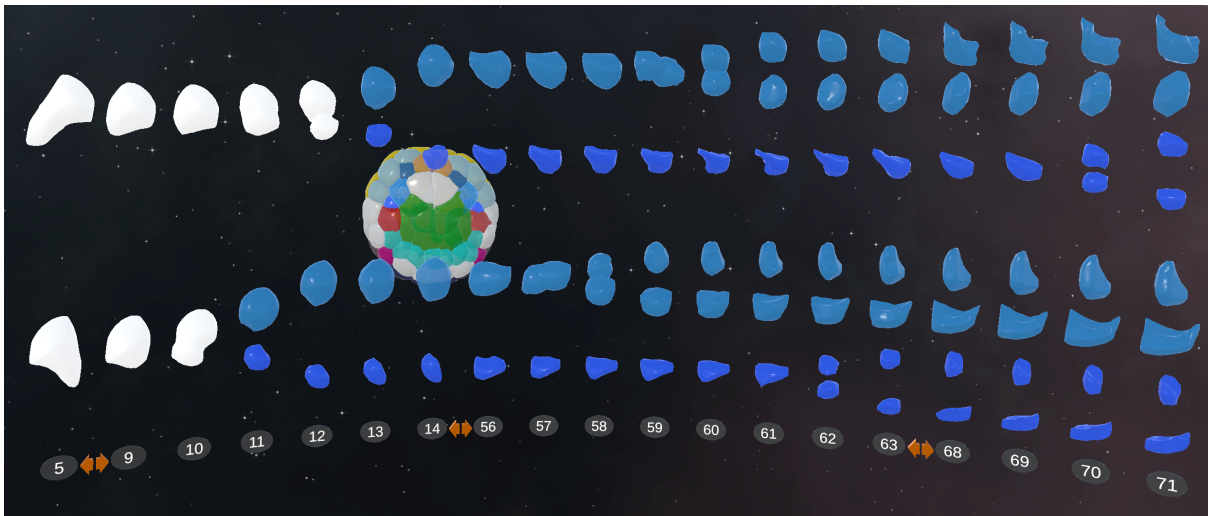


Figure 4.8 – Two sister cells are selected and displayed on the timeline. The information color-mapped corresponds to the fate of the cells. The selected ones start without annotation and are determined after a first division. The tree-like structure of the timeline shows the asymmetry of the division, with one cell significantly larger than the other.

#### 4.3.4 Fusion and Fission

A particularity of the considered dataset is the notion of lifespan, as cell fusion and fission events will modify the number of 3D objects in a given time point. We approached this issue considering that selected 4D objects comprise all of the 3D objects involved in the event, creating different branches. In case of a fusion event, the object will have two branches before and one after the event; in case of a fission, there will be one branch before and two after the event. We propose an adapted layout for the 3D timeline design to represent the branches. The resulting layout is a graph of temporal relation between the objects in the dataset. In our specific use case, as there is mostly fission events, i.e. cell divisions, we end up with a tree visualization, oriented along a timeline, as shown in Figure 4.8. This visualization is similar to a lineage tree [167] displaying and allowing comparison of the cell shape evolution, which was one of the main tasks detailed for the use case.

#### 4.3.5 Expert Feedback

In this section, we gather and summarize the feedback obtained during the evaluation sessions. They participated in sessions of about an hour by groups of 2 or 3, in order to try the application and discuss potential application of 3D timeline visualizations in their respective fields. We presented them the dataset used and the application controls, and let them explore the data using

the timeline designs proposed and the analytic techniques described previously.

The embryology specialists were overall positive about the visualization. They could analyze value evolution over different cells, as in Figure 4.1, identify outlier behaviors, and obtain information about a cell differentiation, as shown in Figure 4.8, where an undetermined cell is selected and differentiate itself after division. They also considered how such visualization could help in comparing multiple embryos, which they can hardly do with their current visualization tools. The specialists from other domains could not go into such details with this dataset, yet they projected how they could benefit from 3D timelines for their own data. They quoted several examples of adapted use case with other S4D datasets such as imaging of organoids [176], in context of immunology or cancer research. They also mentioned how 3D timelines could help visualize colocalization over time of objects of different nature in multi-channel imaging.

Most of the drawbacks reported were about improving the application design to integrate it in the analysis workflow. Several key points in the analysis process should be included to answer completely the use case, including raw data visualization, standard data formatting or annotation options. The integration of VR equipment is also an obstacle, yet several people mentioned they would be willing integrate it in their work stations if the mentioned options were implemented.

## 4.4 Conclusion

In this chapter, we proposed an extension of the 2D timeline design space proposed by Brehmer et al. [111] into a 3D timeline design space, focusing on their use for S4D dataset visualization. To do so, we extended the *representation* dimension, using 3D curves as guiding lines for timelines, and introduced an additional dimension describing the 3D geometry on which several timeline branches could be displayed, named *support* dimension. We proposed to use these timelines in a VR environment, leveraging the benefits of the material to enhance the exploration and interaction with such structures. Relying on 3D interaction techniques, we also proposed an interaction process to explore the timeline and define spatio-temporal regions of interest. We tested two 3D timeline designs against a baseline visualization based on a 3D render and time slider, on tasks oriented toward the exploration of a S4D dataset. The experiment results led us to conclude that 3D timelines significantly improved the achievements of tasks requiring to explore the local temporal context, yet could not conclude on the benefits of one or the other timeline. Finally, an application implementing 3D timelines and adequate interaction methods on a embryo S4D dataset was tested by 20 biologists. Their feedback was very positive, both for the specific datasets illustrated but also opening to various use cases in other biology domains.



# SPACE-THEN-TIME: TOWARD SELECTION METHODS FOR PUNCTUAL EVENTS IN 3D TEMPORAL DATA THROUGH 3D INTERACTION

---



---

5.1	Time-then-Space or Space-then-Time? . . . . .	100
5.2	Visualizing the Right Data . . . . .	100
5.3	Selecting 3D Information . . . . .	102
5.4	Disambiguation in Time . . . . .	103
5.5	Implementation Details . . . . .	105
5.6	Conclusion . . . . .	105

---

In this chapter, we propose a method to improve the selection of 3D temporal events features that appear punctually in time, i.e. 4D objects with small temporal component. For simplicity and even though these objects might not be punctual in the 3D space, we will refer to them as “punctual 4D objects”. Visualizing these objects individually is thus mostly reliant on 3D visualization, but selecting them in the potentially large time dimension of a 3D temporal dataset can be quite challenging.

Therefore, we propose an interaction process to improve the selection of punctual 4D objects, based on a spatial selection first, and then a temporal disambiguation, as opposed to an exploration in time and then selection in space in usual visualizations. We identified 3 main axes to approach the design of such selection method, namely how to visualize the 3D temporal data to support this selection method, how to select in space, and finally how to select in time. In the following,

we explore and propose different methods that could efficiently be used to approach each of the three axes. We illustrate our argument with images based on the astrocyte recording and calcium signal simulation dataset, the third one described in Chapter 2, Section 2.1.3.

## 5.1 Time-then-Space or Space-then-Time?

Traditional methods usually explore 3D temporal datasets by first exploring in time until noticing a 3D region of interest. In the case of punctual 4D objects, this can be particularly challenging. Figure 5.1 illustrates a calcium signal of type *wave*, supposedly longer than other types of signals, yet only lasts for 4 time points out of the 100 of the dataset. In this context, lookup tasks are especially difficult: relying on a naive temporal exploration, finding such object consists in a spatial exploration multiplied by the number of time points in the dataset, i.e. a 1D x 3D exploration task. The approach we propose in this chapter consists of an interaction process starting with a selection in space, then a disambiguation in time, overall a 3D + 1D exploration task.

Such interaction process implies several issues:

- The selection in 3D must be done without exploration of time. How does the user have the information about where is the object they are looking for? In other words, what information should be visualized for the user to do such selection?
- What 3D information needs to be selected before exploring time? How the selection in 3D will allow the identification of the correct zone in time?
- Once the 3D selection is correctly made, how to explore the temporal dimension remaining? How to disambiguate between the potentially selected objects in time?

In the following, we discuss methods that could be used to handle each of the three main axes described.

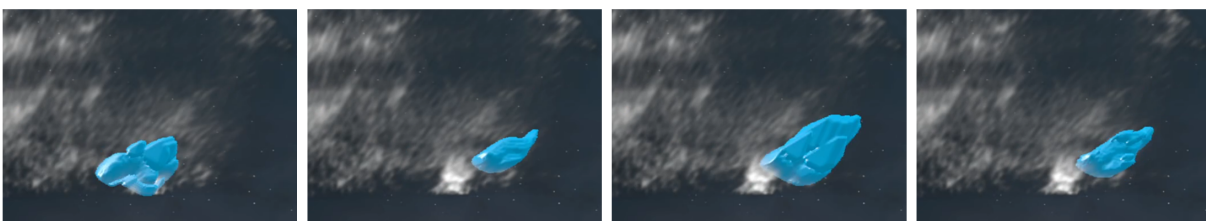


Figure 5.1 – Complete lifespan of 4 time points of a calcium signal of type *wave* (blue), in the imaging of the astrocyte.

## 5.2 Visualizing the Right Data

In this section, we approach the issue of the visualization of the data to support the 3D space selection step of the interaction process. The challenge here is to display sufficient information for the user to identify the 3D position related to the 4D object they are looking for. We discuss here several methods that could help in tackling the issue, based on either dimension reduction, juxtaposition or dynamic approaches.

**Collapsing the Information** Dimension reduction consists in a transformation of the data in order to obtain a lower-dimension displayable visualization, as we did in Chapter 3, collapsing the STH into a STC according to a user-defined plane. However, the STC visualization we proposed in Chapter 3 would not be adapted to represent punctual 4D objects, as they would only appear in only a few slices of the volume. Nonetheless, collapsing the STH along the time axis could reveal elements appearing at any moment in time. A direct collapse along time would show efficiently where objects are in space, yet with a large number of objects, the visualization would be too dense to exploit. Collapsing into a density map, as shown in Figure 5.2, give a less cluttered visualization, yet places where few punctual 4D object appear might be difficult to discern, even with an adapted transfer function.

**Animation-based methods** Animations could show all of the information regarding object positions quite quickly, and give enough insight for the user to identify a region of interest in space. The user could control the playback speed, define a windows of time to display, or even control directly the time point displayed with a slider. Time warping methods, such as Memento [100], could also enhance the animation, allowing the user to slow time in moments of interest, and speed up moments when nothing appears. Such speed adjustments can be defined either manually through a control of curves, or through automatic methods, computing a cost function according to the amount of 4D objects present at each time point. Nonetheless, such dynamic approach might create mental workload since the user needs to remember what appears along the animation to estimate the relevance of a region of interest.

**Small multiples** The small multiple approach would allow us to divide the issues of the previously described methods by multiplying the number of views. The density map could be separated into multiple density maps, each computed along a temporal window, thus creating a partition of the temporal space. This method could highlight more properly the punctual 4D objects appearing along each temporal window. On the other hand, small multiples could support

the time-warping based method separating the 3D space into multiple sections. Each section could be provided with a different playback speed curve, slowing down and highlighting events of importance in the local spatial context. However, multiplying the views also implies multiplying the number of spatial explorations required, meaning a compromise needs to be found not to counter the benefits of the space-then-time selection method.

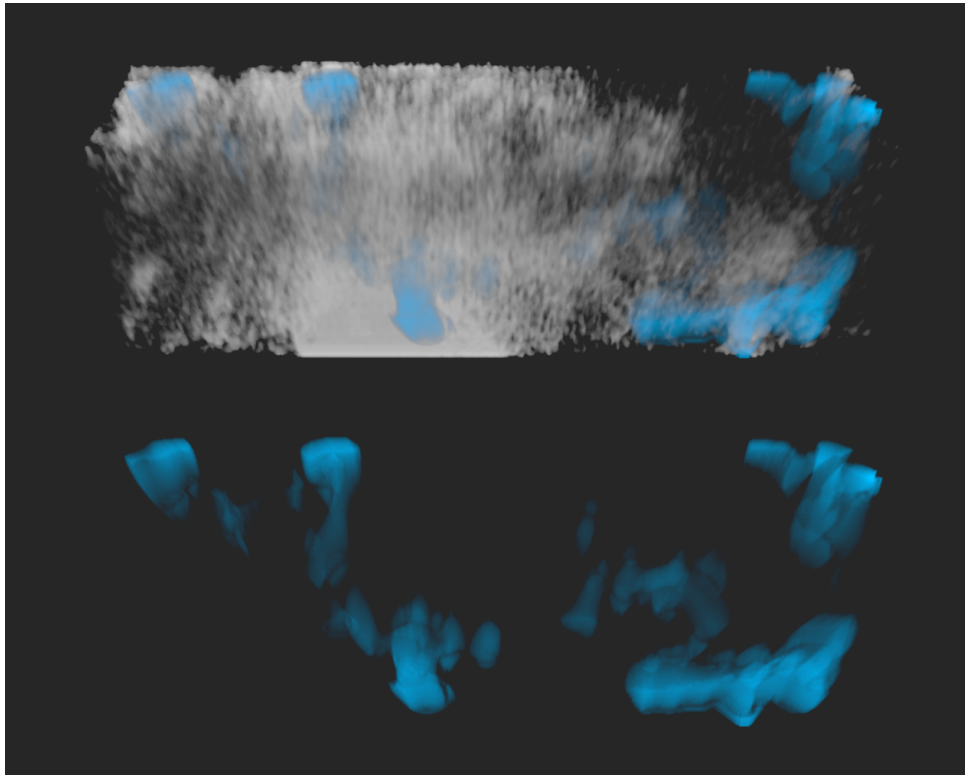


Figure 5.2 – Density map of the calcium signals (blue), with and without the astrocyte imaging, respectively top and bottom.

### 5.3 Selecting 3D Information

Based on one of the visualizations discussed in the previous section, the user should have enough information to select spatial information related to the punctual 4D object of interest. In this section, we propose ways for users to select enough spatial information to identify as precisely as possible the object required. We discuss methods based on a brushing interaction, on the placement of landmarks, or on the definition of a trajectory.

**Brushing** Brushing selection is often used for selection or annotation tasks in volumetric or point cloud data. The user marks a zone in the volume through natural 3D interaction, as illustrated in Figure 5.3, with a brushing selection appearing in yellow over the density map visualization. The 4D objects selected can be chosen through intersection between the brushed zone and the object at one time point, or at all time points, depending on the level of selectivity required. The brushed zone can be selected to match the movement of the object, helping to describe in a versatile way the behaviors of various types of 4D objects. Nonetheless, no temporal or directional information is provided with a brushing selection, which can be lacking in some use cases.

**Placing Landmarks** Like the brushing selection, the placement of landmarks is a simple interaction that takes advantage of natural 3D interactions and stereoscopic vision. The position of the landmarks can then be compared to the center of gravity of the objects at each time point to define which objects are selected. This approach is faster than brushing, yet gives less spatial information, so it might be less precise. Moreover, it shares the same drawback as brushing, regarding the lack of temporal and directional information.

