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Collaborative Immersive Analytics for Meteorological and Climatological Data

Inoussa Ouedraogo

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Collaborative Immersive Analytics for Meteorological and Climatological Data

*Immersive Analytics Collaborative sur des Données
Météorologiques et Climatologiques*

Thèse de doctorat de l'université Paris-Saclay

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Numérique** (Unité Mixte du CNRS et de l'Université Paris-Saclay),
sous la direction de **Patrick BOURDOT**, Directeur de Recherche,
et le co-encadrement de **Thi Thuong Huyen NGUYEN**, Maître de
Conférences.

Thèse soutenue à Paris-Saclay, le 02 octobre 2024, par

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Titre: Immersive Analytics Collaborative sur des Données Météorologiques et Climatologiques

Mots clés: Réalité Augmentée, Réalité Mixte, Analyse Immersive, Techniques d'Interaction, Travail Coopératif Assisté par Ordinateur, Ontologie, Données Liées.

Résumé: L'explosion des données au cours des dernières décennies a remis en question les processus d'analyse de données existants dans le but de découvrir des connaissances et d'extraire des informations importantes en quasi temps réel. La complexité des données quant à leur hétérogénéité, leur quantité, leur qualité ou leur absence de qualité, ainsi que la vitesse à laquelle elles sont générées, pose des défis importants pour le pipeline d'analyse de données. Ce pipeline comprend des tâches telles que l'acquisition de données, le stockage, la gestion, le transfert, la requête, la visualisation, la mise à jour, le partage et la création des connaissances. Étant donné que la prise de décision basée sur l'analyse des données massives est fréquemment le résultat de travail collaboratif, l'infrastructure d'analyse de données et de prise de décision doit être collaborative. Cela signifie permettre aux utilisateurs de communiquer, d'interagir avec des collaborateurs et de coordonner efficacement leurs activités.

L'objectif de recherche de cette thèse est de fournir un framework qui facilite l'analytique collaborative en utilisant des technologies immersives, aidant les utilisateurs de divers niveaux d'expertise à visualiser, interagir avec et analyser les données. Je vise à explorer comment les nouvelles technologies d'interaction et d'affichage immersives peuvent être utilisées pour faciliter l'exploration des données, le raisonnement analytique et la prise de décision dans l'analytique visuelle. La contribution principale de cette dissertation est de proposer et d'explorer de nouvelles techniques d'interaction dans un cadre d'Analytique Immersive Collaborative avec l'humain dans la boucle. Ma dissertation explore de nouvelles techniques de sélection et d'intégration des données dont le but est d'accélérer le pipeline d'analyse de données, en particulier pour interagir avec des nuages de points de données denses en Réalité Augmentée (RA) basée sur l'interaction à travers des casques. Ma recherche met également en évidence une nouvelle approche de partition automatique de l'espace physique en RA co-localisée. De plus, dans l'effort commun de lutte contre le changement clima-

tique et le réchauffement climatique, mon travail se concentre sur l'analyse des données climatologiques et météorologiques, et dans une large mesure sur les ensembles de données complexes de tempêtes et de cyclones provenant d'observations météorologiques réelles et de modèles de simulation. En effet, les catastrophes climatiques liées aux cyclones se produisent chaque année dans le monde entier, causant des dévastations généralisées, y compris des pertes humaines, des dommages infrastructurels importants, des revers économiques et environnementaux. Ce projet contribuera aux efforts urgents actuels pour minimiser les dégâts causés par les tempêtes et les cyclones au niveau international, en développant des techniques permettant aux chercheurs en climatologie et en météorologie, et aux parties prenantes clés de mieux accéder aux données disponibles et de les comprendre.

Plus en détail, j'ai d'abord proposé et étudié une solution pour améliorer la sélection des points de données. La technique d'interaction proposée était basée sur l'expansion des points de données pour améliorer la sélection des utilisateurs lorsqu'ils utilisent la RA basée sur des casques. Ensuite, j'ai exploré l'approche basée sur l'ontologie et les données liées pour intégrer différentes sources de données, permettant aux utilisateurs d'effectuer des requêtes et des filtrages de données pendant l'interaction et d'améliorer leurs performances dans le processus analytique des ensembles de données météorologiques. Une étude utilisateur a été menée pour montrer la validité de cette approche proposée. Enfin, je présente une technique qui permet aux utilisateurs de partitionner automatiquement l'espace de travail physique partagé en plusieurs sous-espaces en fonction de l'espace disponible et de la position des utilisateurs en RA co-localisée utilisant des casques. J'ai étudié l'effet de cette technique de partitionnement de l'espace physique dans le contexte collaboratif de l'analyse des données de tempête. De plus, l'impact des aspects privés et publics de ces espaces collaboratifs co-localisés a également été évalué.

Title: Collaborative Immersive Analytics for Meteorological and Climatological Data

Keywords: Augmented Reality, Mixed Reality, Immersive Analytics, Interaction Techniques, Computer-Supported Cooperative Work, Ontology, Linked Data.

Abstract: The explosion of data in recent decades has challenged existing data analysis processes tasked with uncovering patterns and extracting valuable insights in near real time. The complexity of data due to its heterogeneity, quantity, quality or the lack thereof, as well as the speed at which it is generated, places significant challenges on data analytics pipeline. This pipeline encompasses tasks such as data acquisition, storage, management, transfer, querying, visualisation, update, sharing, and the creation of insights. Given that decision-making based on big data analysis is frequently the outcome of collaborative endeavours, the data analytics and decision-making infrastructure must be collaborative. This means enabling users to communicate, interact with collaborators, and effectively coordinate their activities.

The research focus of this Ph.D. thesis is to provide a framework that facilitates collaborative visual analytics using immersive technologies, assisting users with varying expertise to visualise, interact with, and analyse data. I aim to investigate how new immersive interaction and display technologies can be used to facilitate data exploration, analytics reasoning, and decision-making in visual analytics. The main contribution of this dissertation is to propose and explore novel interaction techniques in a Collaborative Immersive Analytics framework supporting visual analytics with human in the loop. My dissertation explores new techniques of selection and data integration whose aim is to speed up the data analytics pipeline, especially for interacting with dense data point cloud in Head-Mounted-Display (HMD)-based Augmented Reality (AR). My research also highlights a novel approach of automatic spatial partition of physical space in co-located AR. Moreover, in the

common effort of fighting against climate change and global warming, my work focuses on data analytics for climatology and meteorology, and to a great extent on complex storm and cyclone datasets from real weather observations and predicted simulation model projections. Indeed, cyclone climate disasters occur each year globally, causing widespread devastation including human casualties, gross infrastructural damage, economic and environmental setbacks. This project will contribute to current urgent efforts to minimise storm and cyclone damage internationally, by developing techniques that allow climate researchers and key stakeholders to better access and understand available data.

In more detail, I first proposed and studied a solution to improve the selection of data points. The proposed interaction technique was based on expanding data points to improve users' selection when using HMD-based AR. Second, I explored the Ontology-and-Linked-Data-based approach to integrate different data sources that allows the users to perform queries and filtering of data during the interaction and to enhance their performance in the analytics process of meteorological datasets. A user study was conducted to show the validity of this proposed approach. Finally, I present a technique that allows the users to automatically partition the shared physical workspace into several sub-spaces based on the available space and the position of the users in co-located AR using HMDs. I studied the effect of this physical space partitioning technique in the collaborative context of storm data analysis. In addition, the impact of the private and public aspects of these co-located collaborative spaces was also evaluated.

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Synthèse

Cette thèse s'intéresse à l'analyse immersive collaborative à l'aide de technologies de Réalité Augmentée, et son application à la Météorologie ou la Climatologie. L'immersive analytics collaborative combine les technologies immersives et des techniques d'analyse de données pour permettre à des utilisateurs de collaborer pour visualiser et analyser des ensembles de données complexes. En terme d'immersion, nous avons opté pour les technologies de Réalité Augmentée (RA) qui présentent certains avantages pour la collaboration co-localisée, mais aussi pour permettre aux utilisateurs de faire cohabiter leur espace de travail usuel avec un espace collaboratif virtuel. L'environnement RA proposé, pour la visualisation immersive et l'interaction collaborative avec des données météorologiques et climatologiques, a du résoudre plusieurs problématiques: l'élaboration de nouvelles techniques de sélection de points de données (ou *Data Points*) au sein de nuages de points très denses, l'intégration d'informations sémantiques à base d'ontologies pour faciliter l'analyse des données, et enfin la gestion des informations publiques et privées en termes de visualisation et d'espace de travail pour la collaboration immersive co-localisée en RA.