**Drawing a Trajectory** The definition of a trajectory by the user can be done either by placing a series of landmarks, or by free drawing. This interaction is more difficult than the previous ones, yet includes temporal information. It can be especially relevant in use cases where the user aims at selecting objects showing a specific behavior, or following a certain direction, such as a dendrite of the astrocyte in the illustrating dataset.

## 5.4 Disambiguation in Time

Multiple objects might match the spatial selection made by the user, since different objects might appear at the same place but at different instants. The next step of the selection consists in exploring in time in order to choose among the matching 4D objects. In this section, we describe various methods that could support the disambiguation in time, with manual methods based on either lists of information or visualization of the 4D objects, or through automatic methods.

**List of the objects** A first option to disambiguate is to list the related objects, for example on a side panel, with textual information specific to the 4D object, such as a name or identifier, lifespan start, end and duration, or any other categorical or numerical information. The selection



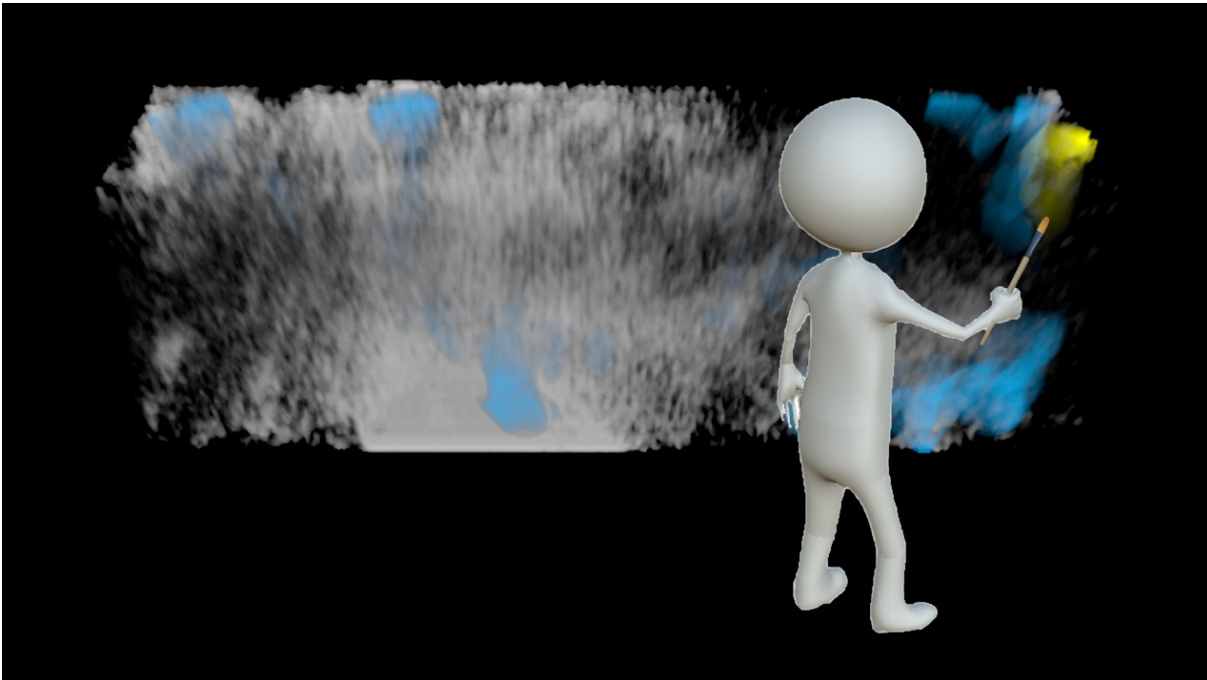


Figure 5.3 – Brushing interaction on the density map. The user is represented with a brush tool, and their selection appears in yellow on the density map.

can then be done by scrolling and clicking on the required 4D object. If this method does not include directly any visualization of the 4D object, the textual information displayed can actually be more critical for the selection of the 4D object in the analytical process.

**Timelines** The selected 4D objects could be displayed using 3D timelines. A faceted layout could allow their juxtaposition and comparison. The objects could be aligned along their starting points using a relative scale, with adequate labels on the initial time point. Using a cubic support, the 4D objects could be arranged according to a categorical information, for instance by type of calcium signal in our illustrating dataset. The representation is overall less relevant here, since the objects have very short lifespan.

**Automatic methods** With the information provided by the spatial selection, 4D objects could be ordered to identify the one most corresponding to the user input. This ordering needs to be based on a scoring function, which parameters depend on the spatial selection method used. For example, with the brushing selection, we can compute the intersection between the selected zone and each 4D object. Therefore, the number of pixels intersected, the proportion of the object covered by the selection, the proportion of over selection can influence the scoring. In

the case of landmarks or trajectory, the distance between the center of gravity of the object and the landmark, or corresponding time point of the trajectory, would be a major parameter for the scoring function.

Nonetheless, to avoid imprecision by selecting the highest score, we could use this ordering to complete the timeline or list approach to finish the disambiguation. To avoid aberrant selection, either the top few objects would be displayed, or the ones over a certain threshold.

## 5.5 Implementation Details

We implemented the functionalities shown in the illustrations of this chapter, in order to test for technical feasibility. The dataset used in the illustrations of this chapter contains 100 images of size 170 x 512 x 48, resulting in a 1.6GB dataset. The images are rendered through direct raycasting algorithm, maintaining 90FPS, on a computer equipped with a NVidia GeForce RTX2080 GPU.

Relying on GPU computation, the density map is also computed interactively, i.e. less than 10ms. Therefore, the time window included in the density map could be changed by the user interactively. But it also implies that a whole range of complex computations involving the whole 100 images could be implemented and executed without disturbing interaction. Especially, the information necessary for the cost function described in Section 5.4 could be recovered and the disambiguation computed without delay, which is necessary for the quality of the interaction. Nonetheless, further tests in an actual implementation of the method and with bigger datasets might be required to evaluate actual technical limitations.

## 5.6 Conclusion

In this chapter, we analyzed the task of selecting punctual 4D objects and detailed a set of methods that could be used in order to achieve such task. We propose an interaction process consisting in a space-then-time selection: it is composed of a compact visualization of 3D temporal data, supporting a selection of spatial information, and ending with a disambiguation in time to choose the relevant 4D object. We proposed several methods that could handle each of these three tasks. For each, we discussed the benefits and drawbacks to consider when using an interaction process based on the space-then-time model for an analytical use case. Nonetheless, formal evaluation is required to confirm the benefits of a space-then-time selection compared to traditional selection methods in the context of punctual 4D objects.



# CONCLUSION

---

This thesis presented a series of contributions to the issues regarding the visualization and interaction of 3D temporal data, following three main research questions, regarding how to represent the data, how to visualize them and how to interact with them.

## 6.1 Contributions

In Chapter 2, we reported works from the literature to describe the context of the research domains surrounding this thesis subject. We first presented the definitions and main research challenges in the domains of Visualization, Visual Analytics and Immersive Analytics, and detailed the benefits of the latter in terms of perception and interaction. We then described techniques to visualize the temporal dimension in general types of datasets, focusing on the static temporal visualization methods of Space-Time Cube and Timelines. Finally, we presented Immersive Analytics applications and techniques developed in the context of scientific visualization, information visualization, and also applications exploring collaborative visualization.

In Chapter 3, we presented the Space-Time Hypercube representation as an extension of the Space-Time Cube for 3D temporal data. We used this representation as a support to create new visualizations, relying on a projection from 4D to 3D data defined interactively by the user. This projection consists in capturing a cut-away view of the 3D data at each time point and stack them into a Space-Time Cube. We proposed to integrate this resulting volume in an immersive environment to take advantage of the perceptual and interactive benefits of Virtual Reality, and implemented a set of general tools adapted to its exploration. A user-study with naive participants was designed to evaluate this method through a biology use case, and biology experts also provided with feedback on the visualization for its use in an analytical context.

The results of these evaluations and feedback led us to conclude that the method was particularly useful in the visualization of 3D temporal features with large temporal component, such as movements of the general structure, behaviors of entities or quantitative values evolving over time.

In Chapter 4, we proposed a design space for 3D timelines. This design space extends the existing one for 2D timelines, by exploring ways to display a timeline in a 3D environment, notably taking advantage of the large workspace of immersive environments. We suggested that such 3D timelines can support the visualization of 3D temporal data, using the representation of 3D temporal data through 4D objects. We introduced interaction processes leveraging the interaction benefits of the high-degree of freedom viewpoint and inputs of VR devices, in order to efficiently explore the timeline and select regions of interest that can be defined both in space and time. We reported a user-study evaluating 3D timelines on general visualization tasks, as well as informal evaluations from biology experts on the exploration of biology imaging datasets using 3D timelines.

The results of these studies suggest that 3D timeline visualizations and the interaction processes associated were useful for the exploration of the data, notably on tasks requiring the analysis of a local temporal context, i.e. 3D temporal features of short to medium temporal range.

In Chapter 5, we discussed an interaction method to select objects that are punctual in time. This method relies on a selection process starting with a 3D spatial selection and then a temporal disambiguation, as opposed to traditional selections involving a temporal exploration then selection in a 3D render. We discuss the three main components of the method, namely how to display enough information for the spatial selection, how to select spatially and then how to select temporally. We expect this interaction method to effectively support the selection of 3D temporal features with short to punctual temporal range.

Additionally, despite the fact that the question of representation of the 3D temporal was not the main focus of the contributions described above, we did nonetheless propose several approaches through this manuscript. We approached the issue of representation of 3D temporal data in Chapter 3 through the Space Time Hypercube representation, which uses the temporal dimension as a Euclidean dimension resulting in a 4D volume. This approach supports the creation of visualizations extracted from a 4D structure, as we showed in Chapter 3. This representation approaches the dataset in its entirety, and thus was adapted to 3D temporal features with large temporal and spatial importance. In Chapter 2, Section 2.1.3, we developed a representation of the data through 4D objects. These 4D objects represent 3D temporal features that appear in the datasets, and consist in the definition of a continuous 3D shape, and its associated occurrences continuously over time. This approach revealed itself more adapted to support visualization and interaction of most types of features existing in the datasets we worked with. It allowed a logic

---

partitioning of the data which could be used to exploit juxtaposition techniques in visualization, as shown through Chapter 4 on 3D timelines, or to support filtering operations.

## 6.2 Perspectives

Our contributions proposed several approaches answering partially the main research questions we presented at the beginning of this work. This section presents future works that could be pursued on our contributions and on the research questions.

### 6.2.1 Short-Term Perspectives

- First, in Chapter 3, we introduced a projection operator for the STH. A limitation of this operator is that it implies an important loss of spatial information, involving a difficulty for the user to define properly the projection. It can be sensible to strong motions as objects close to the cutting plane that can result in wrong interpretations (e.g. an object shrinking when it is just moving away from the clipping plane). Future works should explore how to adapt the projection operation according to their analytical needs. For example, the clipping plane could be adjusted over time to track an object of interest or take into account the internal motions of the objects, potentially extending the cutting plane to an arbitrary surface. More use-case-dependent approaches for the projection operator could result in more user-friendly interactions, but also in visualizations that are more robust and precise regarding the highlighting of 3D temporal features. Furthermore, the main purpose of using the STH in an immersive virtual reality context was to take advantage of the increased depth perception [46, 105] and interaction capabilities [141]. Although we exploited those two characteristics, we did not fully exploit the large workspace provided by immersive VR. In this direction, a number of additional follow-up works could be envisioned. Multiple STC visualizations could be juxtaposed either generated by different projection operators, or encoding different qualitative and quantitative data. Exploded views or other methods to reduce visual clutter [9] could also be considered. These propositions would provide new means to explore and interact with the STC visualizations.
- In Chapter 4, we proposed a design space for 3D timelines, notably based on the design space for 2D timelines proposed by Brehmer et al. [111]. As opposed to said design space, we are not classifying existing examples of timelines. By extending the 2D design space, we could propose a mostly usable and general 3D design space, yet it also implies our

design space might be less exhaustive. We suggest that both the representation and support dimension could be even further explored, exploiting the 3-dimension space through even more innovative ways. We notably expect that the use of the method on different types of dataset, or the tackling of different analytical use-cases, could inspire other design choices, which would also enrich our design space. Furthermore, future works could improve and enrich the interaction pallet we provided. The use of 6-degree-of-freedom 3D interface allowed us to implement efficient yet basic exploration and manipulation of S4D datasets for general tasks. However, the literature proposes finer techniques, notably for selection and navigation [39], that could be more adapted notably depending on the 3D timeline design choices. Nonetheless, our evaluation only showed the usability of 3D timelines in general cases. Yet, a comprehensive evaluation of the design space would be interesting to properly evaluate the benefits and drawbacks of each component of the design.

- In Chapter 5, we proposed a method for the selection of punctual events through a space-then-time interaction process. The method is still at a stage of conceptualization and prototyping. Each component of the selection method could be explored further. The information visualized could be adapted depending on the features to be observed, or could be designed to support other spatial selection methods. The disambiguation in time could rely on a cost function refined through machine-learning algorithms, although it requires recorded interaction information, preferably on various datasets. Finally, the method requires an evaluation, in order to compare the different propositions evoked in Chapter 5, and to compare with a traditional time-then-space selection.

## 6.2.2 Long-term Perspectives

On the issue of representing 3D data, our 4D object approach allowed to qualify a wide variety of 3D temporal features, yet presents multiple limitations. First, parts of the datasets we presented could not be qualified into 4D objects, and more specifically elements of background. Indeed, our approach relies on both existing separation of elements of interest, and also tracking information of these elements. Some datasets can include such information by design, notably trajectory or mesh-based datasets. On the other hand, other types of datasets, such as point clouds or volumetric, require the use of segmentation and tracking algorithms, often followed by manual curation of the output. We believe that a unified approach for 3D temporal features would greatly help further research on 3D temporal data. Methods could be shared easily between domains, either on the topic of segmentation and tracking algorithms, or about visualization

and interaction techniques. Furthermore, a unified approach could encourage optimizations on analysis and rendering algorithms, but also support easier communication between domains and help research reproducibility. Eventually, we identify two main directions to improve the representation of 3D temporal features. A first objective would be to explore more the notion of 4D objects, generalizing the approach to other types of 3D temporal datasets and features, e.g. trajectory datasets or point clouds, which we did not approach here. A second objective would be to propose methods to qualify background and contextual elements, which can difficultly be qualified as 4D objects. As the 4D object approach is probably not exhaustive to represent all the features in 3D temporal datasets, a complementary approach might be necessary to include the information in the analysis of the complete dataset.

Moreover, future works should focus on the issue of comparison. Among the methods we proposed, 3D timelines could allow comparison of 4D objects taking advantage of faceted timeline designs. Nonetheless, further methods could improve the comparison of multiple datasets, for example to compare a dataset to a ground truth, or two simulations with different parameters. Comparison could extend existing 3D comparison methods, involving 4D set operations (e.g. intersection, exclusion). Else, it could exploit the large workspace of virtual environment for juxtaposition-based methods. Adapted 3D interaction methods could be synchronized along the multiple views of the multiple datasets displayed, further supporting comparison. Furthermore, there is a need for comparison of the additional categorical and numerical data related to each object. Colormaps can easily encode one dimension of information, and switching from one information to the other makes for a difficult comparison, according to the "Eyes Beat Memory" slogan. Such comparison could rely on juxtaposing two copies of the same object with different colormaps, use multi-variate colormaps, juxtapose two colormaps on a same object through adequate texturing, or involve other perceptual channels (e.g. sound, haptic feedback). Perceptual studies will then be required to evaluate the optimal solution according to different use cases.