Techniques de Sélection en Réalité Augmentée pour l'Analyse Immersive de Données

La première problématique abordée au cours de cette thèse a été la sélection de points 2D ou 3D dans des environnements immersifs de RA. Dans de nombreux domaines d'analyse de données, ces points sont porteurs de nombreux attributs, d'où leur dénomination de points de données ou *Data Points*. En météorologie et climatologie, par exemple, à un point donné de latitude, de longitude et d'altitude, pour un instant donné, correspondent de nombreuses valeurs d'attributs tels que : la pression, la température, la quantité d'eau de ruissellement, le taux d'humidité de l'air, la pluviométrie, la vitesse du vent, etc. Interagir avec ces points de données est donc très important, mais se heurte à la difficulté que ces points sont visuellement présentés au sein de nuages (3D) ou de cartes (2D) extrêmement denses. Or, les paradigmes interactifs proposés sur les systèmes de RA (que ce soit des approches vidéo ou optiques sur les casques en question) n'ont pas la précision requise pour permettre des sélections efficaces au sein de visualisations à forte densité de points.

Notre contribution sur cette problématique est double. Tout d'abord, nous avons mené une étude systématique des techniques de sélection multimodales disponibles en RA. Cette étude a révélé que la plupart des techniques proposées sont fatigantes pour les utilisateurs et peu précises. En particulier, la direction du regard ou le pointage avec la main n'offrent pas de grandes différences en termes

de précision, et sont fortement affectées par la technique de confirmation utilisée. De plus, les confirmations basées sur des gestes ou des clics sur manette augmentent notablement les imprécisions. La reconnaissance vocale, bien que parfois défaillante et provoquant des répétitions ou des commandes intempestives, reste encore la technique de confirmation qui semble la plus robuste. Au-delà de cette étude, nous avons ensuite développé une technique pour améliorer la sélection dans des visualisations denses de points. L'approche proposée est basée sur l'expansion des points de données, ce qui permet une sélection plus précise et plus rapide. Cette méthode d'expansion des points offre aux utilisateurs une plus grande facilité de manipulation, réduisant ainsi la fatigue et augmentant la précision dans les environnements immersifs. Bien que développée et évaluée sur des cartes 2D, nous avons ensuite proposé plusieurs généralisations de cette technique pour son extension dans des nuages de points 3D.

Cette étude et cette approche ont été validées via une expérimentation qui a permis de comparer diverses techniques de pointage (par la tête ou la main) et de confirmation (commande vocale ou gestuelle i.e. *Air-Tap*), ainsi que d'évaluer l'impact des modèles de points utilisés lors de la sélection (expansion et non-expansion) l'analyse immersive de points de données en AR. L'objectif était de déterminer quelles techniques offraient le meilleur compromis en termes de précision, de temps de réalisation des tâches (*TCT*) et de satisfaction des utilisateurs. Les résultats ont montré que le temps de réalisation des tâches n'était pas significativement influencée par les interactions entre les 6 conditions issues des 3 variables considérées : techniques de pointage, commandes de confirmation et modèles de point. Cependant, la technique de confirmation par geste est significativement plus lente que la commande vocale. En ce qui concerne la précision (*Total Error Distance - TED*), les tests ont révélé qu'avec une confirmation gestuelle, le pointage avec la tête est plus efficace que le pointage manuel. L'avantage d'une répartition multimodale du pointé et de la confirmation sur différents canaux n'a pour autant pas été confirmé de façon significative pour la commande vocale, bien que les utilisateurs expriment clairement leur préférence pour sa combinaison avec n'importe qu'elle des techniques de pointé. Concernant le modèle de points, les utilisateurs ont noté que l'expansion des points de données réduit significativement leur fatigue et qu'elle est plus intuitive pour l'analyse de ce type de données en situation immersive. Au surplus, les mesures d'erreur ont démontré que cette technique améliorerait la précision des sélections. Globalement, les utilisateurs ont exprimé une nette préférence pour une technique combinant commande vocale, pointé de tête et expansion de point.

Ce volet de ma thèse a été présenté et publié dans les actes de la conférence *ACM Symposium on Virtual Reality Software and Technology (VRST)* en Novembre 2022.

Analyse Immersive de Données Météorologiques: une étude exploratoire sur une approche sémantique basée ontologie

La deuxième problématique abordée au cours de cette thèse est la gestion de la complexité des données météorologiques dans des environnements immersifs à base de technologies de Réalité Virtuelle et Augmentée. En effet, la complexité des données météorologiques réside principalement dans leur hétérogénéité et leur volume. Ces données proviennent en effet de multiples sources, telles que des satellites, des radars, des stations météorologiques, ou encore des simulations numériques, et elles présentent des formats variés, des résolutions spatiales et temporelles différentes, ainsi que des structures de données diverses. Cette grande diversité rend la gestion et l'analyse de ces données particulièrement complexes, notamment lorsqu'il s'agit d'intégrer ces différentes sources pour obtenir des informations cohérentes.

Dans la littérature, les outils actuels proposés pour la visualisation immersive des données sont limités en termes de capacité d'affichage, mais aussi en termes d'échantillonnage des données. Pour répondre à ces défis, nous avons proposé une approche sémantique basée sur des ontologies. Les ontologies permettent de structurer les données en définissant des relations sémantiques entre différents concepts, facilitant ainsi l'intégration et l'interopérabilité entre des ensembles de données hétérogènes. Cette approche sémantique permet non seulement d'interroger les données de manière plus efficace, mais aussi d'améliorer la vitesse d'exploration des données par les utilisateurs. Grâce à cette intégration sémantique, les utilisateurs peuvent effectuer des requêtes complexes, affiner leur exploration des ensembles de données et identifier plus rapidement des tendances ou des anomalies.

Ainsi, le deuxième ensemble de contributions de cette thèse est la conception et le développement d'une interface utilisateur en RA basée sur une approche sémantique. Grâce à l'introduction de la sémantique sur les données, l'utilisateur peut formuler des requêtes d'affichage pour ne visualiser que les données qui sont appropriées à sa tâche, ce qui facilite ses interactions et améliore ses performances dans le processus d'analyse des données. Pour explorer cette approche sémantique dans les applications de RA, j'ai étudié les ontologies existantes en météorologie et climatologie, et proposé une ontologie faisant la synthèse de plusieurs d'entre-elles, tout en prenant en compte les contraintes imposées par l'interaction en RA. En effet, les ontologies météorologiques et climatologiques présentes dans la littérature sont souvent volumineuses et complexes en termes de concepts et de dépendances à d'autres ontologies, ce qui réduit les performances des requêtes dans les systèmes utilisant des technologies immersives. De plus, ces ontologies manquent de règles et de concepts spécifiques permettant à l'utilisateur de formuler avec précision des requêtes sur certaines parties de nos ensembles de données complexes. Au-delà de l'élaboration de ce modèle sémantique, mon autre contribution a alors été d'évaluer le potentiel d'une telle approche Analyse Immersive pour l'analyse immersive de données en RA. L'étude visait à comparer les performances de deux approches, l'une assistée par ontologie et l'autre non assistée. Les résultats ont

montré que l'approche assistée par ontologie a nettement surpassé la méthode non assistée, notamment en ce qui concerne le temps de complétion des tâches et le nombre d'essais nécessaires pour réussir. Les participants ont réalisé les tâches plus rapidement et avec moins d'erreurs lorsqu'ils utilisaient l'ontologie pour interroger et filtrer les données. De plus, les évaluations de la charge cognitive, mesurées à l'aide de l'outil *NASA-TLX*, ont révélé que les utilisateurs percevaient une charge cognitive nettement inférieure avec l'approche sémantique. Enfin, les retours d'expérience des participants ont mis en avant une forte préférence pour la méthode assistée, avec des scores de satisfaction utilisateur élevés (*SUS*). Cette contribution a été publiée aout 2024 dans le journal *Springer Virtual Reality*.

Collaboration Immersive Co-localisée en RA: confidentialité des espaces de travail et de la visualisation des données

En plus de l'amélioration des techniques d'interaction, une autre problématique clef abordée dans cette thèse est la gestion de l'espace de travail dans le cadre du travail collaboratif co-localisé en analyse immersive de données. La collaboration entre plusieurs utilisateurs est essentielle dans des domaines tels que la météorologie, où des experts de différents domaines doivent travailler ensemble pour analyser des phénomènes complexes. Cependant, la gestion de l'espace de travail pour la collaboration immersive co-localisée en réalité augmentée reste un défi. Par exemple, afficher des données partout dans l'espace physique peut être perturbant ou distrayant pour d'autres collaborateurs, surtout lorsque certaines parties des données ne sont pas pertinentes pour tous. D'autre part, les relations spatiales et le positionnement des individus à proximité peuvent avoir un impact significatif sur les performances et le comportement des utilisateurs lors de la collaboration. Pour améliorer l'expérience collaborative, nous avons conçu un mécanisme de partitionnement automatique de l'espace de travail. Ce mécanisme divise l'espace physique partagé en zones privées et publiques, permettant aux utilisateurs d'organiser leur environnement sans interférer avec les autres. Trois techniques de visualisation des frontières de ces zones ont été testées : les frontières linéaires, opaques et semi-transparentes. Le troisième ensemble de contribution concerne la gestion de l'espace de travail dans le cadre du travail collaboratif co-localisé en RA. J'ai tout d'abord proposé un algorithme de partitionnement de l'espace qui permet aux utilisateurs de diviser l'espace de travail et j'ai implémenté de cette technique dans une application d'Analyse Immersive de données. De plus, j'ai proposé différentes formes d'affichage des frontières des espaces de travail, affichage servant à pour montrer aux collaborateurs les différents espaces de travail disponibles pour la collaboration. Enfin j'ai globalement mené une étude sur l'apport de ce partitionnement de l'espace de travail dans ce type de collaboration immersive. Deux expérimentations ont été menées pour évaluer l'efficacité de la partition de l'espace physique et la gestion de la confidentialité des vues dans un contexte de

collaboration immersive en réalité augmentée.

La première portait sur l'évaluation des techniques de visualisation des frontières pour le partitionnement de l'espace de travail. Bien que les temps de réalisation des tâches n'aient pas montré de différences significatives entre les différentes méthodes de visualisation des frontières (lignes, frontières opaques ou semi-transparentes), les utilisateurs ont préféré la technique des « lignes » pour sa clarté et sa simplicité. Cette étude a été acceptée pour publication dans les actes des Posters de la conférence internationale *EuroXR 2024*.

La deuxième expérimentation s'est concentrée sur l'impact de la partition de l'espace physique (non divisé/divisé, ce dernier étant donc constitué d'une zone publique et de deux zones privées) et des conditions de confidentialité des vues (public/privé) sur une tâche collaborative d'analyse de données météorologiques. Les résultats ont montré, d'une part, que la partition de l'espace n'a pas d'impact significatif sur le temps total d'exécution des tâches, et que, d'autre part, la confidentialité des vues joue un rôle important dans la performance individuelle. Les utilisateurs ont obtenu de meilleurs résultats dans les tâches réalisées en vue privée, indiquant que la gestion de la confidentialité dans les espaces collaboratifs immersifs est cruciale pour optimiser la performance et minimiser les distractions. Dans l'interview des utilisateurs, il apparaît que la flexibilité de pouvoir rendre public ou non un objet est préférée à la contrainte de devoir le placer dans un espace public prédéterminé, même si la cohabitation des utilisateurs en collaboration immersive co-localisée en RA suppose un minimum de partitionnement de l'espace de travail. Cette deuxième partie a été publiée à *ACM Symposium on Spatial User Interaction (SUI 2024)* en Octobre 2024.

Conclusions et Perspectives

Dans cette thèse, plusieurs techniques ont été développées pour l'analyse collaborative immersive, notamment la sélection de points de données, la gestion des données à travers une approche sémantique, et la gestion de l'espace physique pour la collaboration co-localisée. Les contributions de cette thèse ne se limitent pas au domaine de la météorologie. Les techniques développées peuvent être appliquées à d'autres secteurs nécessitant l'analyse collaborative de données massives, comme la santé, la géologie ou encore l'urbanisme. Cependant, ces solutions présentent certaines limites, ouvrant ainsi des pistes pour des travaux futurs.

L'une des premières perspectives à court terme consiste à étudier les facteurs influençant les différentes techniques proposées. Par exemple, pour la technique d'expansion des points de données, il serait intéressant d'étudier l'impact de la taille finale des points une fois étendus et sa corrélation avec la taille initiale. Ensuite l'optimisation du temps de réponse des requêtes ontologiques est une autre priorité à court terme. Actuellement, le temps de réponse augmente de façon exponentielle avec le nombre de points de données interrogés, rendant cette approche peu

adaptée aux systèmes interactifs en temps réel pour les ensembles de données volumineux. Une solution envisagée est l'implémentation d'un indexage basé sur des graphes et une amélioration du traitement des requêtes au sein de l'architecture client-serveur utilisée par le système.

À plus long terme, il est prévu d'étendre ces techniques à des scénarios plus complexes. Une piste majeure consisterait à améliorer tous les aspects de la visualisation météorologique et climatologique en utilisant la réalité augmentée (RA). En outre, l'impact de cette approche immersive sur une longue période, avec un plus grand nombre de participants experts, doit être étudié afin de mieux comprendre son utilité dans des environnements professionnels.

D'autres travaux futurs à long terme pourraient consister à explorer des techniques alternatives telles que le curseur bulle 3D ou des techniques de sélection prédictive. Ces approches permettraient de rendre les objets masqués visibles ou d'anticiper les cibles à sélectionner en fonction de la proximité de l'utilisateur. De plus, l'intégration d'algorithmes d'apprentissage automatique ou de réseaux neuronaux profonds pourrait offrir des alternatives aux ontologies pour le traitement des données complexes.

Enfin, un autre axe de recherche serait d'améliorer la compatibilité entre différentes interfaces (ordinateurs de bureau, RA et RV) pour créer un système interopérable, utilisable dans des contextes de collaboration synchrone et asynchrone, à la fois co-localisée et distribuée. Cela permettrait à divers profils d'utilisateurs, tels que météorologues, ingénieurs ou responsables de la santé publique, de travailler ensemble de manière plus efficace lors de la gestion des crises climatiques.

1 - Introduction

The rapid expansion of data collection and the increasing speed at which it is generated make effective information processing essential. Moreover, the diversity of data types — from structured numerical entries to unstructured text and multimedia formats — poses significant challenges in data processing. For example, in the meteorological domain, each data point typically includes several key properties (e.g., temperature, pressure, velocity, and surface runoff) that vary over time and space, and originate from different sources like satellites and radars. These properties are crucial for understanding and predicting various meteorological phenomena. Collaboration amongst individuals with diverse scientific knowledge and expertise is necessary to visualise and interpret these multiple parameters, with each person potentially focusing on specific aspects crucial to a common task. Consequently, data analytics tasks demand versatile integration and analysis tools that support collaborative work to ensure comprehensive coherence and utility of the data processing. However, the limitations of desktop-based data visualisation are increasingly apparent in this context. In response to this big data problem, this thesis adopts COLLABORATIVE IMMERSIVE ANALYTICS (CIA) using Augmented Reality (AR) technology. COLLABORATIVE IMMERSIVE ANALYTICS, according to Billinghamurst *et al.* [1], is a multidisciplinary approach that combines visual analytics, immersive techniques, and Computer-Supported Collaborative Work (CSCW) (Fig. 1.1).

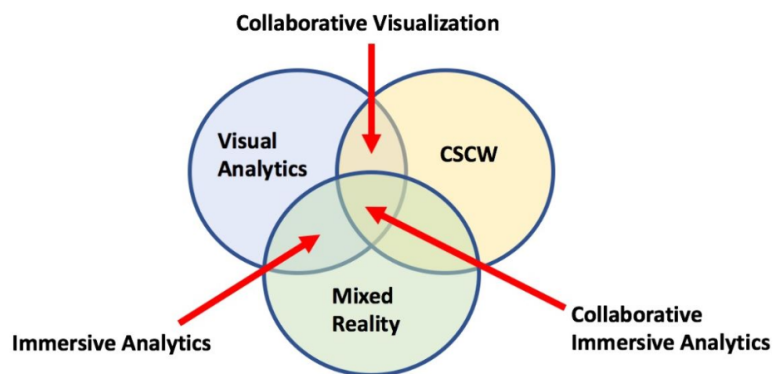


Figure 1.1 – collaborative Immersive Analytics and its related fields according to Billinghamurst *et al.* [1].

Before discussing about my main research questions and contributions in this work, I will first introduce different aspects of Visual and Immersive Analytics as well as CSCW and CIA. I will also present the rationale of why I considered AR technology for CIA and which types of AR devices used in this context. A more in-depth literature review of these related domains will be presented in Chapter 2.

Meteorological and Climatological Data

Meteorological and climatological data are closely linked, particularly in how short-term weather events accumulate over time to form long-term climate patterns. For example, recurring heatwaves (meteorological data) over several decades contribute to an observable trend of rising temperatures (climatological data). These relationships can be analyzed from multiple perspectives:

- **Phenomenological Relationships:** Meteorological events like cyclones, heatwaves, and droughts are manifestations of underlying climate conditions. For instance, global warming intensifies tropical storms, increasing their frequency and severity [19].
- **Physical Relationships:** The physical laws of thermodynamics and fluid dynamics govern the behavior of both short-term weather systems and long-term climate patterns. Rising ocean temperatures, for example, fuel the energy required for more intense storms [20].
- **Statistical Relationships:** Climatologists use statistical models to identify correlations between meteorological variables (e.g., temperature, precipitation) and long-term climate trends. These models are essential for predicting future climate conditions based on historical data [21].

Meteorologists and climate analysts have different analytical requirements based on the temporal scope of their work. Meteorologists, who focus on real-time data, need tools that can process and visualize information quickly to make accurate short-term forecasts. This includes the ability to perform on-the-fly data processing, highlight critical regions (e.g., cyclone paths), and collaborate with other specialists in real-time.

Climate analysts, on the other hand, focus on long-term data to identify trends and anomalies in the global climate. Their work relies on robust statistical models capable of simulating future scenarios based on historical datasets (over periods of 30 years or more, following the guidelines of the World Meteorological Organization (WMO) [22]). Climate analysts often need to compare past trends with current data to detect significant climate changes [23]. For instance, LATMOS (Laboratoire Atmosphères, Observations Spatiales) scientific teams are tasked with the analysis of complex atmospheric datasets, employing various techniques and methods. The following table outlines the primary tasks, objectives, and challenges faced in this type of data analysis:

Meteorological and Climatological data from systems such as **GPM (Global Precipitation Measurement)**, **MERRA-2 (Modern-Era Retrospective analysis for Research and Applications)**, **GLDAS_NOAH (Global Land Data Assimilation System)**, and others are vast in size due to their high spatial resolution, large coverage areas, and the extensive range of variables they track.