## 6.3 About Visualization in Bioinformatics

During the conception and the evaluation of the works presented in this thesis, we interacted with biology experts regularly, in order to get insight on the main issues they encounter as well as feedback on the methods we proposed.

On our side, we understood progressively along this collaboration the variety and struggles around 3D temporal datasets. They involve lots of different issues, as such datasets have a wide variety of topologies and specific analytical use cases. Actually interacting with the datasets



and discussing with the specialists behind them completed our point of view on how to answer our research questions. Furthermore, as we presented a VR application to users naive to the technology, a “wow effect” was often the first reaction we could get, especially when demonstrating visualization occupying the whole space and with some basic navigation and manipulation controls. Yet, over the successive demonstrations, the domain experts started mastering the tool and actually realizing the potential behind the technology and the methods we developed, sometimes provoking a deeper interest in it. The feedback got more and more precise regarding the issues we were tackling, and also regarding how to improve our method and application for end-users.

Consequently, and as we reported in the related parts in Chapter 3 and 4, an important part of the feedback concerned enhancement of the application. The remarks were either related to quality-of-life improvements, i.e. simplify some interactions, make them more user-friendly or add more controls on some parameters, or were related to adding features present in their usual software. In order to integrate Immersive Analytics tools in experts’ workflows, efficient methods are not enough: the application has to either implement a complete workflow, and preferably be compatible with the other software used. Among the most important missing features, annotation was the most noticed: seeing is not enough, analysts need to keep trace, place markers and actually add information. Indeed, their objectives with visualization software are notably to curate the results of automatic algorithms, in order to create ground truth, support the analysis of further datasets and communicate with other analysts.

Reflecting on this fruitful collaboration, we suggest that works of Immersive Analytics should make an effort on the realization of user-friendly applications. It should notably integrate important features that are often overlooked, as Fonnet and Prié [58] pointed out a lack in the literature around tasks of Aggregation, Annotation, Import, Derive and Record. Moreover, the collaboration and regular demonstrations with the end-users is crucial along the development of the methods and the application: first, it ensures that the development is made in the right direction to answer the needs and research issues of analysts; second, it helps the solicited end-users to get used to the methods and the associated material; third, it opens the mind and grab the interest of end-users, as they can see and experiment themselves the potential of the techniques, through diverse use-cases and datasets.

## **6.4 Concluding word**

3D temporal datasets are becoming more and more common ground, allowing new points of view and potentially leading to discoveries in various fields. With these new issues, the human capacity will be challenged, and Immersive Analytics have the potential to give new tools to approach them. Yet is still in a middle position between Mixed Reality and Visualization innovations. We hope this work will participate in the development of this field, and motivate others to keep pushing in this direction.



# AUTHOR'S PUBLICATIONS

---

## Peer-Reviewed Journal

- **Gwendal Fouché**, Ferran Argelaguet, Emmanuel Faure, Charles Kervrann. *Immersive and Interactive Visualization of 3D Spatio-Temporal Data using a Space Time Hypercube*. *Frontiers on Bioinformatics*, 2022, vol. 2.
- Valades-Cruz\*, Cesar Augusto\*, Ludovic Leconte\*, **Gwendal Fouché\***, Thomas Blanc\*, Nathan Van Hille\*, Kevin Fournier, Tao Laurent et al. *Challenges of intracellular visualization using virtual and augmented reality*. *Frontiers in Bioinformatics*, 2022, vol. 2. (\* These authors have contributed equally to this work and share first authorship.)

## Peer-Reviewed Conferences

- **Gwendal Fouché**, Ferran Argelaguet, Emmanuel Faure, Charles Kervrann. *Timeline Design Space for Immersive Exploration of Time-Varying Spatial 3D Data*. In *Proceedings of the 28th ACM Symposium on Virtual Reality Software and Technology* (pp. 1-11), 2022.

## Miscellaneous

- Audinot, Alexandre, Diane Dewez, **Gwendal Fouché**, Rebecca Fribourg, Thomas Howard, Flavien Lécuyer, Tiffany Luong et al. *3Dexterity: Finding your place in a 3-armed world*. In *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, pp. 521-522. IEEE, 2020.
- Cheymol, Antonin, **Gwendal Fouché**, Lysa Gramoli, Yutaro Hirao, Emilie Hummel, Maé Mavromatis, Yann Moullec, Ferran Argelaguet, and Florian Nouviale. *The Rubber Slider Metaphor: Visualisation of Temporal and Geolocated Data*. In *2022 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)*, pp. 904-905. IEEE, 2022.



# RÉSUMÉ EN FRANÇAIS

---

## Introduction

### Pourquoi cette thèse?

Cette thèse, intitulée "Visualisation immersive et interactive de données 3D temporelles", présente les contributions de recherche que nous avons proposées pour aborder les questions relatives à l'immersion, la visualisation et l'interaction avec des données provenant d'autres domaines scientifiques. Dans cette première section, nous introduisons les principales parties du titre de cette thèse, fournissons des éléments de définition pour chacun de ces termes et illustrons l'inspiration qui nous a conduit à explorer le sujet.

**Pourquoi des données temporelles 3D ?** Les ensembles de données augmentent en taille et en dimensions, et de plus en plus d'analystes ont des difficultés à traiter leurs données. Tout un champ de recherche, le Big Data, explore notamment les méthodes d'analyse des ensembles de données composés d'énormes quantités d'entrées de données. Nous avons choisi de nous concentrer sur la question émergente des jeux de données temporelles 3D. Les données temporelles 3D sont adoptées dans de nombreux domaines, comme l'imagerie biologique par microscopie, l'imagerie médicale ou les informations géographiques à l'échelle macro. Comme la technologie pour traiter les données temporelles 3D arrive à maturité, le nombre de jeux de données existants de ce type augmente, et avec lui l'intérêt pour ce sujet. La taille des ensembles de données, mesurable parfois en téraoctets, peut maintenant être acquise, stockée et affichée grâce aux techniques matérielles et logicielles développées au cours des dernières décennies. Ces ensembles de données sont riches en informations et pourraient donner un nouveau point de vue sur de nombreux sujets que nous pensions déjà maîtrisés. Pourtant, le développement de méthodes permettant d'analyser correctement ces données reste un véritable défi.

**Pourquoi la visualisation ?** La vue est le sens le plus important, puisqu'elle fournit plus de 80% des informations perçues, selon Roseblum [1]. Les gens veulent toujours voir, car c'est le moyen le plus facile de comprendre les objets, les mécanismes, les phénomènes, en fait la plupart des choses qui se passent et existent autour de nous. En effet, voir est en réalité une tâche complexe, impliquant l'observation, l'extraction d'éléments d'intérêt, leur analyse, leurs caractéristiques physiques, leur activité et leur lien avec le contexte environnant. De nombreux jeux sont conçus autour de la difficulté de cette tâche, de "Où est Charlie" aux jeux de tir, ou même lorsqu'on cherche une pièce de Lego dans une énorme boîte (voir Figure B.1). La visualisation est le domaine qui tente de formaliser et de résoudre ces problèmes quotidiens en s'appuyant sur la vision, dans le contexte de l'analyse des données. Comme nous l'avons mentionné plus haut, les ensembles de données sont de plus en plus volumineux et complexes, de sorte que les analystes de divers domaines ont du mal à gérer leurs données, ce qui crée de nouveaux défis pour la visualisation.



Figure B.1 – Le défi de trouver cette pièce-là.

**Pourquoi l'interaction ?** L'interaction constitue l'ensemble des actions consistant à déplacer, saisir ou pousser des objets. Ces actions peuvent favoriser l'observation. Par exemple, pour trouver la pièce de Lego manquante, les gens fouillent dans la boîte, jusqu'à ce que cette pièce spécifique ne soit pas cachée et qu'elle soit dans une position et une orientation que votre œil peut facilement discerner. Les interactions permettent de développer des stratégies pour trouver des éléments pertinents dans un grand ensemble d'informations. Pourtant, voir un élément d'intérêt n'est que la première étape. L'interaction aide également à comprendre la nature de cet élément

particulier. Tourner l'objet pour en discerner la forme, le faire bouger, exercer une pression, sentir la surface, le lancer... Autant d'actions que ferait un bébé en découvrant un nouveau jouet. Par conséquent, l'interaction avec les données est cruciale pour soutenir les différentes étapes de la visualisation, autant qu'elle est naturelle.

**Pourquoi l'immersion ?** L'immersion est la capacité à s'adapter à un environnement différent de l'habituel, avec des règles et des références différentes. L'être humain s'adapte très vite à de nouveaux environnements, et notamment à des environnements simulés. Les notions de présence, c'est-à-dire le sentiment d'"être là", et d'incarnation, c'est-à-dire le fait de percevoir un avatar comme soi-même, sont étudiées en profondeur avec les environnements virtuels. Dans le contexte de l'analyse de données, l'immersion peut nous aider à comprendre des modèles d'objets d'échelles très différentes, d'un système planétaire à des entités se déplaçant dans une cellule. Les technologies supportant les technologies immersives ont également beaucoup mûri ces dernières années. Les écrans montés sur la tête ont désormais une haute résolution, une fréquence d'images élevée et un faible coût. Ces écrans stéréoscopiques affichent deux images 2D, une pour chacun de nos yeux, ce qui simule la même "3D" que nous avons l'habitude de voir. Les dispositifs de suivi suivent les mouvements de notre tête, de nos mains et de l'ensemble de nos mouvements avec une grande précision et une faible latence. Dans l'ensemble, l'immersion simule les visuels d'une manière similaire à celle de nos yeux, ainsi que l'interaction naturelle et surnaturelle. Cela peut potentiellement soutenir la visualisation.

## Contexte de la thèse

Les domaines de la biologie et de l'imagerie médicale ont connu d'importantes améliorations ces dernières années, notamment en ce qui concerne l'acquisition et la gestion d'ensembles de données temporelles tridimensionnelles. Des techniques d'imagerie en direct révolutionnaires, telles que les Selective Plane Illumination Microscopy (*SPIM*) et Lattice Light Sheet Microscopy (*LLSM*), sont désormais capables de créer des images 3D temporelles à une vitesse et une résolution suffisantes pour observer et détecter des caractéristiques temporelles importantes, qu'il s'agisse de comportements généraux ou d'événements ponctuels. L'analyse automatique ou semi-automatique des données a fait l'objet d'une grande attention dans les communautés respectives, et des méthodes basées sur le calcul par GPU ou des algorithmes d'apprentissage profond ont émergé. Ces méthodes produisent des informations supplémentaires, telles que la segmentation, le suivi, ou des informations numériques et catégorielles concernant l'entité imagée, ce qui donne des ensembles de données 3D temporelles complexes et de haute dimension. Pourtant, la détection



des régions d'intérêt et la visualisation de ces données complexes présentent des lacunes, de sorte que les scientifiques spécialisés ont des difficultés à explorer leurs images et peuvent passer à côté d'informations essentielles. Cette thèse a été rédigée dans le cadre du Challenge Inria Naviscope. Ce projet vise à créer un ensemble complet de méthodes pour l'analyse d'images multidimensionnelles et multivaluées, en particulier dans le contexte de l'imagerie biologique et médicale. Ces méthodes comprennent des techniques de navigation, de manipulation et de visualisation d'images volumétriques, permettent une analyse semi-automatique et mettent un accent particulier sur l'étude des caractéristiques temporelles des données. Un système mettant en œuvre de telles techniques serait d'une aide précieuse pour les scientifiques afin de mieux comprendre les quantités massives d'informations et d'en extraire les éléments les plus pertinents.

Des défis similaires apparaissent dans divers domaines de recherche, car les ensembles de données à haute dimension, en 3D ou temporelles, sont de plus en plus courants. La dimension temporelle dans ces derniers introduit d'autant plus de difficultés, dans la représentation, l'affichage et l'interaction avec les données. Le besoin d'outils adaptés permettant aux analystes de comprendre et d'extraire des informations pertinentes de ces jeux de données devient crucial. Parmi les domaines de recherche qui tentent d'aborder ces questions, le domaine de la visualisation développe des solutions pour aider les utilisateurs à observer et explorer les données. Ces méthodes s'appuient sur une représentation visuelle adaptée, qui met en valeur ou filtre une partie des données, en faisant un compromis entre la quantité d'informations à afficher et la capacité de l'analyste à les interpréter. En outre, le domaine des Visual Analytics tente de compléter les méthodes de visualisation en utilisant des concepts issus de domaines adjacents. Il inclut des techniques allant de la gestion des données à l'interaction homme-machine, afin de donner des outils supplémentaires aux analystes. Les Immersive Analytics, un autre domaine de recherche dérivé des Visual Analytics, tentent d'aborder les mêmes questions en utilisant des technologies immersives. Les méthodes de ce domaine reposent sur des affichages stéréoscopiques, des points de vue à haut degré de liberté et des dispositifs permettant d'exploiter efficacement de grands environnements 3D. Les méthodes visant à améliorer la navigation dans un espace 3D, la sélection et la manipulation d'objets dans divers types d'environnements 3D peuvent s'avérer efficaces pour résoudre les tâches de visualisation classiques. En ce qui concerne les données 3D temporelles, la taille et le nombre de dimensions, ainsi que les capacités d'interaction des utilisateurs deviennent un centre d'intérêt pour aborder les nouveaux défis de la visualisation. Par conséquent, les Immersive Analytics peuvent probablement montrer leur potentiel.

## **Problématique de Recherche**

Afin d'aborder les problèmes de visualisation des données 3D temporelles présentés dans la section précédente, nous abordons trois questions de recherche principales :

**Question de recherche 1 : Comment représenter les données 3D temporelles?** La première question porte sur la représentation des données 3D temporelles, et notamment de leur quatrième dimension, le temps. Les représentations du temps dans les données de dimension inférieure [2–4] et des données 3D [5–8] sont des défis bien explorés dans la communauté de la visualisation. Pourtant, alors que les ensembles de données 3D temporelles sont de plus en plus courants, les abstractions nécessaires pour définir correctement les caractéristiques 3D temporelles font défaut. Une approche visant à caractériser et à formaliser les diverses caractéristiques 3D temporelles est nécessaire pour soutenir des méthodes de visualisation et d'interaction adaptées.

**Question de recherche 2 : Comment visualiser différents types de régions 3D temporelles d'intérêt?** La visualisation d'ensembles de données temporelles en 3D est limitée, d'une part, par la quantité de dimensions disponibles pour afficher l'ensemble des données et, d'autre part, par la capacité de l'utilisateur à interpréter une grande quantité de dimensions et d'informations. Les données 3D temporelles souffrent des problèmes d'affichage des informations temporelles et des données 3D. D'une part, les données 3D souffrent de problèmes d'occlusion, et la densité et l'encombrement visuel implicite limitent encore la perception humaine de l'information. De telles limitations nécessitent des solutions telle que des fonctions de rendu ou de navigation adéquates. D'autre part, la représentation de l'information temporelle implique souvent des obstacles à l'affichage de l'information, car son encodage coûte une dimension supplémentaire. Les visualisations adaptées aux données 3D temporelles doivent soit compenser ces inconvénients, soit trouver un compromis optimal pour mettre en évidence les principales caractéristiques du jeu de données.