For instance, data from **GPM**, including instruments like **DPR (Dual-frequency Precipitation Radar)** and **GMI (GPM Microwave Imager)**, primarily contains global precipitation data. These data cover areas between **60°N and 60°S**, with a

Table 1.1 – Overview of Main Tasks, Objectives, and Challenges in Climate Data Analysis at LATMOS

Main Task	Description / Objectives	Challenges
Identifying the Area of Interest	Locate areas presenting specific structures (e.g., brightness temperatures indicating rain).	Manipulating multiple images without automated tools, visual comparison.
Selection of the Area	Isolate and explore a zone of interest in more detail to refine the data within that zone.	If the data is coarse, it must be refined after zooming.
Multi-Platform Data Preparation	Compare data from multiple sources to find spatiotemporal correspondence.	Problem aligning data from different platforms (distinct satellites).
Check algorithm output	Validate AI algorithm results by corroborating data from different sources.	Current tools do not easily allow large-scale data cross-referencing.

spatial resolution of **5 km**. GPM also measures additional variables such as cloud properties, water vapor, and the vertical structure of precipitation. The satellite revisits most locations every **3 hours**, generating millions of data points daily. Due to its high resolution and frequent temporal coverage, GPM produces **terabytes** of data each year.

Similarly, **MERRA-2** provides atmospheric reanalysis data for the entire globe, offering variables such as air temperature, pressure, wind speed, humidity, and aerosol concentrations. With a spatial resolution of **0.5° x 0.625°** and hourly time intervals, MERRA-2 contains billions of data points spanning back to **1980**. The dataset, covering several decades of meteorological information, totals in the **petabytes** due to its extensive historical range and the number of variables it includes, such as radiation fluxes, soil moisture, and cloud cover.

GLDAS_NOAH focuses on simulating land surface conditions, including variables such as soil moisture, surface temperature, snow depth, and evapotranspiration. It operates with a spatial resolution of **0.25°** and a temporal resolution of **3 hours**. GLDAS_NOAH covers the global land surface, producing billions of data points annually. Its datasets grow into **terabytes** of information, containing detailed simulations of the Earth's surface processes, which are critical for water

resource management, agriculture, and climate modeling.

In addition, the **ERA5** reanalysis dataset provides global atmospheric, land surface, and sea surface data with a spatial resolution of **0.25°** and hourly intervals. ERA5 includes variables such as air pressure, temperature, wind velocity, humidity, soil moisture, and radiation fluxes. It spans back to **1950**, generating trillions of data points and accumulating into several **petabytes** due to its long time series and fine spatial and temporal resolutions.

Other meteorological datasets, such as those from **MODIS (Moderate Resolution Imaging Spectroradiometer)**, contain information on cloud properties, aerosol concentrations, and land surface conditions like vegetation health and land cover, with spatial resolutions as fine as 250 meters and near-daily coverage of the Earth's surface. These data products generate hundreds of terabytes annually, with archives that have grown into the petabyte scale.

Visual Analytics

Since the early 2000s, the exponential growth of data collection posed new challenges for understanding and extracting valuable insights from immense and complex datasets, leading to the emergence of Visual Analytics (VA) domain. VA was established as a significant milestone in this evolution, with two researchers Cook and Thomas [24] coining the term in their technical report in 2005. VA stands at the intersection of visualisation, human-computer interaction, and perception, aiming to facilitate the data analytics process by visually highlighting the relationships between data that may be difficult to discern using only compartmentalised techniques from these separate domains. VA process is depicted by Keim *et al.* [2] in Fig. 1.2. This process integrates automatic and human-centred visual analysis techniques, closely interconnected through human interaction to extract knowledge from data.

Specifically, the process includes various transitions:

- Transformation and Mapping: Data may initially undergo a pre-processing step in order to be transformed and derived with different representations suitable for further exploration. This may include data cleaning, normalisation, and integration of heterogeneous data sources.
- Model Building: Depending on the analysis needs, one can choose between visually interactive and automatic analysis methods. If automated analysis is chosen, data mining techniques are applied to create models from the data.
- Model Visualisation: The visual representation of models helps to assess the outcomes of automatic analyses, facilitating an iterative cycle of verification and refinement. This iterative approach helps identify misleading results early, leading to more reliable outcomes.
- Visual Data Exploration and User Interaction: Visualisation process enables

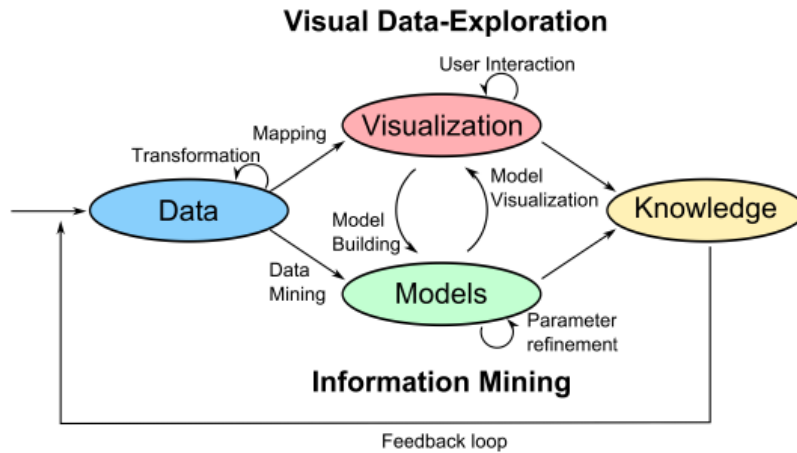


Figure 1.2 – Illustrative diagram of the Visual Analytics process proposed by Keim *et al.* [2]. Different stages and objects are illustrated by ovals and transitions by arrows.

analysts to interact with the models by tweaking parameters or selecting different algorithms for analysis. This interaction allows for the evaluation of model findings and supports the refinement of these models based on visual feedback.

- **Feedback Loop:** The whole process includes a feedback mechanism where insights gained from visual data exploration can guide further model building and refinement in automated analysis.

Visual Analytics, primarily relying on two-dimensional interfaces, can encounter limitations in effectively representing multi-dimensional data and complex spatial relationships. Although VA employs various visual characteristics to visualise additional dimensions of data such as colour, size, or shape, these strategies can sometimes result in overcrowded or ambiguous visualisations. To expand the horizon of visual data analytics, a new approach has been introduced, known as Immersive Analytics.

Immersive Analytics

Combining Visual Analytics (VA) with immersive technologies, Immersive Analytics (IA) field was born. While VA emphasises on analytical reasoning and decision making process through the “human-in-the-loop” [25], IA takes advantage of immersive systems to allow users to be immersed in the data world for better data analytics performance [26]. Its primary objective is to provide an engaging and interactive environment that allows the users to explore and interact with complex data in a more intuitive and immersive way. In IA, data is typically presented and manipulated within a 3D virtual and/or real space. The users can navigate within this space, manipulate data, and visualise patterns and relationships [27] in

a manner that closely resembles natural interactions with physical objects.

Immersive Analytics holds potential applications across various domains, including data exploration and analysis [28, 29], scientific research [30], healthcare [31, 32], and architecture [33, 34]. It offers a promising avenue for transforming how we interact with and derive insights from data [35], ultimately leading to enhanced decision-making and problem-solving.

Collaborative Immersive Analytics

Computer-Supported Collaborative Work (CSCW) [36] refers to a research field that focuses on understanding how people collaborate through the use of computer and on designing systems that effectively support this collaboration. According to Ellis *et al.*'s taxonomy [3] (Fig. 1.3), groupware systems are categorised based on the time and place of interaction amongst the users. Specifically, the taxonomy is generally divided into four quadrants:

- **Same time, same place (synchronous and co-located)**: Users interact in real-time while being physically present in the same location.
- **Same time, different place (synchronous and distributed)**: Users interact in real-time but from different physical locations.
- **Different time, same place (asynchronous and co-located)**: Users interact at different times, but share the same physical space for their interactions (though not simultaneously).
- **Different time, different place (asynchronous and distributed)**: Users interact at different times and from different locations.

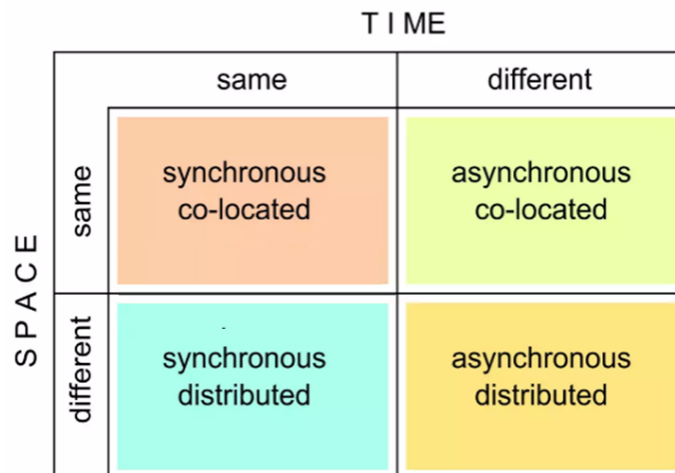


Figure 1.3 – Space-time collaboration matrix based on Ellis *et al.*'s collaboration taxonomy [3].

Collaboration in visual analytics facilitates groups of people working together for sense-making [37, 38, 39] and understanding big and complex data [37]. Ac-

cording to Isenberg *et al.* [40], collaborative visualisation is “the shared use of computer-supported interactive visual representations of data by more than one person with the common goal of contribution to joint information processing activities.” Following the groupware taxonomy of Ellis *et al.*, this thesis deals with synchronous co-located immersive collaboration. Detailed related work in this field will be presented later in Chapter 2.

Mixed Reality

Milgram and Kishino [4] defined Mixed Reality (MR) as the interval between the real and the virtual environment well known as Reality-Virtuality continuum (Fig. 1.4). Extended Reality (XR) is considered as the whole spectrum that covers MR and Virtual Reality (VR). Within the MR spectrum, Augmented Reality (AR) aims to overlay and integrate digital contents into the real world, and Augmented Virtuality (AV) is defined as integrating the real objects into the virtual world. In his survey in 1997, Azuma [41] argued that “AR allows the user to see the real world, with virtual objects superimposed upon or composited with the real world.” To avoid any confusion, he defined AR as a system with the following three characteristics: combination of real and virtual, real-time interaction, and 3D registration. AR interfaces are often the main subject of comparison with other types of devices in different applications, for instance, in-depth perception [42], exposure therapy [43], consumer purchase intentions [44], or simulation [45].

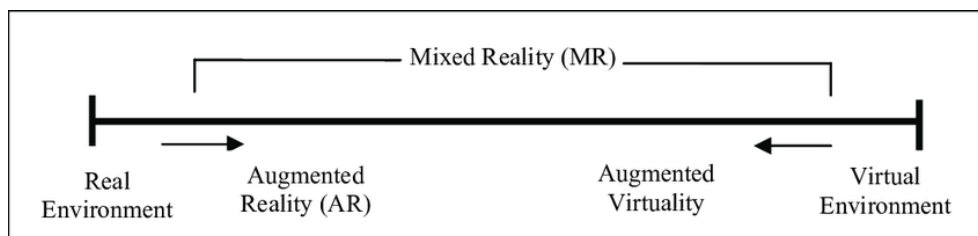


Figure 1.4 – Milgram and Kishino’s Reality-Virtuality Continuum [4].

In the context of data analytics, in the early days, Belcher *et al.* [46] explored the use of AR in visualising complex graph links, comparing AR interfaces to desktop interfaces. The experiment showed that AR interfaces can be effectively used for graph link analysis. Similarly, a user study has been conducted by Hedley *et al.* [47] to evaluate the performance of an AR interface against its desktop version in helping users develop mental models of spatial data visualisation in geographic data visualisation. Findings indicate that AR interfaces may offer enhanced spatial understanding, providing more detailed and complete cognitive representations of geographic visualisations. More recently, Bach *et al.* [48] evaluated AR Head-Mounted Displays (HMD), handheld tablet, and desktop setups for 3D point clouds visualisation tasks. They found that the desktop generally offers superior precision

and speed. However, AR shows promise for spatial manipulation tasks, suggesting potential areas for future improvement and application designs.

Later, Whitlock *et al.* [49] conducted a study to measure how a user performs analysis tasks using various interfaces (desktop, VR, and AR) to interpret data visualisations over five visual factors (i.e. colour, size, height, orientation, and depth). The conclusion was that while each display type has its own advantages, desktop displays generally allow for more precise data analysis, confirming Bach *et al.*'s study [48]. Nonetheless, in cases where spatial manipulation is crucial, immersive displays like AR and VR show potential benefits. The authors, therefore, confirmed the benefits of stereoscopic viewing when the user works in three-dimensional (3D) space and concluded that AR encourages navigation but decreases performance with colour-based visualisation. More recently, Lisle *et al.* [50] explored the comparative effectiveness of AR and VR in supporting the sense-making process. They concluded that AR enhances user satisfaction by allowing the integration of real-world tools, whereas VR offers a more focused task environment by isolating the user from physical distractions.

In research for collaboration using immersive technologies, many studies have been conducted to determine the best interface for collaborative tasks, especially between the AR and the other interfaces. For instance, Szalavri *et al.* [51] argued that their collaborative AR system provides benefits beyond traditional desktop-based visualisation. Nilsson *et al.* [52] compared the AR collaborative system with traditional paper for supporting joint planning tasks. Their results show that the users positively appreciated working with the AR system compared to their traditional tools and would like to use it in real work. Later, Prytz *et al.* [53] studied the effect of eye contact in AR compared to the traditional use of paper. They concluded that the decreased stakeholder's eye contact with HMDs does not affect the collaboration directly. Recently, Wang and Dunston [54] showed that AR systems can improve performance time and mental effort in collaborative design tasks compared to paper-based drawing. In a user study comparing immersive VR and AR, Billinghamurst *et al.* [55] found that there was no significant difference in task completion time; however, the subjective data showed that the participants perceived that they performed better when using AR mode as they could see the real world and their real collaborators. Additionally, Kiyokawa *et al.* [56] demonstrated that AR is more effective than VR for collaborative target selection tasks.

Moreover, besides comparison with other interfaces, many studies showed the benefit of AR for collaboration. For example, Poelman *et al.* [57] argued that crime scene investigators using AR for collaboration can support mutual understanding, lead to consensus, and support hypothesis testing. Dong *et al.* [58] showed that collaborative AR can facilitate communication and discussion of engineering processes. More recently, Mohan *et al.* [59] study's results demonstrated promising potential for AR collaboration for air traffic control.

Although my thesis did not involve augmenting real objects with digital con-

tent as often indicated as the main purpose of AR, I focused on HMD-based AR interfaces for several reasons. First, they uphold the advantages found in HMD-based VR systems for big data visualisation by providing the users with an extended workspace that does not need to be anchored to physical monitors [60]. Moreover, compared to VR, AR interfaces facilitate a hybrid and flexible working environment on a daily basis, making possible a cohabitation between immersive data analysis and interaction with conventional tools (e.g., desktops, office stationary for taking notes) without the users having to remove their headset. In addition, given the demonstrated effectiveness of AR in collaborative tasks in literature, AR's ability to enhance understanding, support consensus-building, and improve task performance aligns with my goal of facilitating complex data visualisation through collaborative efforts.

Augmented Reality Devices for Immersive Analytics

This section provides an overview of the AR devices and discuss their limitations. The AR devices can be categorised into two broad categories: mobile and stationary setups. While the stationary setups are mostly anchored to a desktop or laptop computer, mobile setups are portable, which can be handheld or wearable devices.

The stationary category is considered to be fixed in physical space. For example, HoloDesk [5], illustrated in Fig. 1.5, consists of a half-silvered mirror, a Kinect sensor, and a projector, creating a see-through display where users can view and interact with virtual and physical objects simultaneously. Stationary setups can be increasingly elaborated which generally make use of highly advanced tracking technology for accurate 3D registration of spatial AR rendering. However, their main disadvantage lies in their limited mobility and fixed setup requirements, as they may not be easily adaptable to diverse tasks and contexts of everyday workflow.

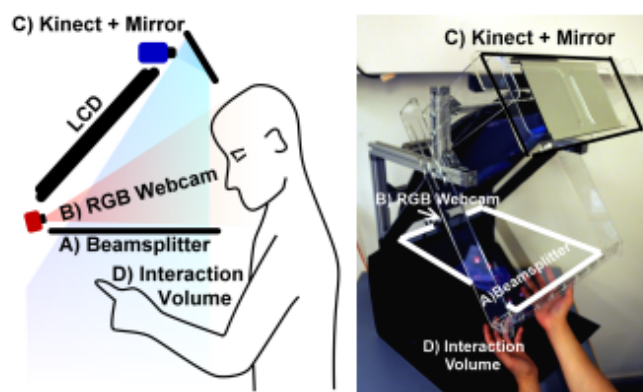


Figure 1.5 – A physical setup of HoloDesk with its main components [5].

Handheld AR devices are the devices that are often held in the user's hand for

interaction, such as smartphones or tablets. Handheld devices are often equipped with a camera that captures the real environment and a screen that displays digital content on top of the video feed. They are easy to use, versatile and almost everyone has one for use nowadays. However, they have some limitations, such as a small field of view and low computing capacity. This type of devices occupies the users' hands and needs them to maintain an uncomfortable posture in prolonged interactions. All these limitations make these devices unsuitable for long-lasting data analysis tasks. For example, Fig.1.6 illustrates the position the user should hold their smartphone when they are interacting.



Figure 1.6 – Users using handheld devices (tablets) for AR interaction [6].