**Question de recherche 3 : Comment interagir avec différents types de régions d'intérêt 3D temporelles ?** L'interaction est souvent présentée comme un élément clé pour pallier les limites de la visualisation. Diverses méthodes ont été développées pour améliorer l'interaction dans les environnements 3D et notamment pour explorer les données 3D. La navigation interactive dans le temps est également recommandée pour trouver un compromis entre l'utilisation d'un axe euclidien supplémentaire et la charge de travail cognitive des animations. La sélection, la manipulation et l'exploration de régions temporelles d'intérêt en 3D impliquent ces deux

contraintes. Par analogie avec les limites de la perception humaine pour la visualisation, la capacité humaine doit être prise en compte pour l'interaction, tant en termes de capacité et de précision physiques que de capacité cognitive. Par conséquent, l'interaction doit être adaptée soit pour mettre en correspondance de manière efficace et naturelle l'entrée de l'utilisateur avec une action sur la région temporelle d'intérêt en 3D, afin de faciliter son analyse.

## Défis Scientifiques

Les questions de recherche présentées précédemment conduisent à plusieurs défis. Nous avons identifié quatre défis qui doivent être relevés pour répondre à nos questions de recherche.

**Défi 1 : Approcher différents types de régions d'intérêt** Selon l'entité observée ou représentée, les méthodes de génération ou d'acquisition, les données 3D temporelles présenteront des caractéristiques variées, qui peuvent nécessiter une approche potentiellement différente pour la représentation et la visualisation. Les variations dans la nature des données (par exemple, volumétriques, nuages de points, etc.), la densité ou l'encombrement visuel peuvent ajouter des obstacles à la visualisation. D'autre part, les régions d'intérêt peuvent être de nature différente (par exemple, trajectoire, objets évoluant dans le temps), ou avoir des tailles de différents ordres de grandeur. Ces différences de taille sont pertinentes non seulement dans l'espace, c'est-à-dire petits vs grands objets, mais aussi dans le temps, événements ponctuels vs étendus.

Ces variations dans le contexte et les régions d'intérêt auront un impact sur la perception et l'exploration des données par l'utilisateur. La conception des méthodes de visualisation et d'interaction doit tenir compte de cet obstacle.

**Défi 2 : Naviguer dans le temps** Le temps est souvent représenté de manière spatiale ou temporelle. Représenter le temps comme un axe euclidien augmente la complexité de la visualisation, et est particulièrement difficile pour les données spatiales 3D. Les animations contrôlées réduisent le nombre de dimensions, en encodant l'information temporelle sur un axe temporel "réduit", mais cela entre en conflit avec le slogan "Les yeux battent la mémoire", c'est-à-dire la difficulté pour l'utilisateur d'interpréter et de comparer des données qui ne sont pas directement visibles. En utilisant l'une ou l'autre de ces approches, la navigation dans le temps et l'exploration des informations temporelles restent un défi. Tout d'abord, les interactions doivent faire correspondre les entrées de l'utilisateur, généralement définies dans l'espace, à des actions cohérentes sur les informations temporelles. Deuxièmement, les méthodes de navigation doivent optimiser l'accès aux informations pertinentes.

**Défi 3 : Gérer la vue pour la visualisation et l'interaction en 3D et dans le temps** La gestion de la vue est un problème classique lors de l'exploration d'environnements 3D, et donc également lors de la visualisation de données 3D. Tout d'abord, elle comprend la gestion de l'occlusion [9] et de l'encombrement visuel, qui sont causés ou augmentés par la densité des données. Deuxièmement, l'espace de travail doit être organisé correctement, notamment lors de l'utilisation de vues juxtaposées. Les problèmes d'occlusion peuvent notamment être compensés par des méthodes de manipulation et de navigation adéquates. Une fois de plus, lorsqu'on est confronté à des données temporelles en 3D, ces problèmes ont tendance à être encore plus importants, notamment en fonction de la méthode utilisée pour visualiser la dimension temporelle. À ce titre, la gestion des occlusions devra faire l'objet d'une attention particulière lors de la conception des visualisations et des interactions.

**Défi 4 : Encodage d'un grand ensemble de données à haute dimension** Comme nous l'avons mentionné précédemment, les ensembles de données 3D temporelles comprennent souvent des dimensions numériques et catégorielles. Elles peuvent être cruciales pour l'exploration et l'analyse des données observées, grâce à des moyens de filtrage et de comparaison. Par conséquent, ces dimensions doivent également être affichées lors de la visualisation des données 3D temporelles. Plusieurs canaux peuvent être utilisés pour afficher ces informations. Le plus souvent, l'information est encodée sur le canal couleur par le biais de cartes de couleurs. Selon la nature de l'information, elle peut également être encodée par le son, le retour haptique, avec des étiquettes ou des vues juxtaposées. Le codage de l'information doit tenir compte de l'objectif analytique, mais il doit également éviter d'encombrer la visualisation ou d'impliquer une charge mentale trop importante pour l'utilisateur.

## **Approche et Contributions**

Comme mentionné à travers les défis scientifiques, la dimension temporelle est une contrainte forte tant pour la visualisation que pour l'interaction homme-machine. En exploitant les progrès récents dans ces deux domaines de recherche, le domaine de l'Immersive Analytics tire parti des avantages de la technologie immersive pour soutenir la visualisation et l'interaction. Les questions relatives à la navigation dans les données temporelles, à l'observation des données 3D et à la gestion globale des vues pourraient être facilitées par les méthodes développées dans ce domaine. C'est pourquoi nous avons décidé d'impliquer les environnements immersifs dans nos approches de visualisation et d'interaction.

La forte variation des données 3D temporelles mise en évidence dans le défi 1 nous a conduit

à envisager une approche globale de nos principales questions de recherche à travers différents types de données. Ainsi, la première étape de notre approche est la caractérisation des données 3D temporelles et des caractéristiques auxquelles nous serons confrontés. De plus, les contraintes dans la représentation du temps demanderont un effort supplémentaire soit sur la visualisation soit sur l'interaction. Les autres étapes de notre approche tenteront d'aborder les principales questions de recherche dans ces différentes situations. Le plan de cette thèse est le suivant :

**Chapitre 2** présente un rapport de littérature décrivant les objectifs et les méthodes développées dans les principaux domaines de recherche entourant le sujet de thèse. Nous présentons d'abord les domaines de la visualisation, des Visual Analytics et des Immersive Analytics, et abordons la question de la représentation de données 3D temporelles dans un contexte d'analyse de données. Ensuite, nous nous concentrons sur les méthodes de représentation et de visualisation de la dimension temporelle dans les données générales, en nous concentrant sur certaines visualisations statiques, à savoir le Cube Spatio-Temporel et les frises chronologiques. Enfin, nous présentons des applications et des méthodes issues des Immersive Analytics pour aborder les problèmes de visualisation.

**Chapitre 3** décrit la représentation Hypercube Spatio-Temporel, qui étend la représentation classique du Cube Spatio-Temporel aux données 3D temporelles. Nous proposons une méthode pour créer des visualisations à partir de l'Hypercube Spatio-Temporel, en définissant des opérateurs d'extraction basés sur un plan de coupe défini par l'utilisateur pour générer une vue 3D affichant l'évolution d'une vue en coupe à travers le temps. Nous concluons que cette méthode de visualisation permet de mettre en évidence des caractéristiques 3D temporelles de taille spatiale significative et leur évolution sur de grands intervalles de temps.

**Chapitre 4** présente un espace de conception pour la création de la visualisation de frises chronologiques 3D afin de soutenir la visualisation d'ensembles de données 3D temporelles. Cet espace de conception étend la visualisation classique des frises chronologiques et explore les moyens de les afficher dans un environnement 3D. En utilisant des outils de navigation, de sélection et de filtrage, l'utilisateur peut définir et affiner efficacement les zones d'intérêt dans l'espace et dans le temps. Cette méthode de visualisation, accompagnée des processus d'interaction adéquats que nous avons proposés, permet de définir des zones d'intérêt locales dans l'espace et dans le temps, avec une portée temporelle courte à moyenne.

**Chapitre 5** explore une méthode de sélection d'événements ponctuels, à travers un processus consistant à sélectionner d'abord la localisation 3D, puis la région d'intérêt dans le temps. Nous discutons d'un processus d'interaction reposant sur trois points essentiels : quelles informations doivent être directement accessibles à l'utilisateur ; comment sélectionner la région d'intérêt dans l'espace ; comment désambiguïser la sélection dans le temps. Nous suggérons qu'une méthode d'interaction basée sur ce concept pourrait augmenter l'efficacité de la sélection de caractéristiques 3D temporelles caractérisées par une courte portée temporelle.

**La Conclusion** conclut ce manuscrit, en résumant nos contributions, ainsi qu'en fournissant des perspectives de travaux futurs sur les méthodes que nous avons proposées, et sur nos propositions aux principales questions de recherche.

## Chapitre 2 : Etat de l'art

Ce chapitre présente une analyse documentaire des recherches menées dans les principaux domaines entourant nos questions de recherche. Cette étude s'attache d'abord à définir ces domaines adjacents et à mettre en évidence les principaux défis qu'ils abordent, afin de contextualiser nos propres contributions. Les problèmes abordés dans des domaines tels que la visualisation, les Visual Analytics et Immersive Analytics, ainsi que l'approche générale proposée dans chacun de ces domaines, constitueront un point de départ pour répondre à nos questions de recherche. Nous nous concentrerons également sur la caractérisation des données 3D temporelles, car il s'agit d'une question émergente, en nous appuyant notamment sur des travaux antérieurs traitant des données 3D et des données temporelles. Nous introduisons la notion d'objets 4D, nous attribuons plusieurs caractéristiques pour les qualifier:

- Un objet 4D est une entité sémantique indépendante.
- Un objet 4D est défini sur un sous-ensemble continu de la dimension temporelle encodée dans l'ensemble de données. Ainsi, il a une durée de vie, une date d'apparition, de disparition et est défini soit de manière continue dans le temps, soit de manière discrète avec une résolution temporelle.
- Un objet 4D contient un sous-ensemble continu de l'espace 3D encodé dans le jeu de données, et a donc une forme, une taille et une position. Ces caractéristiques peuvent évoluer au cours de la dimension temporelle.
- Un objet 4D peut se voir attribuer plusieurs informations catégorielles ou numériques, telles qu'un nom, une couleur ou un poids. Ces caractéristiques peuvent évoluer au cours de la dimension temporelle.

Cette représentation doit permettre la visualisation logique et l'interaction tout en considérant toutes les informations d'une caractéristique temporelle 3D. Dans ce qui suit, nous illustrons comment cette représentation peut être intégrée dans des exemples concrets.

Comme nous avons identifié la question de la navigation dans le temps comme l'un de nos principaux défis, nous présentons ensuite des approches de visualisation pour traiter les données temporelles. Des techniques pour aborder le problème général des données à haute dimension ont été proposées, et des approches plus spécifiques ont affiné ces techniques en exploitant le temps différemment, comme une dimension de nature unique. Deux catégories principales d'approches existent pour visualiser les données variant dans le temps : les méthodes dynamiques, c'est-à-dire l'animation et l'interaction, et les visualisations statiques, soit des données complètes, soit des données extraites de dimension inférieure. Nous comparons ces approches et identifions les

méthodes qui ont attiré notre attention comme bases de nos contributions. Nous nous concentrons ensuite sur deux visualisations particulières, le Cube Spatio-Temporel (*CET*), une représentation utilisant deux axes pour les données et un troisième axe pour le temps ; et les frise chronologique, une visualisation classique pour les données temporelles, qui sont principalement utilisées pour représenter des séries d'événements de façon linéaire ou sous forme d'arbre.

Enfin, nous explorons comment les Immersive Analytics dans la littérature a exploité les avantages des technologies immersives pour répondre aux défis de la visualisation. Comme l'indiquent LaViola et al. [39], les technologies qui prennent en charge les interfaces utilisateur 3D, comme les écrans stéréoscopiques, le suivi 3D ou les dispositifs de pointage, deviennent matures et prolifèrent. Notamment, la sortie de HMD abordables de haute qualité depuis 2016, notamment avec l'Oculus Rift et le HTC Vive, a remplacé le système CAVE [135] devenu populaire à la fin des années 1990. Les applications sont de plus en plus courantes, dans des domaines comme l'art, l'éducation et la formation, l'architecture ou le jeu. Parallèlement, le nombre de publications d'applications de visualisation immersive a augmenté, comme le rapportent Fonnnet et Prié [58]. Ces applications s'appuient sur diverses caractéristiques des environnements virtuels 3D (EV) qui correspondent aux tâches correspondantes : le sentiment de présence fourni par les EV peut améliorer les jeux et la simulation ; les interactions 3D simulent des compétences naturelles et soutiennent ainsi les applications de formation. Dans cette section, nous présentons des applications d'Immersive Analytics pour la visualisation scientifique et la visualisation d'informations, et nous concluons par des applications immersives collaboratives, une préoccupation majeure dans le domaine de l'Immersive Analytics.



## **Chapitre 3 : Visualisation Immersive et Interaction de Données 3D utilisant un Hypercube Spatio-Temporel appliqué à des Données d’Imagerie Biologique**

Notre première approche concerne la visualisation de régions d’intérêt 3D temporelles avec de grandes composantes temporelles. Ces régions décrivent l’évolution continue des valeurs ou de la forme des objets, ce qui est essentiel pour analyser un objet et peut potentiellement donner un aperçu de l’évolution globale du jeu de données.

Dans ce chapitre, nous proposons une extension de la technique de visualisation Cube Espace-Temps (CET) [107] adaptée aux données spatio-temporelles 4D, nommée ci-après Hypercube Espace-Temps (HET). Conceptuellement, le HET est une représentation des données 3D temporelles qui consiste à disposer les données dans un hypercube 4D à trois dimensions spatiales et une dimension temporelle. Pour permettre la visualisation directe de l’hypercube 4D, nous avons étendu les opérations classiques du CET pour générer des visualisations 3D variées et significatives, qui sont juxtaposées pour obtenir une vue d’ensemble compacte des données spatio-temporelles. Précisément, nous proposons une opération de projection sur l’hypercube, indépendante du type de représentation spatiale (par exemple, maillage, volumétrie), qui projette l’hypercube dans un volume 3D qui peut être directement visualisé. L’opération de projection s’appuie sur une section transversale définie par l’utilisateur sur la dimension spatiale. Cette section transversale est ensuite calculée le long de la dimension temporelle et empilée dans un volume 3D, qui peut être enrichi de données numériques et catégorielles (voir Figure. B.2).