On the other hand, wearable devices such as Head-Mounted Displays (HMDs) provide a hands-free AR experience by being worn on the user's head or attached to accessories like glasses. Based on the rendering method, they can be further classified into two other groups: Video See-Through (VST) and Optical See-Through (OST) devices. VST devices (Fig.1.7.A) capture the real-world scene through live video streams from cameras, seamlessly superimposing virtual objects onto it in real-time (e.g., Varjo XR-3 [61], Meta Quest 3 [7]). The primary issue with VST devices is that if the device ceases to operate, the user's field of view becomes entirely obstructed. OST devices (Fig.1.7.B) operate by projecting digital content onto a transparent or semi-transparent display, thereby superimposing digital information onto the user's real-world environment (e.g., Microsoft HoloLens [8], Magic Leap [62]). These devices have some limitations with regard to the quality of resolution, especially when performing rendering in various lighting conditions.

In this project, I have chosen the HMD OST device for various reasons. First, it is mobile, but unlike handheld devices, it allows a hands-free interaction that is essential in IA, supporting simultaneous interaction with the data, physical world and between collaborators without constraints. Second, it ensures that the users can see digital overlaying directly in their real-world view without the latency or disorientation often associated with HMD VST device. At the time I was starting my project in 2020, Microsoft HoloLens 2 was one of the most advanced HMD OST devices available.



Figure 1.7 – Example of: A) Meta Quest 3 Video See-Through (VST) device [7], and B) Microsoft HoloLens 2 [8] Optical See-Through device (OST).

Objectives and Research Questions

As previously discussed with regard to the main topic and technological choices of this thesis, my research focuses on co-located collaborative Immersive Analysis (IA) using Augmented Reality (AR). Rather than targeting mainstream applications, my work specifically emphasizes the development of research tools to support climatology and meteorology data analysis processes. In the collective effort to combat climate change and global warming, it addresses the challenges of working with complex storm and cyclone datasets from real weather observations and predicted simulation model projections. Cyclone climate disasters occur globally each year, causing widespread devastation, including human casualties, significant infrastructural damage, and economic and environmental setbacks. This project aims to contribute to ongoing urgent efforts to minimize storm and cyclone damage internationally by developing techniques that enable climate researchers and key stakeholders to better access and understand available data. In detail, I studied three main aspects of an IA framework using Head-Mounted Display (HMD)-based AR technology: from data integration to selection techniques and support for collaborative research work.

One of the primary challenges of IA process is data integration. It enables the consolidation of data from various sources to provide a unified, coherent, and comprehensive view and get it ready for visualisation. This step is important for any IA tasks but is also crucial in AR-based systems, especially when it relies on devices with low computing power and often limited fields of view. Therefore, the first objective of this thesis is to study how to effectively integrate multidimensional datasets to facilitate their visualisation and interaction in IA. To achieve this goal, I proposed a semantic-based approach using ontology and linked data to help reduce the complexity of the data as well as to accelerate the analytical reasoning process. This leads to the first main research question:

RQ1: Can the semantic-based approach facilitate visualisation and analysis in immersive analytics for meteorological data?

Interacting with data allows the users to manipulate its multiple variables, observe outcomes, and gain insights through direct manipulation and visualisation. One of the basic but essential interaction operations is data point selection. This selection task enables the users to select specific information, which helps them to focus on particular data points and examine detailed attributes of selected data. Such targeted interaction enhances the users' ability to analyse trends, detect anomalies, and understand correlations within the data. However, one existing limitation of AR-based IA systems using HMDs is that selection operations are often repetitive, tiresome, and imprecise for selecting small objects from a distance. The second objective is to explore new AR interaction techniques to facilitate the exploration of scientific data, especially for multidimensional datasets. I proposed in this project a new selection technique based on expanded data points. This leads to the following research question:

RQ2: Will the selection technique based on expanded data points improve the performance and user experience of data selection in HMD-based AR interfaces?

Furthermore, collaboration is important to be studied in a IA system as it enables the users from different fields of expertise to collaborate for data analysis and decision making. In this project, I studied in a special aspect of synchronous co-located collaboration using AR: how the users can organise themselves within the physical space available of the workspace during individual and collaborative tasks. Indeed, in daily limited workspaces such as offices and meeting rooms, collaborators working on large and complex data sometimes disturb or invade inadvertently each other's physical space. On the other hand, spatial relationships and the positioning of the users can have significant impact on their performance and collaborative behaviour. The third objective of this project is to design and propose a collaborative immersive platform that facilitate collaborative work between the users. I proposed an automatic partitioning technique to divide the available physical space for co-located users using HMD-based AR system, in combination with view privacy aspect of data visualisation. To effectively display the workspace boundaries after the partitioning, I also proposed different visualisation modes for these boundaries on the floor of the workspace, including *Line*, *Opaque*, and *Semi-transparent*. This work leads to two following research questions:

RQ3.1: Which of the three visualisation modes: *Line*, *Opaque*, and *Semi-transparent* is the most appropriate method of displaying the users' workspace boundaries?

RQ3.2: Will the automatic partitioning with a separation of public and private view for each user facilitate the workflow of the immersive analytics work on meteorological data?

Dissertation Organisation

This thesis dissertation is organised as follows:

Chapter 2 provides an overview of related work. It is divided into four parts. The first part summarises existing works on selection in immersive environments, introducing pointing and confirmation (activation) techniques. The second part presents Immersive Analytics (IA). Specifically, I will present different interaction tasks, and some immersive visualisation toolkit. The third part presents the semantic-based approach in immersive environments. It defines the ontology and provides some examples of its application in virtual and augmented reality. The last part introduces collaborative immersive analytics by first presenting collaborative IA frameworks, then discussing users' position arrangements in synchronous co-located collaboration and different privacy management strategies in immersive collaboration.

Chapter 3 focuses on the selection technique study in IA. It first introduces the new technique proposed to improve the selection based on expanded data points. The chapter also presents the user study that has been conducted to evaluate this technique across different factors (pointing and activation) on a head-mounted display (HMD)-based Augmented Reality (AR) interface. I will conclude this chapter by discussing the limits of the technique and its future work.

Chapter 4 introduces a semantic IA framework for meteorological data analytics. It details how the proposed ontology and the IA system were built. It also gives an overview of the evaluation of the ontology's application in this IA framework. Finally, I conclude this chapter by presenting lessons learned for this use case study and discuss existing open problems.

Chapter 5 presents the design of the proposed automatic technique to partition available physical space for the co-located users using AR for IA. It will also detail the co-located collaborative IA system. It introduces the three boundary presentation techniques. Two user studies will be presented in this chapter: the first one evaluating the three proposed boundary presentation techniques, and the second studying the partitioning technique with view privacy strategies. The chapter concludes with a discussion of future work.

In the final chapter, the thesis concludes by summarising the findings and discussing the potential avenues for future research related to this work.

2 - Background Study

This chapter introduces several relevant related works of this thesis: selection techniques in extended reality; immersive analytics; semantic-based approach, especially ontology and linked data for meteorology and climatology and how semantic-based approach has been applied in extended reality; and finally collaborative immersive analytics with a closer look on users' position arrangement and privacy strategies in synchronous co-located collaboration.

2.1. Selection Techniques in Extended Reality

Selection is one of basic but important operations during the interaction in eXtended Reality (XR). In this thesis, one of my objectives was to explore and improve selection for Head-Mounted Display (HMD) based Augmented Reality (AR) interfaces. This section gives an overview of main works on existing selection techniques. From the classification of selection techniques by task decomposition in Bowman *et al.*'s [63] book (p.149-158), I focused mostly on pointing techniques in the phase of indication of object, and event, gesture, and voice command for confirmation of selection.

2.1.1. Pointing Techniques

This section gives an overview of main existing works with regard to pointing techniques for selection. It is one of the most fundamental operations used during selection and manipulation of 3D virtual objects. Indeed, the quality of these elementary interaction techniques has a profound effect on overall user experience in immersive systems. Pointing technique allows the users to indicate one or several objects to be selected for manipulation, especially when they are out of arm's reach. In the early 1980s, Bolt's description of the pointing technique [64] was one of the earliest examples. Since then, many approaches have been proposed (cf. [63, 65]).

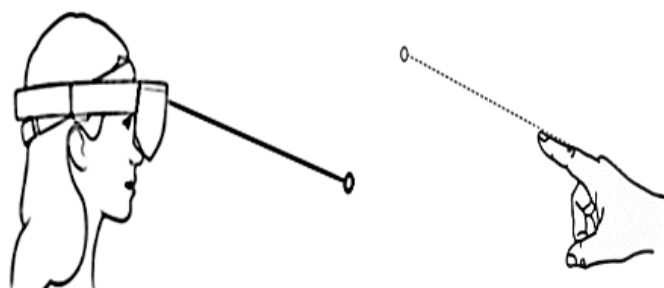


Figure 2.1 – Examples of pointing techniques: The left image shows a user uses a ray casting from their head for pointing, while the right image demonstrates hand-based pointing.

Ray-casting with a virtual pointer (cursor) at its end is the most commonly used pointing method due to its simplicity, ease of use, and affordance. This approach depends on the origin and direction of the ray [66]. On an AR HMD device, its origin and direction can be determined by hand (i.e. using hand position as the origin and wrist as orientation (Fig. 2.1 right)), head (i.e. using head position as the origin and front head direction as orientation (Fig. 2.1 left)), eye (i.e. using eye or head position as the origin and front direction of the head as orientation (Fig. 2.6 left)), or a combination of head and hand (i.e. using the head position as the origin and wrist as orientation). It can also be defined by using two hands: one hand for ray origin, the other to specify where the ray is pointing to [67, 68]. Actually, most of the HMD devices use head- or hand-pointing approach (e.g., Oculus Quest [69] and Microsoft HoloLens [70]).

To determine which modality (i.e. hand, head, eye, or a combined one) is the most appropriate for pointing, many studies have been conducted to compare these different techniques. For instance, Bates and Istance [71] studied eye- and head-based pointing. They concluded that eye-based pointing offers poorer performance, is more unpleasant to use, and requires more effort than head-based pointing. On a HMD device (MicroOptical), Jalaliniya *et al.* [72] compared eye- and head-based pointing to mouse pointing, and they found that the eye-gaze approach is faster and the head-based pointing is more accurate than the others. Later, Kytö *et al.* [73] confirmed Jalaliniya *et al.*'s conclusion with an evaluation on Microsoft HoloLens. Conversely, Hansen *et al.* [74] found that there is no significant difference between eye-gaze- and head-based pointing, except that they are slower than the mouse. Tanriverdi and Jacob [75] compared eye-gaze-based and hand-based pointing in VR. Their results show that eye-gaze-based pointing is significantly faster for distant object selection, and they did not find any significant difference in object selection in close range. In contrast, Cournia *et al.* [76] did not find a performance advantage of eye-gaze-based pointing over hand-based pointing.

Lin *et al.* [77] compared head and hand pointing methods when using a large stereoscopic projection display. The results show that hand pointing has better overall performance, lower muscle fatigue, and better usability, yet head-pointing provides better accuracy. Later, Bernardos *et al.* [78] compared index finger and head pointing on a wall-sized projection screen. They did not find a significant difference between them in task performance.

To improve pointing accuracy, many works proposed to combine different control modalities. For instance, Vanacken *et al.* [9] introduce 3D Bubble Cursor and Depth Ray in VR. The 3D bubble cursor (Fig. 2.2) dynamically resizes a semi-transparent sphere so that it only contains the closest target, ensuring unambiguous selection. It highlights the target in yellow and can make nearby occluded object semi-transparent to aid visibility and selection. The Depth Ray (Fig. 2.3) uses a ray casting technique combined with a depth marker controlled by the user's hand movements. It selects the target closest to the depth marker along the ray, which

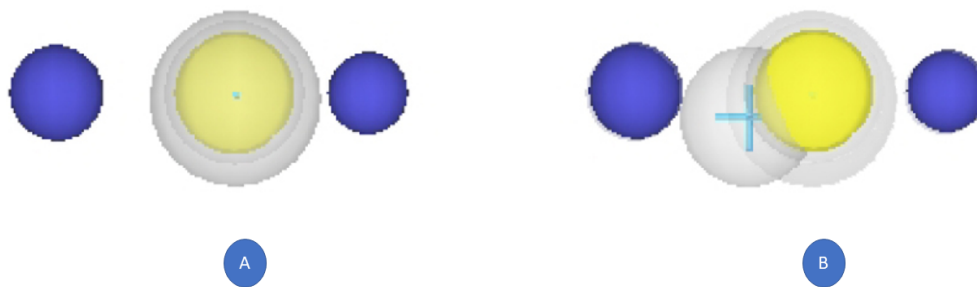


Figure 2.2 – 3D Bubble Cursor as proposed by Vanacken *et al.* [9]: A) 3D bubble cursor is illustrated as a semi-transparent grey sphere. This sphere dynamically resizes to capture only the closest target. The closest target, highlighted in yellow, is the only one that falls within the boundaries of the bubble cursor. A crosshair is visible at the centre of the bubble cursor for additional visual feedback. B) When necessary, a second semi-transparent sphere is rendered around the captured target to ensure that it appears fully contained within the bubble cursor.

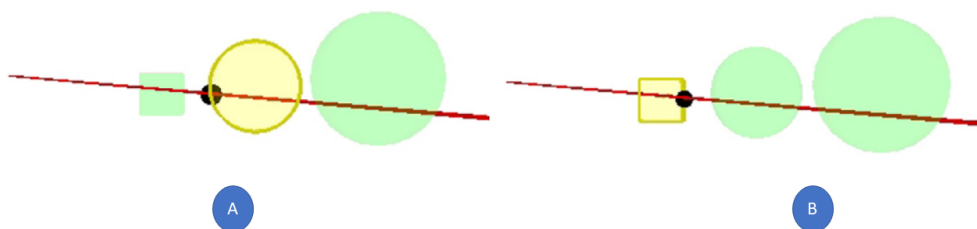


Figure 2.3 – Depth Ray technique as proposed by Vanacken *et al.* [9]: A) The depth ray technique is shown, where a thin red cylinder represents the ray cast into the scene. The depth marker, controlled by the user’s hand movements, is used to select the target. The closest target to the depth marker along the ray is highlighted in yellow, while other intersected targets are highlighted in green. B) This subfigure illustrates the user’s ability to control the position of the depth marker along the ray by moving their hand forwards or backwards. This movement adjusts which target is selected based on proximity to the depth marker.

is rendered as a thin red cylinder. It also highlights the captured target in yellow and uses transparency to make occluded targets visible

Argelaguet *et al.* [10] studied in a CAVE-like system the problem of eye-hand visibility mismatch affecting pointing selection techniques when using hand-base pointing. They developed a new technique that combines image-plane technique and ray control by the users’ hand rotation (Fig. 2.4). This technique outperforms ray casting in complex scenes. Liu *et al.* [79] introduced a pointing technique named Gunslinger (Fig. 2.5) on a large display. This technique allows the users to use hand pointing with arms-down postures.

Recently, Kyoto *et al.* [73] combined primary pointing methods (head or eye-gaze pointing) with a refinement technique (head movement, hand gesture, or handheld device). More recently Wei *et al.* [80] proposed two predictive models

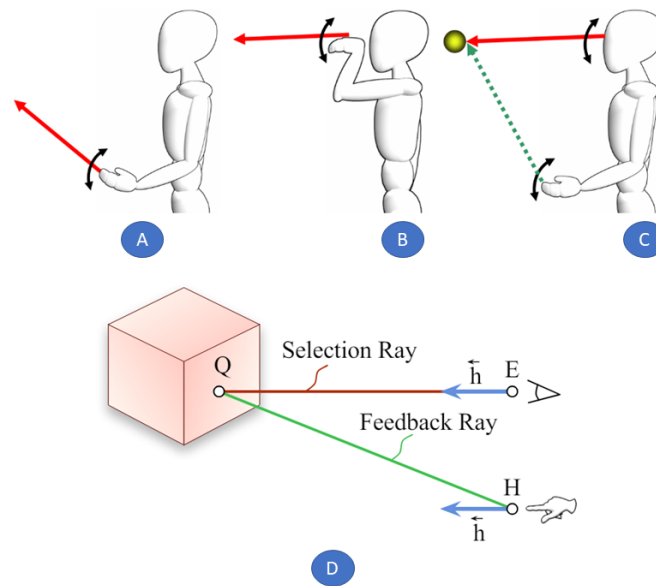


Figure 2.4 - Illustration of the ray casting from the hand and the eye technique of Argelaguet *et al.* [10]: (A) Traditional ray casting where the selection ray originates from the user's hand, which can lead to an eye-hand visibility mismatch. (B) Using traditional ray casting, the user may attempt to align their hand with the viewing direction to mitigate visibility issues, resulting in an uncomfortable posture. (C) Their proposed technique allows the user to use a selection ray originating from their eye, directed by the orientation of their hand. (D) The proposed technique setup involves two rays: the selection ray (red) from the eye position (E), controlled by hand orientation (H), and a feedback ray (green) providing visual feedback by connecting the hand position to the intersection point (Q) on the selection ray.

(Fig. 2.6 right) to improve target selection in AR based on eye and head movements (unimodal model using eyes only and multimodal model using eyes and head to predict target selection).

I have not evaluated all the pointing techniques in the user study conducted in Chapter 3, even though Microsoft HoloLens (1 & 2) allows the users to select virtual objects through different available pointing techniques (eye, hand, or head pointing). I only considered hand and head pointing because, based on previous research, it is known that eye pointing suffers from the 'Midas Touch' problem [81] ('Midas Touch' problem refers to the issue where involuntary selection occurs during interaction), making it difficult to select small objects like data points. Additionally, I have not found any comparative studies regarding accuracy and speed using the two modes, head and hand, on Microsoft HoloLens 2.