Afin d’explorer efficacement la structure 3D complexe générée, nous utilisons le HET dans un environnement immersif et proposons un ensemble d’outils interactifs pour explorer et analyser le jeu de données. L’amélioration de la perception de la profondeur de l’environnement virtuel devrait améliorer l’extraction visuelle des structures significatives de la HET. et l’utilisation d’interfaces utilisateur 3D permettrait aux utilisateurs d’explorer naturellement la HET depuis différentes perspectives. L’ensemble des interactions proposées comprend des méthodes d’exploration naturelle de la structure complexe, mais aussi des méthodes de sélection qui utilisent la notion d’objets 4D définie précédemment, permettant d’autres tâches analytiques. En outre, l’espace d’interaction élargi de la RV permet la juxtaposition de la HET et des instantanés des données spatio-temporelles originales. Cette juxtaposition permet l’exploration et la manipulation synchronisées des deux visualisations. Enfin, le chapitre présente un cas d’utilisation illustrant les usages de la HET pour la visualisation de données spatio-temporelles dans les études de

développement embryonnaire, ainsi qu'une évaluation de cette méthode de visualisation auprès d'utilisateurs non-experts et experts du domaine. Les illustrations utilisées et les cas d'utilisation explorés dans ce chapitre sont basés sur les enregistrements du développement embryonnaire d'une *Phallusia Mammillata*.

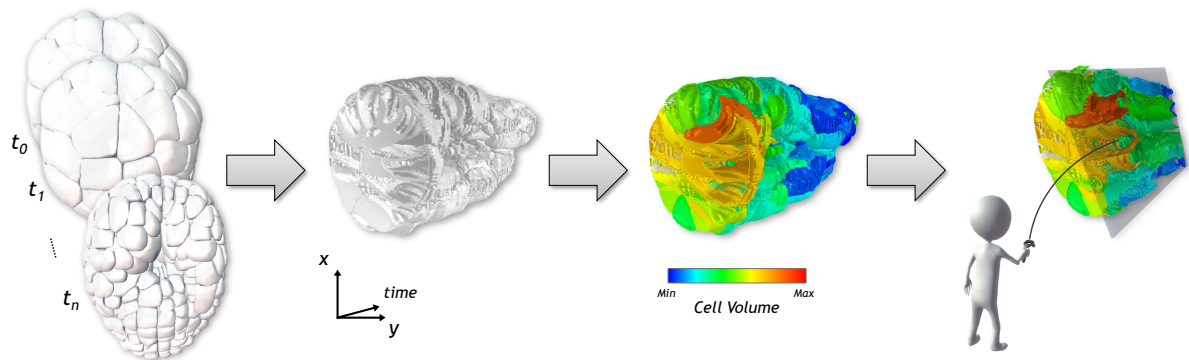


Figure B.2 – À partir d'une coupe transversale sur les données temporelles basées sur la surface 3D montrée sur la première figure, nous générons une visualisation Cube Espace-Temps, affichée sur la deuxième image, montrant l'évolution dans le temps des données spatiales de la coupe transversale affichée sur les axes x et y. La troisième image montre comment la visualisation peut être enrichie avec des données quantitatives et qualitatives en utilisant différents codes de couleur. Un ensemble d'outils d'interaction aide l'utilisateur à explorer la visualisation générée, comme on le voit dans la dernière image.

## Chapitre 4 : Espace de Conception de Frise Chronologique pour l'Exploration Immersive de Données 3D Spatio-Temporelles

Ce chapitre aborde la question de la visualisation des régions temporelles d'intérêt en 3D. L'objectif est de pouvoir définir une zone des données 3D temporelles, délimitée à la fois spatialement et temporellement, avec une portée adaptée à une observation directe par l'analyste.

Pour aborder cette question, nous décrivons dans ce chapitre un espace de conception de frise chronologique étendu pour un environnement 3D, adapté à la visualisation de données 3D temporelles. Cet espace de conception est inspiré de l'espace de conception pour les frises chronologiques 2D décrit par Brehmer et al. [111]. Notre espace de conception étend l'espace original, en adaptant les choix de conception connexes à la dimension supplémentaire de l'espace de travail. Nous décrivons comment les frises chronologiques 3D peuvent partitionner et structurer les données 3D temporelles, représentées sous forme d'objets 4D, dans l'environnement 3D.

En outre, en raison des caractéristiques spécifiques de l'interaction des contextes immersifs et afin de tirer pleinement parti des frises chronologiques 3D, nous discutons de l'ensemble des techniques d'interaction de base pour les explorer et les manipuler. Nous proposons également des processus d'interaction supplémentaires pour aborder plus efficacement des tâches spécifiques d'exploration et d'analyse.

Afin d'explorer les avantages potentiels des frises chronologiques 3D, nous avons effectué deux évaluations. La première évaluation était une évaluation sommative formelle, qui explorait comment les frises chronologiques 3D pouvaient améliorer les tâches d'exploration de données. Pour cette évaluation, nous avons principalement tenu compte des experts en RV et nous nous sommes concentrés sur la performance et la convivialité. La deuxième évaluation, était une évaluation qualitative menée en collaboration avec des experts en biologie. L'objectif était de recueillir des commentaires sur la façon dont les frises chronologiques 3D pourraient être incluses dans leur flux de travail d'analyse, plus précisément, sur la façon dont ils pourraient tirer parti des frises chronologiques 3D pour faciliter le processus d'exploration et de validation de leurs données d'imagerie temporelle 3D.

En résumé, les principales contributions de ce chapitre sont les suivantes :

- Un espace de conception pour les frises chronologiques 3D, affichables dans des environnements 3D et adaptées à la visualisation de données 3D temporelles.
- Des processus d'interaction et d'exploration 3D supportant des tâches analytiques complexes dans une telle visualisation

- Une évaluation formelle des avantages des lignes 3D temporelles dans les tâches générales de visualisation, ainsi que des retours d'experts en biologie donnant un aperçu de l'utilisation concrète de la méthode.

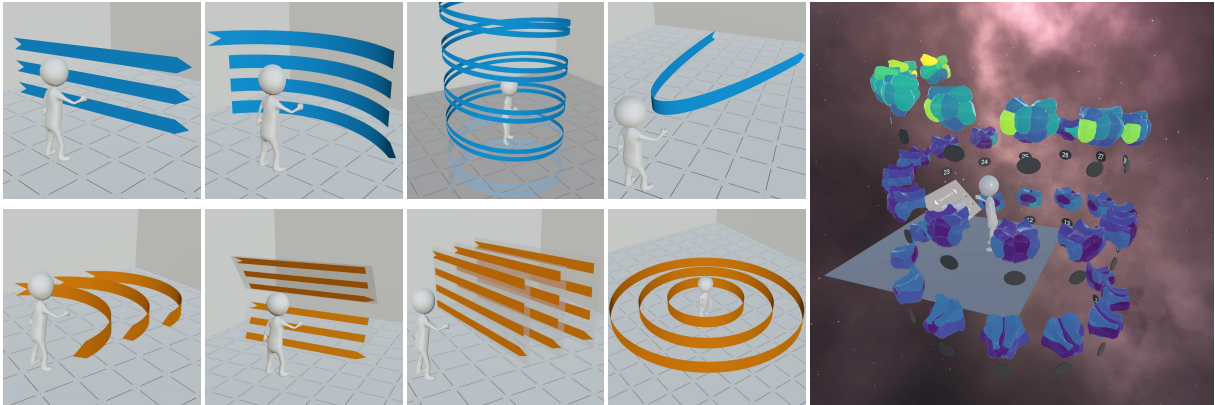


Figure B.3 – Illustration de l'espace de conception de la frise chronologique 3D proposée pour l'exploration immersive de données spatiales 3D variant dans le temps. La première ligne présente différentes représentations de la frise chronologique, c'est-à-dire la courbe directrice de la frise chronologique, tandis que la deuxième ligne présente différentes configurations de support. L'image la plus à droite illustre l'utilisation d'une représentation hélicoïdale pour l'exploration d'un ensemble de données d'imagerie embryonnaire variant dans le temps. La carte de couleurs viridis est utilisée pour coder le rapport d'élongation des cellules impliquées dans les mouvements morphogénétiques.

## **Chapitre 5 : Espace-Puis-Temps : Vers des Méthodes de Sélection pour des Evènements Ponctuels dans des Données 3D Temporelles grâce à l'Interaction 3D**

Dans ce chapitre, nous proposons une méthode pour améliorer la sélection des caractéristiques des événements temporels 3D qui apparaissent ponctuellement dans le temps, c'est-à-dire les objets 4D avec une petite composante temporelle. Pour simplifier et même si ces objets peuvent ne pas être ponctuels dans l'espace 3D, nous les appellerons "objets 4D ponctuels". La visualisation de ces objets individuellement dépend donc principalement de la visualisation 3D, mais leur sélection dans la dimension temporelle potentiellement importante d'un ensemble de données 3D temporelles peut être un véritable défi.

Les méthodes traditionnelles explorent généralement les ensembles de données temporelles en 3D en commençant par explorer le temps jusqu'à ce qu'une région 3D d'intérêt soit détectée. Dans le cas d'objets 4D ponctuels, cela peut être particulièrement difficile. Dans ce contexte, les tâches de recherche sont particulièrement difficiles : en se basant sur une exploration temporelle naïve, trouver un tel objet consiste en une exploration spatiale multipliée par le nombre de points temporels dans l'ensemble de données, c'est-à-dire une tâche d'exploration 1D x 3D. Par conséquent, nous proposons un processus d'interaction pour améliorer la sélection d'un objet 4D ponctuel. Cette approche consiste en un processus d'interaction commençant par une sélection dans l'espace, puis une désambiguïsation dans le temps, globalement une tâche d'exploration 3D + 1D. Nous avons identifié 3 axes principaux pour aborder la conception d'une telle méthode de sélection :

- La sélection en 3D doit se faire sans exploration du temps. Comment l'utilisateur peut-il avoir l'information sur l'endroit où se trouve l'objet qu'il recherche ? En d'autres termes, quelles informations doivent être visualisées pour que l'utilisateur puisse effectuer une telle sélection ?
- Quelle information 3D doit être sélectionnée avant l'exploration du temps ? Comment la sélection en 3D permettra-t-elle d'identifier la bonne zone dans le temps ?
- Une fois la sélection 3D correctement effectuée, comment explorer la dimension temporelle restante ? Comment désambiguïser entre les objets potentiellement sélectionnés dans le temps ?

Dans ce qui suit, nous explorons et proposons différentes méthodes qui pourraient être utilisées efficacement pour aborder chacun de ces trois axes. Nous illustrons notre propos par

des images basées sur un ensemble de données d'enregistrement d'astrocytes et de simulation de signaux calciques.

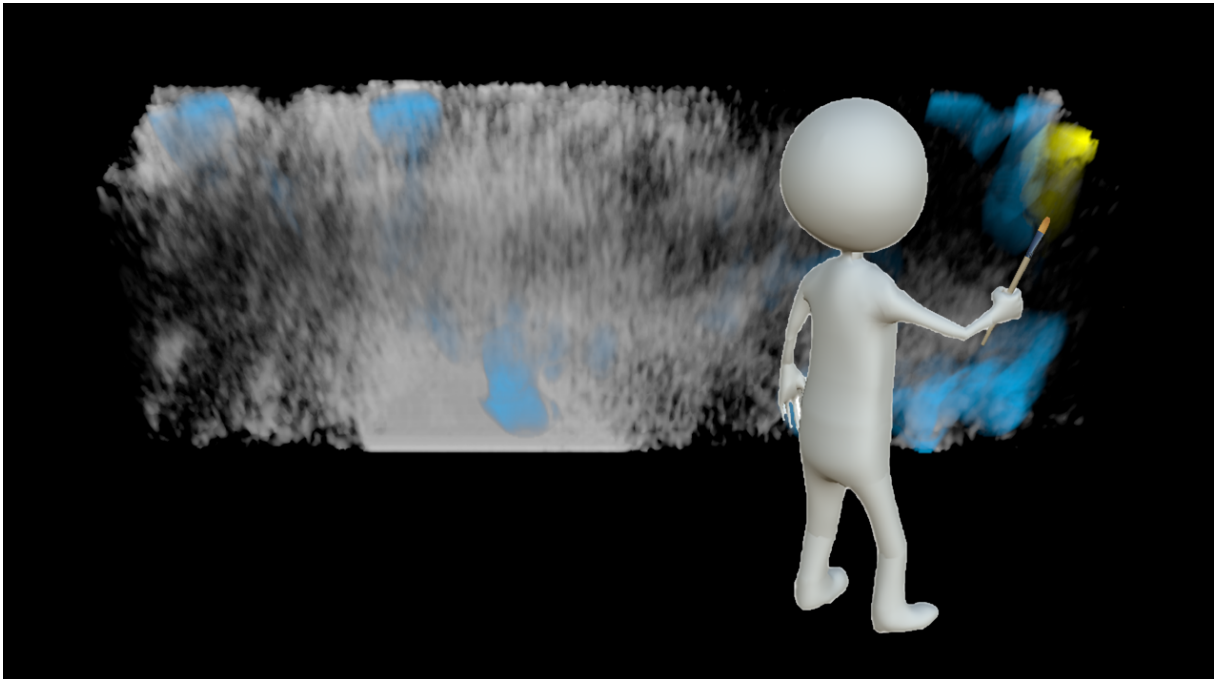


Figure B.4 – Visualisation en carte de densité de vagues calciques (bleu). L'utilisateur effectue une sélection de type brosse (jaune). La désambiguation dans le temps pour sélectionner l'objet 4D se basera sur cette sélection.

## Conclusion

Cette thèse présente une série de contributions aux questions relatives à la visualisation et à l'interaction des données 3D temporelles, en suivant trois questions de recherche principales, concernant la manière de représenter les données, de les visualiser et d'interagir avec elles.

### Autour de la Question de Représentation

Malgré le fait que la question de la représentation du temporel 3D n'était pas l'objet principal des contributions décrites ci-dessus, nous avons tout de même proposé plusieurs approches à travers ce manuscrit. Nous avons abordé la question de la représentation des données 3D temporelles dans le chapitre 3 à travers la représentation Hypercube Spatio-Temporel, qui utilise la dimension temporelle comme une dimension euclidienne résultant en un volume 4D. Cette approche permet la création de visualisations extraites d'une structure 4D, comme nous l'avons montré au chapitre 3. Cette représentation aborde le jeu de données dans son intégralité, et a donc été adaptée aux caractéristiques 3D temporelles ayant une grande importance temporelle et spatiale. Dans le chapitre 2, nous avons développé une représentation des données à travers des objets 4D. Ces objets 4D représentent les caractéristiques 3D temporelles qui apparaissent dans les ensembles de données, et consistent en la définition d'une forme 3D continue, et de ses occurrences associées en continu dans le temps. Cette approche s'est révélée plus adaptée pour supporter la visualisation et l'interaction de la plupart des types de caractéristiques existant dans les jeux de données avec lesquels nous avons travaillé. Elle permettait un partitionnement logique des données qui pouvait être utilisé pour exploiter les techniques de juxtaposition dans la visualisation, comme le montre le chapitre 4 sur les frises chronologiques en 3D, ou pour supporter des opérations de filtrage.

### Perspectives

En ce qui concerne la représentation des données 3D, notre approche des objets 4D a permis de qualifier une grande variété de caractéristiques 3D temporelles, mais présente de multiples limitations. Tout d'abord, certaines parties des jeux de données que nous avons présentés n'ont pas pu être qualifiées en objets 4D, et plus particulièrement des éléments d'arrière-plan. En effet, notre approche s'appuie à la fois sur la séparation existante des éléments d'intérêt, et sur les informations de suivi de ces éléments. Certains jeux de données peuvent inclure ces informations de par leur conception, notamment les jeux de données basés sur

des trajectoires ou des maillages. En revanche, d'autres types de jeux de données, comme les nuages de points ou les données volumétriques, nécessitent l'utilisation d'algorithmes de segmentation et de suivi, souvent suivis d'un traitement manuel des résultats. Nous pensons qu'une approche unifiée pour les caractéristiques 3D temporelles aiderait grandement la recherche future sur les données 3D temporelles. Les méthodes pourraient être facilement partagées entre les domaines, que ce soit sur le sujet des algorithmes de segmentation et de suivi, ou sur les techniques de visualisation et d'interaction. En outre, une approche unifiée pourrait encourager l'optimisation des algorithmes d'analyse et de rendu, mais aussi faciliter la communication entre les domaines et la reproductibilité de la recherche. Finalement, nous identifions deux directions principales pour améliorer la représentation des caractéristiques 3D temporelles. Un premier objectif serait d'explorer davantage la notion d'objets 4D, en généralisant l'approche à d'autres types d'ensembles de données et de caractéristiques 3D temporelles, par exemple des ensembles de données de trajectoires ou des nuages de points, que nous n'avons pas abordés ici. Un deuxième objectif serait de proposer des méthodes pour qualifier les éléments d'arrière-plan et contextuels, qui peuvent difficilement être qualifiés d'objets 4D. L'approche par les objets 4D n'étant probablement pas exhaustive pour représenter toutes les caractéristiques des jeux de données 3D temporelles, une approche complémentaire pourrait être nécessaire pour inclure ces informations dans l'analyse du jeu de données complet.

En outre, les travaux futurs devraient se concentrer sur la question de la comparaison. Parmi les méthodes que nous avons proposées, les lignes 3D temporelles pourraient permettre de comparer des objets 4D en tirant parti des conceptions de lignes temporelles à facettes. Néanmoins, d'autres méthodes pourraient améliorer la comparaison de plusieurs ensembles de données, par exemple pour comparer un ensemble de données à une vérité terrain, ou deux simulations avec des paramètres différents. La comparaison pourrait étendre les méthodes de comparaison 3D existantes, en impliquant des opérations d'ensemble 4D (par exemple, intersection, exclusion). Ou encore, elle pourrait exploiter le grand espace de travail de l'environnement virtuel pour les méthodes basées sur la juxtaposition. Des méthodes d'interaction 3D adaptées pourraient être synchronisées avec les vues multiples des différents ensembles de données affichés, ce qui faciliterait encore la comparaison. En outre, il est nécessaire de comparer les données catégorielles et numériques supplémentaires liées à chaque objet. Les cartes de couleurs peuvent facilement encoder une dimension d'information, et le passage d'une information à l'autre rend la comparaison difficile, conformément au slogan "Eyes Beat Memory". Une telle comparaison pourrait reposer sur la juxtaposition de deux copies du même objet avec des cartes de couleurs différentes, l'utilisation de cartes de couleurs à plusieurs variables, la juxtaposition de deux cartes



de couleurs sur un même objet par le biais d'une texturation adéquate, ou l'utilisation d'autres canaux perceptifs (par exemple, le son, le retour haptique). Des études perceptuelles seront ensuite nécessaires pour évaluer la solution optimale en fonction des différents cas d'utilisation.

# BIBLIOGRAPHY

---

1. Rosenblum, L. D. See what I'm saying: The extraordinary powers of our five senses (WW Norton & Company, 2011).
2. Andrienko, G. *et al.* Space, time and visual analytics. *International Journal of Geographical Information Science* **24**, 1577–1600. ISSN: 1365-8816, 1362-3087 (Oct. 11, 2010).
3. Aigner, W., Miksch, S., Schumann, H. & Tominski, C. Visualization of Time-oriented Data (Springer, 2011).
4. Bai, Z., Tao, Y. & Lin, H. Time-varying volume visualization: a survey | SpringerLink.
5. Bruckner, S. & Gröller, E. Enhancing Depth-Perception with Flexible Volumetric Halos. *IEEE Transactions on Visualization and Computer Graphics* **13**, 1344–1351 (2007).
6. Jönsson, D., Sunden, E., Ynnerman, A. & Ropinski, T. A Survey of Volumetric Illumination Techniques for Interactive Volume Rendering. *Computer Graphics Forum* **33**, 27–51 (2014).
7. Preim, B., Baer, A., Cunningham, D., Isenberg, T. & Ropinski, T. A Survey of Perceptually Motivated 3D Visualization of Medical Image Data. *Computer Graphics Forum* **35**, 501–525 (2016).
8. Díaz, J., Ropinski, T., Navazo, I., Gobbetti, E. & Vázquez, P.-P. An experimental study on the effects of shading in 3D perception of volumetric models. *The visual computer* **33**, 47–61 (2017).
9. Elmqvist, N. & Tsigas, P. A Taxonomy of 3D Occlusion Management for Visualization. *IEEE Transactions on Visualization and Computer Graphics* **14**, 1095–1109. ISSN: 1077-2626 (Sept. 2008).
10. Preim, B. & Bartz, D. Visualization in medicine: theory, algorithms, and applications (Elsevier, 2007).
11. Cutrale, F., Fraser, S. E. & Trinh, L. A. Imaging, visualization, and computation in developmental biology. *Annu. Rev. Biomed. Data Sci* **2**, 223–251 (2019).

- 
12. Ivson, P., Nascimento, D., Celes, W. & Barbosa, S. D. CasCADE: A Novel 4D Visualization System for Virtual Construction Planning. *IEEE Transactions on Visualization and Computer Graphics* **24**, 687–697. ISSN: 1077-2626 (Jan. 2018).
  13. Sanders, B. C., Senden, T. & Springel, V. Focus on visualization in physics. *New Journal of Physics* **10**, 125001 (2008).
  14. Brodlie, K. W. *et al.* Scientific visualization: techniques and applications (Springer Science & Business Media, 2012).
  15. Chen, C. Information visualization. *Wiley Interdisciplinary Reviews: Computational Statistics* **2**, 387–403 (2010).
  16. Munzner, T. Visualization Analysis and Design. 430 pp. ISBN: 978-1-4987-5971-7 (CRC Press, Dec. 1, 2014).
  17. Kovesi, P. Good Colour Maps: How to Design Them. *arXiv:1509.03700 [cs]*. arXiv: 1509.03700 (Sept. 11, 2015).
  18. Cheng, S., Xu, W. & Mueller, K. ColorMapND: A Data-Driven Approach and Tool for Mapping Multivariate Data to Color. *IEEE Transactions on Visualization and Computer Graphics* **25**, 1361–1377. ISSN: 1941-0506 (Feb. 2019).
  19. Borland, D. & Li, R. M. T. Rainbow color map (still) considered harmful. *IEEE computer graphics and applications* **27**, 14–17 (2007).
  20. Simpson, R., LaViola, J., Laidlaw, D., Forsberg, A. & van Dam, A. Immersive VR for scientific visualization: a progress report. *IEEE Computer Graphics and Applications* **20**, 26–52. ISSN: 02721716 (Dec. 2000).
  21. Cook, K. A. & Thomas, J. J. Illuminating the path: The research and development agenda for visual analytics. Tech. rep. (Pacific Northwest National Lab.(PNNL), Richland, WA (United States), 2005).
  22. Keim, D. *et al.* in *Information Visualization* (eds Kerren, A., Stasko, J. T., Fekete, J.-D. & North, C.) 154–175 (Springer Berlin Heidelberg, Berlin, Heidelberg, 2008).
  23. Keim, D. A., Mansmann, F., Schneidewind, J. & Ziegler, H. Challenges in visual data analysis. in *Tenth International Conference on Information Visualisation (IV'06)* (2006), 9–16.
  24. Shneiderman, B. in *The craft of information visualization* 364–371 (Elsevier, 2003).

- 
25. Prigent, S. *et al.* BioImageIT: Open-source framework for integration of image data-management with analysis. *bioRxiv* (2021).
  26. Allan, C. *et al.* OMERO: flexible, model-driven data management for experimental biology. *Nature methods* **9**, 245–253 (2012).
  27. Chiu, C.-L., Clack, N., *et al.* napari: a Python Multi-Dimensional Image Viewer Platform for the Research Community. *Microscopy and Microanalysis* **28**, 1576–1577 (2022).
  28. Rasband, W. S. *et al.* ImageJ. 1997.
  29. Schindelin, J. *et al.* Fiji: an open-source platform for biological-image analysis. *Nature methods* **9**, 676–682 (2012).
  30. Kehrer, J. & Hauser, H. Visualization and Visual Analysis of Multifaceted Scientific Data: A Survey. *IEEE Transactions on Visualization and Computer Graphics* **19**, 495–513. ISSN: 1941-0506 (Mar. 2013).
  31. Skarbez, R., Polys, N. F., Ogle, J. T., North, C. & Bowman, D. A. Immersive Analytics: Theory and Research Agenda. *Frontiers in Robotics and AI* **6**. ISSN: 2296-9144 (2019).
  32. Smith, N. G. *et al.* ArtifactVis2: Managing real-time archaeological data in immersive 3D environments. in *2013 Digital Heritage International Congress (DigitalHeritage)* **1** (2013), 363–370.
  33. Zhang, S. *et al.* An immersive virtual environment for DT-MRI volume visualization applications: a case study. in *Proceedings Visualization, 2001. VIS'01.* (2001), 437–584.
  34. Kageyama, A., Tamura, Y. & Sato, T. Visualization of vector field by virtual reality. *Progress of Theoretical Physics Supplement* **138**, 665–673 (2000).
  35. Bach, B., Sicat, R., Beyer, J., Cordeil, M. & Pfister, H. The Hologram in My Hand: How Effective is Interactive Exploration of 3D Visualizations in Immersive Tangible Augmented Reality? *IEEE Transactions on Visualization and Computer Graphics* **24**, 457–467. ISSN: 1077-2626 (Jan. 2018).
  36. Raja, D., Bowman, D. A., Lucas, J. & North, C. Exploring the Benefits of Immersion in Abstract Information Visualization, 8.
  37. Chandler, T. *et al.* Immersive Analytics. in *2015 Big Data Visual Analytics (BDVA)* (Sept. 2015), 1–8.
  38. Marriott, K. *et al.* in *Immersive Analytics* (eds Marriott, K. *et al.*) 25–55 (Springer International Publishing, Cham, 2018).

- 
39. Bowman, D. A., Kruijff, E., LaViola Jr., J. J. & Poupyrev, I. 3D User Interfaces : Theory and Practice. ISBN: 978-0-201-75867-2 (Addison-Wesley, 2005).
  40. Andrews, C., Endert, A. & North, C. Space to think: large high-resolution displays for sensemaking. in *Proceedings of the SIGCHI conference on human factors in computing systems* (2010), 55–64.
  41. Andrews, C., Endert, A., Yost, B. & North, C. Information visualization on large, high-resolution displays: Issues, challenges, and opportunities. *Information Visualization* **10**, 341–355 (2011).
  42. Bandyopadhyay, P. Immersive Space to Think: the Role of 3D Immersive Space in Sensemaking of Textual Data. PhD thesis (Virginia Tech, 2020).
  43. Lisle, L., Chen, X., Gitre, J. E., North, C. & Bowman, D. A. Evaluating the benefits of the immersive space to think. in *2020 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)* (2020), 331–337.
  44. Lisle, L., Davidson, K., Gitre, E. J., North, C. & Bowman, D. A. Sensemaking strategies with immersive space to think. in *2021 IEEE Virtual Reality and 3D User Interfaces (VR)* (2021), 529–537.
  45. McIntire, J. P., Havig, P. R. & Geiselman, E. E. Stereoscopic 3D displays and human performance: A comprehensive review. *Displays* **35**, 18–26. ISSN: 01419382 (Jan. 2014).
  46. Laha, B., Sensharma, K., Schiffbauer, J. D. & Bowman, D. A. Effects of Immersion on Visual Analysis of Volume Data. *IEEE Transactions on Visualization and Computer Graphics* **18**, 597–606. ISSN: 1941-0506 (Apr. 2012).
  47. Chen, J. & Bowman, D. A. Domain-specific design of 3d interaction techniques: An approach for designing useful virtual environment applications. *Presence* **18**, 370–386 (2009).
  48. Argelaguet, F. & Andujar, C. A survey of 3D object selection techniques for virtual environments. *Computers & Graphics* **37**, 121–136. ISSN: 0097-8493 (May 1, 2013).
  49. Moore, A. *et al.* The Importance of Intersection Disambiguation for Virtual Hand Techniques. in *2019 IEEE International Symposium on Mixed and Augmented Reality (ISMAR)* (Oct. 2019), 310–317.

- 
50. Vanacken, L., Grossman, T. & Coninx, K. Multimodal selection techniques for dense and occluded 3D virtual environments. *International Journal of Human-Computer Studies. Current trends in 3D user interface research* **67**, 237–255. ISSN: 1071-5819 (Mar. 1, 2009).
  51. Mendes, D., Caputo, F. M., Giachetti, A., Ferreira, A. & Jorge, J. A Survey on 3D Virtual Object Manipulation: From the Desktop to Immersive Virtual Environments. *Computer Graphics Forum* **38**, 21–45. ISSN: 1467-8659 (2019).
  52. Song, P., Goh, W. B., Hutama, W., Fu, C.-W. & Liu, X. A handle bar metaphor for virtual object manipulation with mid-air interaction. in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (2012), 1297–1306.
  53. Conner, B. D. *et al.* Three-dimensional widgets. in *Proceedings of the 1992 symposium on Interactive 3D graphics* (1992), 183–188.
  54. Bowman, D. A. & Hodges, L. F. An evaluation of techniques for grabbing and manipulating remote objects in immersive virtual environments. in *Proceedings of the 1997 symposium on Interactive 3D graphics* (1997), 35–ff.
  55. Stoakley, R., Conway, M. J. & Pausch, R. Virtual reality on a WIM: interactive worlds in miniature. in *Proceedings of the SIGCHI conference on Human factors in computing systems* (1995), 265–272.
  56. Poupyrev, I., Billingham, M., Weghorst, S. & Ichikawa, T. The go-go interaction technique: non-linear mapping for direct manipulation in VR. in *Proceedings of the 9th annual ACM symposium on User interface software and technology* (1996), 79–80.
  57. Frees, S., Kessler, G. D. & Kay, E. PRISM interaction for enhancing control in immersive virtual environments. *ACM Transactions on Computer-Human Interaction (TOCHI)* **14**, 2–es (2007).
  58. Fonnet, A. & Prie, Y. Survey of Immersive Analytics. *IEEE Transactions on Visualization and Computer Graphics*, 1–1. ISSN: 1077-2626, 1941-0506, 2160-9306 (2019).
  59. Cheymol, A. *et al.* The Rubber Slider Metaphor: Visualisation of Temporal and Geolocated Data. in *2022 IEEE Conference on Virtual Reality and 3D User Interfaces Abstracts and Workshops (VRW)* (Mar. 2022), 904–905.
  60. Keefe, D. F. *et al.* Scaling up multi-touch selection and querying: Interfaces and applications for combining mobile multi-touch input with large-scale visualization displays. *International Journal of Human-Computer Studies* **70**, 703–713 (2012).

- 
61. Moere, A. V. Infoticles: Information modeling in immersive environments. in *Proceedings Sixth International Conference on Information Visualisation* (2002), 457–461.
  62. Azzag, H., Picarougne, F., Guinot, C. & Venturini, G. in *Processing and Managing Complex Data for Decision Support* 318–339 (IGI Global, 2006).
  63. Maletic, J. I., Leigh, J. & Marcus, A. Visualizing software in an immersive virtual reality environment. in *Proceedings of ICSE* **1** (2001), 12–13.
  64. Osawa, N., Asai, K. & SUGtMOTO, Y. Y. Immersive Graph Navigation Using Direct Manipulation and Gestures, 6.
  65. Li, Y. *et al.* Analyzing growing plants from 4D point cloud data. *ACM Transactions on Graphics* **32**, 157:1–157:10. ISSN: 0730-0301 (Nov. 1, 2013).
  66. Lu, A. & Shen, H. Interactive Storyboard for Overall Time-Varying Data Visualization. in *2008 IEEE Pacific Visualization Symposium* (Mar. 2008), 143–150.
  67. Neuroth, T. A., Sauer, F. & Ma, K. L. An Interactive Visualization System for Large Sets of Phase Space Trajectories. *Computer Graphics Forum* **38**, 297–309. ISSN: 1467-8659 (2019).
  68. Huang, X. *et al.* TrajGraph: A Graph-Based Visual Analytics Approach to Studying Urban Network Centralities Using Taxi Trajectory Data. *IEEE Transactions on Visualization and Computer Graphics* **22**, 160–169. ISSN: 1941-0506 (Jan. 2016).
  69. Liu, D. *et al.* SmartAdP: Visual Analytics of Large-scale Taxi Trajectories for Selecting Billboard Locations. *IEEE Transactions on Visualization and Computer Graphics* **23**, 1–10. ISSN: 1941-0506 (Jan. 2017).
  70. Hurter, C., Tissoires, B. & Conversy, S. FromDaDy: Spreading Aircraft Trajectories Across Views to Support Iterative Queries. *IEEE transactions on visualization and computer graphics* **15**, 1017–24 (Nov. 1, 2009).
  71. Amirkhanov, A. *et al.* ManyLands: A Journey Across 4D Phase Space of Trajectories. *Computer Graphics Forum* **38**, 191–202. ISSN: 1467-8659 (2019).
  72. Andrienko, G., Andrienko, N., Fuchs, G. & Garcia, J. M. C. Clustering Trajectories by Relevant Parts for Air Traffic Analysis. *IEEE Transactions on Visualization and Computer Graphics* **24**, 34–44. ISSN: 1941-0506 (Jan. 2018).
  73. Waser, J. *et al.* World Lines. *IEEE Transactions on Visualization and Computer Graphics* **16**, 1458–1467. ISSN: 1941-0506 (Nov. 2010).

- 
74. Schindler, B., Waser, J., Ribičić, H., Fuchs, R. & Peikert, R. Multiverse Data-Flow Control. *IEEE Transactions on Visualization and Computer Graphics* **19**, 1005–1019. ISSN: 1941-0506 (June 2013).
  75. Kim, K., Carlis, J. V. & Keefe, D. F. Comparison techniques utilized in spatial 3D and 4D data visualizations: A survey and future directions. *Computers & Graphics* **67**, 138–147. ISSN: 0097-8493 (Oct. 1, 2017).
  76. Andrienko, N. & Andrienko, G. Visual Analytics of Movement: An Overview of Methods, Tools and Procedures. *Information Visualization* **12**, 3–24 (Jan. 1, 2013).
  77. Guignard, L. *et al.* Contact-dependent cell-cell communications drive morphological invariance during ascidian embryogenesis. *bioRxiv*, 238741 (Feb. 22, 2018).
  78. Schroeder, W. J. & Martin, K. M. in *Visualization Handbook* 593–614 (Elsevier, 2005). ISBN: 978-0-12-387582-2.
  79. Cignoni, P. *et al.* MeshLab: an Open-Source Mesh Processing Tool, 8.
  80. Brozovic, M. *et al.* ANISEED 2017: extending the integrated ascidian database to the exploration and evolutionary comparison of genome-scale datasets. *Nucleic Acids Research* (Nov. 2017).
  81. Valades-Cruz, C. A. *et al.* Challenges of intracellular visualization using virtual and augmented reality. *Frontiers in Bioinformatics* **2** (2022).
  82. Pols, M. S. & Klumperman, J. Trafficking and function of the tetraspanin CD63. *Experimental cell research* **315**, 1584–1592 (2009).
  83. Chen, B.-C. *et al.* Lattice light-sheet microscopy: Imaging molecules to embryos at high spatiotemporal resolution. *Science* **346**. ISSN: 0036-8075, 1095-9203 (Oct. 24, 2014).
  84. Liu, T. *et al.* Multi-color live-cell STED nanoscopy of mitochondria with a gentle inner membrane stain. *bioRxiv* (2022).
  85. Oxford Instruments plc. Imaris Software. <https://imaris.oxinst.com/>. 1993.
  86. Tinevez, J.-Y. *et al.* TrackMate: An open and extensible platform for single-particle tracking. *Methods* **115**, 80–90 (2017).
  87. Badoual, A. *et al.* Simulation of astrocytic calcium dynamics in lattice light sheet microscopy images. in *2021 IEEE 18th International Symposium on Biomedical Imaging (ISBI)* (2021), 135–139.



- 
88. Demšar, U. & Virrantaus, K. Space–time density of trajectories: exploring spatio-temporal patterns in movement data. *International Journal of Geographical Information Science* **24**, 1527–1542. ISSN: 1365-8816 (Oct. 11, 2010).
  89. Woodring, J. & Shen, H. Multi-variate, Time Varying, and Comparative Visualization with Contextual Cues. *IEEE Transactions on Visualization and Computer Graphics* **12**, 909–916 (Sept. 2006).
  90. Comon, P. in *Higher-Order Statistics* (ed J-L.Lacoume) 29–38 (Elsevier, June 1992).
  91. Ivosev, G., Burton, L. & Bonner, R. Dimensionality Reduction and Visualization in Principal Component Analysis. *Analytical Chemistry* **80**, 4933–4944. ISSN: 0003-2700 (July 1, 2008).
  92. Mika, S., Ratsch, G., Weston, J., Scholkopf, B. & Mullers, K. Fisher discriminant analysis with kernels. in *Neural Networks for Signal Processing IX: Proceedings of the 1999 IEEE Signal Processing Society Workshop (Cat. No.98TH8468)* (Aug. 1999), 41–48.
  93. Roweis, S. T. & Saul, L. K. Nonlinear Dimensionality Reduction by Locally Linear Embedding. *Science* **290**, 2323–2326. ISSN: 0036-8075, 1095-9203 (Dec. 22, 2000).
  94. Gu, Y. & Wang, C. TransGraph: Hierarchical Exploration of Transition Relationships in Time-Varying Volumetric Data. *IEEE Transactions on Visualization and Computer Graphics* **17**, 2015–2024 (Dec. 2011).
  95. Duran, D. *et al.* Visualization of Large Molecular Trajectories. *IEEE Transactions on Visualization and Computer Graphics* **25**, 987–996. ISSN: 1077-2626, 1941-0506, 2160-9306 (Jan. 2019).
  96. Al-maneea, H. M. & Roberts, J. C. Towards Quantifying Multiple View Layouts in Visualisation as Seen from Research Publications. in *2019 IEEE Visualization Conference (VIS)* (Oct. 2019), 121–121.
  97. Wang Baldonado, M. Q., Woodruff, A. & Kuchinsky, A. Guidelines for using multiple views in information visualization. in *Proceedings of the working conference on Advanced visual interfaces* (Association for Computing Machinery, New York, NY, USA, May 1, 2000), 110–119. ISBN: 978-1-58113-252-6.
  98. Coffey, D. *et al.* Visualizing Motion Data in Virtual Reality: Understanding the Roles of Animation, Interaction, and Static Presentation. *Computer Graphics Forum* **31**, 1215–1224. ISSN: 1467-8659 (2012).

- 
99. Akiba, H., Wang, C. & Ma, K. AniViz: A Template-Based Animation Tool for Volume Visualization. *IEEE Computer Graphics and Applications* **30**, 61–71 (Sept. 2010).
  100. Solteszova, V., Smit, N. N., Stoppel, S., Grüner, R. & Bruckner, S. Memento: Localized Time-Warping for Spatio-Temporal Selection. *Computer Graphics Forum* **39**, 231–243. ISSN: 1467-8659 (2020).
  101. Buchmüller, J., Jäckle, D., Cakmak, E., Brandes, U. & Keim, D. A. MotionRugs: Visualizing Collective Trends in Space and Time. *IEEE Transactions on Visualization and Computer Graphics* **25**, 76–86. ISSN: 2160-9306 (Jan. 2019).
  102. Hägerstrand, T. What about people in Regional Science? *PAPERS OF THE REGIONAL SCIENCE ASSOCIATION*, 16 (1970).
  103. Ssin, S. Y., Walsh, J. A., Smith, R. T., Cunningham, A. & Thomas, B. H. GeoGate: Correlating Geo-Temporal Datasets Using an Augmented Reality Space-Time Cube and Tangible Interactions. in *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)* (Mar. 2019), 210–219.
  104. Leduc, T., Tourre, V. & Servières, M. The space-time cube as an effective way of representing and analysing the streetscape along a pedestrian route in an urban environment. *SHS Web of Conferences* **64**, 03005. ISSN: 2261-2424 (2019).
  105. Filho, J. A. W., Stuerzlinger, W. & Nedel, L. Evaluating an Immersive Space-Time Cube Geovisualization for Intuitive Trajectory Data Exploration. *IEEE Transactions on Visualization and Computer Graphics* **26**, 514–524. ISSN: 1941-0506 (Jan. 2020).
  106. Cassinelli, A. & Ishikawa, M. in *ACM SIGGRAPH 2005 Emerging technologies 10–es* (2005).
  107. Bach, B., Dragicevic, P., Archambault, D., Hurter, C. & Carpendale, S. A Review of Temporal Data Visualizations Based on Space-Time Cube Operations, 20 (2014).
  108. Bach, B., Dragicevic, P., Archambault, D., Hurter, C. & Carpendale, S. A Descriptive Framework for Temporal Data Visualizations Based on Generalized Space-Time Cubes. *Computer Graphics Forum* **36**, 36–61. ISSN: 1467-8659 (2017).
  109. Woodring, J., Chaoli Wang & Han-Wei Shen. High dimensional direct rendering of time-varying volumetric data. in *IEEE Visualization, 2003. VIS 2003.* (Oct. 2003), 417–424.
  110. Krone, M. *et al.* Molecular Surface Maps. *IEEE Transactions on Visualization and Computer Graphics* **23**, 701–710. ISSN: 1941-0506 (Jan. 2017).

- 
111. Brehmer, M., Lee, B., Bach, B., Riche, N. H. & Munzner, T. Timelines Revisited: A Design Space and Considerations for Expressive Storytelling. *IEEE Transactions on Visualization and Computer Graphics* **23**, 2151–2164. ISSN: 2160-9306 (Sept. 2017).
  112. Lab, N. U. K. TimelineJS. <http://timeline.knightlab.com/>. 2013.
  113. Shaw, A., Larson, J. & Welsh, B. TimelineSetter. <https://propublica.github.io/timeline-setter/>. 2011.
  114. Wongsuphasawat, K. *et al.* LifeFlow: visualizing an overview of event sequences. in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Association for Computing Machinery, New York, NY, USA, May 7, 2011), 1747–1756. ISBN: 978-1-4503-0228-9.
  115. Burch, M., Beck, F. & Diehl, S. Timeline trees: visualizing sequences of transactions in information hierarchies. in *Proceedings of the working conference on Advanced visual interfaces* (Association for Computing Machinery, New York, NY, USA, May 28, 2008), 75–82. ISBN: 978-1-60558-141-5.
  116. Di Bartolomeo, S. *et al.* Evaluating the Effect of Timeline Shape on Visualization Task Performance. in *Proceedings of the 2020 CHI Conference on Human Factors in Computing Systems* (ACM, Honolulu HI USA, Apr. 21, 2020), 1–12. ISBN: 978-1-4503-6708-0.
  117. Beedocs 3D Timeline. <http://www.beedocs.com/timeline3D>.
  118. Cantu, A., Duval, T., Grisvard, O. & Coppin, G. HeloVis: A Helical Visualization for SIGINT Analysis Using 3D Immersion. in *2018 IEEE Pacific Visualization Symposium (PacificVis)* (Apr. 2018), 175–179.
  119. Kullberg, R. L. Visualizing Historical Information in Three Dimensions, 50 (1995).
  120. Ansah, J. *et al.* A Graph is Worth a Thousand Words: Telling Event Stories using Timeline Summarization Graphs. in *The World Wide Web Conference* (Association for Computing Machinery, New York, NY, USA, May 13, 2019), 2565–2571. ISBN: 978-1-4503-6674-8.
  121. Abdelhaq, H., Sengstock, C. & Gertz, M. Eventweet: Online localized event detection from twitter. *Proceedings of the VLDB Endowment* **6**, 1326–1329 (2013).
  122. Liu, B., Niu, D., Lai, K., Kong, L. & Xu, Y. Growing story forest online from massive breaking news. in *Proceedings of the 2017 ACM on Conference on Information and Knowledge Management* (2017), 777–785.

- 
123. Nichols, J., Mahmud, J. & Drews, C. Summarizing sporting events using twitter. in *Proceedings of the 2012 ACM international conference on Intelligent User Interfaces* (2012), 189–198.
  124. Fulda, J., Brehmer, M. & Munzner, T. TimeLineCurator: Interactive Authoring of Visual Timelines from Unstructured Text. *IEEE Transactions on Visualization and Computer Graphics* **22**, 300–309. ISSN: 1941-0506 (Jan. 2016).
  125. Charles, F., Porteous, J., Cavazza, M. & Teutenberg, J. Timeline-based navigation for interactive narratives. in *Proceedings of the 8th International Conference on Advances in Computer Entertainment Technology* (Association for Computing Machinery, New York, NY, USA, Nov. 8, 2011), 1–8. ISBN: 978-1-4503-0827-4.
  126. Chen, Z., Wang, Y., Wang, Q., Wang, Y. & Qu, H. Towards Automated Infographic Design: Deep Learning-based Auto-Extraction of Extensible Timeline. *IEEE Transactions on Visualization and Computer Graphics* **26**, 917–926. ISSN: 1941-0506 (Jan. 2020).
  127. Blascheck, T. *et al.* Exploration strategies for discovery of interactivity in visualizations. *IEEE transactions on visualization and computer graphics* **25**, 1407–1420 (2018).
  128. Card, S. K., Suh, B., Pendleton, B. A., Heer, J. & Bodnar, J. W. Time Tree: Exploring Time Changing Hierarchies. in *2006 IEEE Symposium On Visual Analytics Science And Technology* (Oct. 2006), 3–10.
  129. Dachsel, R. & Weiland, M. TimeZoom: a flexible detail and context timeline. in *CHI '06 Extended Abstracts on Human Factors in Computing Systems* (Association for Computing Machinery, New York, NY, USA, Apr. 21, 2006), 682–687. ISBN: 978-1-59593-298-3.
  130. Schwab, M. *et al.* Evaluating pan and zoom timelines and sliders. in *Proceedings of the 2019 chi conference on human factors in computing systems* (2019), 1–12.
  131. Morawa, R., Horak, T., Kister, U., Mitschick, A. & Dachsel, R. Combining Timeline and Graph Visualization. in *Proceedings of the Ninth ACM International Conference on Interactive Tabletops and Surfaces* (Association for Computing Machinery, New York, NY, USA, Nov. 16, 2014), 345–350. ISBN: 978-1-4503-2587-5.
  132. Drossis, G., Grammenos, D., Adami, I. & Stephanidis, C. 3D Visualization and Multimodal Interaction with Temporal Information Using Timelines. in *Human-Computer Interaction – INTERACT 2013* (eds Kotzé, P., Marsden, G., Lindgaard, G., Wesson, J. & Winckler, M.) (Springer, Berlin, Heidelberg, 2013), 214–231. ISBN: 978-3-642-40477-1.

- 
133. Denning, J. D., Kerr, W. B. & Pellacini, F. *MeshFlow*: interactive visualization of mesh construction sequences. in *ACM SIGGRAPH 2011 papers* (Association for Computing Machinery, New York, NY, USA, July 25, 2011), 1–8. ISBN: 978-1-4503-0943-1.
  134. Doboš, J., Mitra, N. J. & Steed, A. 3D Timeline: Reverse engineering of a part-based provenance from consecutive 3D models. *Computer Graphics Forum* **33**, 135–144. ISSN: 1467-8659 (2014).
  135. Cruz-Neira, C., Sandin, D. J., DeFanti, T. A., Kenyon, R. V. & Hart, J. C. The CAVE: audio visual experience automatic virtual environment. *Communications of the ACM* **35**, 64–73 (1992).
  136. El Beheiry, M. *et al.* DIVA: natural navigation inside 3D images using virtual reality. *Journal of molecular biology* **432**, 4745–4749 (2020).
  137. Blanc, T., El Beheiry, M., Caporal, C., Masson, J.-B. & Hajj, B. Genuage: visualize and analyze multidimensional single-molecule point cloud data in virtual reality. *Nature Methods* **17**, 1100–1102. ISSN: 1548-7105 (Nov. 2020).
  138. Gaugne, R. *et al.* eXtended Reality for Cultural Heritage. 2022.
  139. Lécuyer, F. *et al.* INSIDE interactive and non-destructive solution for introspection in digital environments. in *2018 3rd Digital Heritage International Congress (DigitalHERITAGE) held jointly with 2018 24th International Conference on Virtual Systems & Multimedia (VSMM 2018)* (2018), 1–4.
  140. Hurter, C. *et al.* FiberClay: Sculpting Three Dimensional Trajectories to Reveal Structural Insights. *IEEE Transactions on Visualization and Computer Graphics* **25**, 704–714. ISSN: 1941-0506 (Jan. 2019).
  141. Johnson, S. *et al.* Bento Box: An Interactive and Zoomable Small Multiples Technique for Visualizing 4D Simulation Ensembles in Virtual Reality. *Frontiers in Robotics and AI* **6**. ISSN: 2296-9144 (2019).
  142. Liu, J., Prouzeau, A., Ens, B. & Dwyer, T. Design and Evaluation of Interactive Small Multiples Data Visualisation in Immersive Spaces. in *2020 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)* (Mar. 2020), 588–597.
  143. Sicat, R. *et al.* DXR: A Toolkit for Building Immersive Data Visualizations. *IEEE Transactions on Visualization and Computer Graphics* **25**, 715–725. ISSN: 1077-2626, 1941-0506, 2160-9306 (Jan. 2019).

- 
144. Cordeil, M. *et al.* IATK: An Immersive Analytics Toolkit. in *2019 IEEE Conference on Virtual Reality and 3D User Interfaces (VR)* (IEEE, Osaka, Japan, Mar. 2019), 200–209. ISBN: 978-1-72811-377-7.
  145. Satyanarayan, A., Moritz, D., Wongsuphasawat, K. & Heer, J. Vega-Lite: A Grammar of Interactive Graphics. *IEEE Transactions on Visualization and Computer Graphics* **23**, 341–350. ISSN: 1077-2626 (Jan. 2017).
  146. Satyanarayan, A., Russell, R., Hoffswell, J. & Heer, J. Reactive vega: A streaming dataflow architecture for declarative interactive visualization. *IEEE transactions on visualization and computer graphics* **22**, 659–668 (2015).
  147. Ens, B. *et al.* Grand Challenges in Immersive Analytics. in *Proceedings of the 2021 CHI Conference on Human Factors in Computing Systems* (Association for Computing Machinery, New York, NY, USA, May 6, 2021), 1–17. ISBN: 978-1-4503-8096-6.
  148. Margery, D., Arnaldi, B. & Plouzeau, N. in *Virtual Environments '99* (eds Gervautz, M., Schmalstieg, D. & Hildebrand, A.) red. by Hansmann, W., Hewitt, W. T. & Purgathofer, W., 169–178 (Springer Vienna, Vienna, 1999).
  149. Cordeil, M. *et al.* Immersive Collaborative Analysis of Network Connectivity: CAVE-style or Head-Mounted Display? *IEEE Transactions on Visualization and Computer Graphics* **23**, 441–450. ISSN: 1077-2626 (Jan. 2017).
  150. Fleury, C., Duval, T., Gouranton, V. & Arnaldi, B. A New Adaptive Data Distribution Model for Consistency Maintenance in Collaborative Virtual Environments. in (Sept. 27, 2010).
  151. Donalek, C. *et al.* Immersive and collaborative data visualization using virtual reality platforms. in *2014 IEEE International Conference on Big Data (Big Data)* (IEEE, Washington, DC, USA, Oct. 2014), 609–614. ISBN: 978-1-4799-5666-1.
  152. Kurillo, G. / i.-. j. & Forte, M. Telearch–Integrated visual simulation environment for collaborative virtual archaeology. *Mediterranean Archaeology and Archaeometry* **12**, 11–20 (2012).
  153. Li, N., Nittala, A. S., Sharlin, E. & Costa Sousa, M. in *CHI'14 Extended Abstracts on Human Factors in Computing Systems* 1291–1296 (2014).
  154. Isenberg, T. An interaction continuum for visualization. in *VIS Workshop on “Death of the Desktop: Envisioning Visualization without Desktop Computing”* (2014).

- 
155. Reda, K. *et al.* Visualizing Large, Heterogeneous Data in Hybrid-Reality Environments. *IEEE Computer Graphics and Applications* **33**, 38–48. ISSN: 1558-1756 (July 2013).
  156. Leigh, J. & Brown, M. D. Cyber-commons: Merging real and virtual worlds. *Communications of the ACM* **51**, 82–85 (2008).
  157. Febretti, A. *et al.* CAVE2: a hybrid reality environment for immersive simulation and information analysis. in *The Engineering Reality of Virtual Reality 2013* **8649** (International Society for Optics and Photonics, Mar. 4, 2013), 864903.
  158. Cavallo, M., Dholakia, M., Havlena, M., Ocheltree, K. & Podlaseck, M. Dataspace: A reconfigurable hybrid reality environment for collaborative information analysis. in *2019 IEEE conference on virtual reality and 3D user interfaces (VR)* (2019), 145–153.
  159. Chenechal, M. L., Duval, T., Gouranton, V., Royan, J. & Arnaldi, B. Vishnu: virtual immersive support for HelpiNg users an interaction paradigm for collaborative remote guiding in mixed reality. in *2016 IEEE Third VR International Workshop on Collaborative Virtual Environments (3DCVE)* (Mar. 2016), 9–12.
  160. Reski, N., Alissandrakis, A., Tyrkkö, J. & Kerren, A. in *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society 5*, 1–12 (Association for Computing Machinery, New York, NY, USA, Oct. 25, 2020). ISBN: 978-1-4503-7579-5.
  161. Reski, N., Alissandrakis, A. & Kerren, A. An Empirical Evaluation of Asymmetric Synchronous Collaboration Combining Immersive and Non-Immersive Interfaces Within the Context of Immersive Analytics. *Frontiers in Virtual Reality* **2** (2022).
  162. Snowdon, D., Churchill, E. F. & Munro, A. J. in *Collaborative Virtual Environments: Digital Places and Spaces for Interaction* (eds Churchill, E. F., Snowdon, D. N. & Munro, A. J.) 3–17 (Springer, London, 2001). ISBN: 978-1-4471-0685-2.
  163. Reski, N., Alissandrakis, A. & Kerren, A. in *Proceedings of the 11th Nordic Conference on Human-Computer Interaction: Shaping Experiences, Shaping Society 33*, 1–11 (Association for Computing Machinery, New York, NY, USA, Oct. 25, 2020). ISBN: 978-1-4503-7579-5.
  164. Stegmaier, S., Strengert, M., Klein, T. & Ertl, T. A simple and flexible volume rendering framework for graphics-hardware-based raycasting. in *Fourth International Workshop on Volume Graphics, 2005*. (June 2005), 187–241.

- 
165. Loomis, J. & Knapp, J. in *Virtual and adaptive environments: Applications, implications, and human performance issues* 21–46 (Lawrence Erlbaum Associates Publishers, Mahwah, NJ, US, 2003). ISBN: 978-0-8058-3107-8.
  166. Leggio, B. *et al.* MorphoNet : an interactive online morphological browser to explore complex multi-scale data. *Nature Communications* **10**, 1–8. ISSN: 2041-1723 (June 27, 2019).
  167. Sulston, J. E., Schierenberg, E., White, J. G. & Thomson, J. N. The embryonic cell lineage of the nematode *Caenorhabditis elegans*. *Developmental Biology* **100**, 64–119. ISSN: 0012-1606 (Nov. 1, 1983).
  168. Weber, M., Alexa, M. & Muller, W. Visualizing time-series on spirals. in *IEEE Symposium on Information Visualization, 2001. INFOVIS 2001*. (IEEE, San Diego, Ca, USA, 2001), 7–13.
  169. Ware, C. Using hand position for virtual object placement. *The Visual Computer* **6**, 245–253. ISSN: 1432-2315 (Sept. 1, 1990).
  170. Brument, H., Olivier, A.-H., Marchal, M. & Argelaguet, F. Does the Control Law Matter? Characterization and Evaluation of Control Laws for Virtual Steering Navigation. in *ICAT-EGVE 2020 - International Conference on Artificial Reality and Telexistence & Eurographics Symposium on Virtual Environments* (Florida, United States, Dec. 2020), 1–10.
  171. Dachsel, R. & Hübner, A. Three-dimensional menus: A survey and taxonomy. *Computers & Graphics* **31**, 53–65. ISSN: 0097-8493 (Jan. 1, 2007).
  172. SUS: A 'Quick and Dirty' Usability Scale | 35 | Usability Evaluation I.
  173. Kourtesis, P., Collina, S., Doumas, L. A. A. & MacPherson, S. E. Validation of the Virtual Reality Neuroscience Questionnaire: Maximum Duration of Immersive Virtual Reality Sessions Without the Presence of Pertinent Adverse Symptomatology. *Frontiers in Human Neuroscience* **13**. ISSN: 1662-5161 (2019).
  174. Keshavarz, B. & Hecht, H. Validating an Efficient Method to Quantify Motion Sickness. *Human Factors* **53**, 415–426. ISSN: 0018-7208 (Aug. 1, 2011).
  175. Wobbrock, J. O., Findlater, L., Gergle, D. & Higgins, J. J. The aligned rank transform for nonparametric factorial analyses using only anova procedures. in *Proceedings of the SIGCHI Conference on Human Factors in Computing Systems* (Association for Computing Machinery, New York, NY, USA, May 7, 2011), 143–146. ISBN: 978-1-4503-0228-9.



- 
176. Drost, J. & Clevers, H. Organoids in cancer research. *Nature Reviews Cancer* **18**, 407–418.  
ISSN: 1474-1768 (July 2018).



---

**Titre :** Visualisation Immersive et Interactive de Données 3D Temporelles

**Mot clés :** Réalité Virtuelle, Visualisation, Données 3D Temporelles, Cube Espace-Temps, Frise Chronologique

**Résumé :** Les données 3D temporelles sont de plus en plus présentes grâce aux progrès des techniques d'acquisition et de génération, notamment dans le domaine de l'imagerie biologique. Cependant, les méthodes pour visualiser ces ensembles de données peuvent être insuffisantes. Dans cette thèse, nous présentons une série de contributions exploitant des techniques de Visualisation et de Réalité Virtuelle, permettant l'exploration de divers types de données 3D temporelles. Nous illustrons ces contributions à travers des exemples tirés d'embryologie et d'enregistrements intracellulaires. Premièrement, nous définissons la notion d'objets 4D pour qualifier des entités sémantiques logiques présentes dans les données 3D temporelles, permettant l'interaction et la visualisation naturelles des données. Deuxièmement, nous étendons la représentation en Cube Spatio-Temporel pour les don-

nées 3D temporelles, résultant en un volume 4D, l'Hypercube Spatio-Temporel. Une vue 3D peut en être extraite par un opérateur de projection défini par l'utilisateur, et explorée par des interactions 3D adaptées. Troisièmement, nous proposons un espace de création de frises chronologiques 3D. Ces frises exploitent l'espace 3D et permettent la visualisation de données 3D temporelles. Nous proposons des processus interactifs pour aider la manipulation et la navigation efficaces à travers cette visualisation. Finalement, nous proposons une technique de sélection pour des objets 4D ponctuels dans le temps, basée sur un processus Spatial-puis-Temporel. Nous décrivons des techniques de visualisation, de sélection de l'espace 3D et de désambiguïsation dans le temps pour sélectionner des objets 4D.

---

**Title:** Immersive and Interactive Visualization of 3D Temporal Data

**Keywords:** Virtual Reality, Visualization, 3D Temporal Data, Space-Time Cube, Timelines

**Abstract:** 3D temporal data are more and more present as acquisition and generation methods improve, notably in the field of biological imagery. However, visualization methods to analyze these datasets can be insufficient. In this thesis, we present a series of contributions leveraging techniques from the fields of Virtual Reality and Visualization to support the exploration and interaction with various types of 3D temporal datasets, and illustrate our proposed methods through examples from biology, notably embryos and intra-cellular imaging. First, we introduce the notion of 4D objects to qualify 3D temporal features in order to highlight semantically logic entities, supporting natural visualization and interaction. Second, we extend the traditional Space-Time Cube representation to 3D temporal data, resulting in a 4D volume named Space-Time

Hypercube. A 3D view can be extracted from this 4D volume through a user-driven projection operation, which can be explored with adapted 3D user interaction. Third, we propose a design space to create 3D timelines to support the visualization of 3D temporal data. It extends the existing design space for usual timeline visualizations, yet exploits the 3D space offered by virtual environments. We propose adapted 3D user interaction processes to help manipulating and navigating through this visualization efficiently. Finally, we propose a selection technique for 4D objects punctual in time, based on a Space-then-Time selection process. We discuss techniques to visualize the data, to support adapted methods to select a region in the 3D space, and finally disambiguate in time to select the right 4D object.