2.1.2. Confirmation of Selection

Techniques of confirmation of selection allow users to confirm and activate the selection of object(s). The most commonly used techniques are *dwell* (or *dwell-on-object* [82]), *button click* (or *press-to-select*) [74, 83], speech [84, 85], and hand

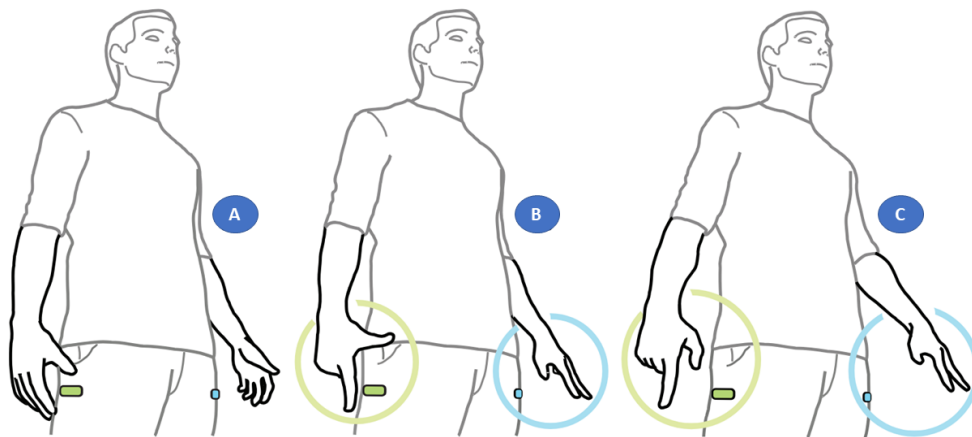


Figure 2.5 – Gunslinger pointing technique metaphor: A) Both hands are in a neutral position, hanging down naturally beside the body. B) Command modes are activated by specific hand postures. For instance, the dominant hand’s thumb and index finger form a pointing gesture (green circle) while two fingers on the non-dominant hand indicate a zoom gesture (blue circle). C) Events or parameters are manipulated through finger movements, such as folding the thumb down on the right hand to click or moving the two fingers to zoom in or out.

gestures [86, 87].

Dwell technique has been widely studied (e.g., [74, 88, 89]). It consists in triggering the selection when the ray or virtual cursor dwells on the target for a certain amount of time. For instance, Muller [90] proposed between 350-600 ms depending on the application. It has been studied as hand-free input to solve the ‘Midas Touch’ problem of the gaze pointing [91, 92]. Even if different studies show that dwell’s activation makes the least error [83, 93] compared to other techniques, a short or long dwell threshold can affect selection as a whole, making it sensitive to the ‘Midas Touch’ problem. Therefore, it is difficult to use such technique for the selection of small objects (like data points).

Button click activation (press of a button to trigger a selection) has also been evaluated. For example, Hansen *et al.* [74] compared it with dwell confirmation technique. Dwell activation was faster than click activation. Recently Esteves *et al.* [93] compared the five confirmation techniques: dwell, speech, clicker, and mid-air gesture. They found that clicker was the best during hands-on input. Later Mutasim *et al.* [83] did not find any difference between click and pinch. Although the research studies have shown the benefits of confirmation with this technique, it may induce the Heisenberg effect [86] (Heisenberg effect in refers to the unintended changes in user behavior or accuracy that occur due to the process of interacting with a control mechanism) in the following situations: using head pointing and clicking on confirmation button on the side of the headset, or when using the same hand for pointing/holding the controller and clicking on the button.

Voice can be used to activate a selection by voice-only interaction or by com-

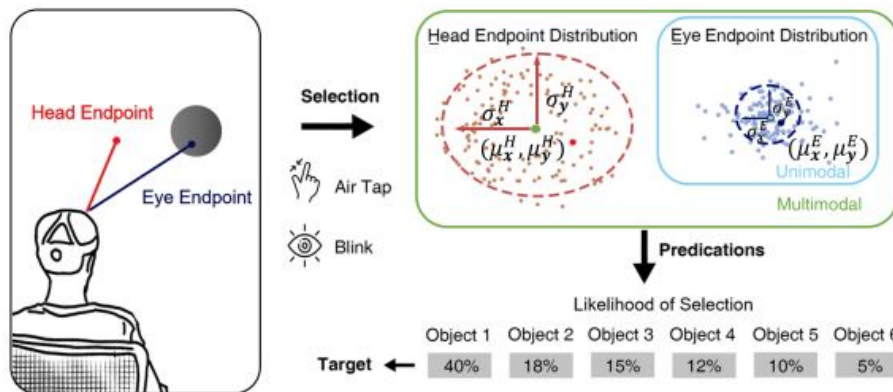


Figure 2.6 – Left: A user uses eye-pointing for selection on an AR headset. Right: Wei *et al.*'s [80] predictive model: after each selection, the final positions of the eye and head are recorded, establishing patterns of typical user behavior regarding where they look and how they orient their head. The model uses this data to predict which object the user is most likely to select, effectively identifying the most probable target.

binning it with the pointing technique. For instance, when the user says the name of objects in [94, 95], these objects are selected. However, voice is not a reliable input channel in a noisy environment. Combining voice activation and hand pointing may reduce the Heisenberg effect compared to button click and pinch during a selection task. However, I did not find any user study evaluating the combination of voice activation with hand and head pointing.

Hand gestures can also be used as a selection activator. The user must perform a pinch gesture [86] to trigger the selection. This technique can be sensible to the Heisenberg effect the the user uses the same hand to point and activate selection. To minimize this effect, for instance, Vogel and Balakrishnan [87] proposed the AirTap and Thumb Trigger, and other researchers suggested to combine head or gaze pointing with pinch [83, 93, 96]. However, I did not find any work comparing pinch and other selection activation techniques (dwell, click, and voice) apart from the recent study conducted by Mutasim *et al.* [83]. They concluded that compared to dwell and click, the pinch is slower and increases more errors.

2.2. Immersive Analytics

This section discusses previous research in Immersive Analytics (IA) and explores the application of Augmented Reality (AR) in Meteorology and Climatology.

2.2.1. Data Visualisation using Extended Reality

In the literature different visualisation techniques have been used for data visualisation. Kraus *et al.* [97], in their survey, identified eight visualisation techniques as node-link graphs, scatter plots, parallel coordinates, glyphs, geographic, volume,

flow, and others including all visualisation techniques which could not be assigned to any of the seven previous groups.

Node-link graphs [98] (Figure 2.7) is a visual representation of networks where entities are depicted as nodes (or vertices), and the relationships between them are shown as links (or edges).

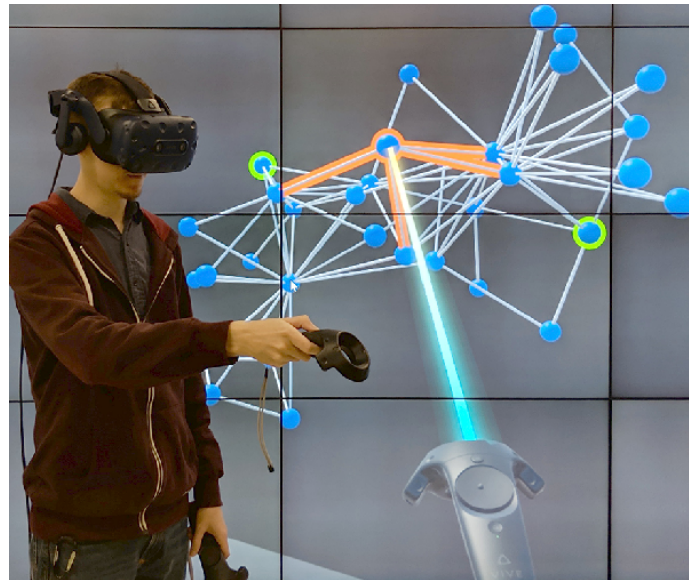


Figure 2.7 – Immersive node-link graphs visualisation [11]

Scatter plots [11] (Figure 2.8) are the data visualisation technique that uses Cartesian coordinates to display data points in 2D/3D visualisation systems. The data point typically represents an individual unit of information or an observation collected from a dataset. For the sake of simplicity, I will call them data points (or points) even though they can come in different shapes and sizes. Indeed, size, colour, texture, or other attributes of these data points can be used to encode different data dimensions or properties.

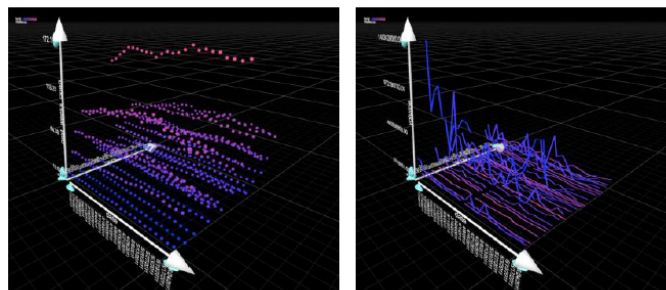


Figure 2.8 – An example of scatter plots visualisation using IATK [12].

Unlike scatter plots, parallel coordinates [99] (Figure 2.9) are used to display

data by plotting each data point as a line that intersects several parallel axes, each axis representing a different dimension of the data. It is particularly useful for exploring patterns and relationships across multiple variables simultaneously.

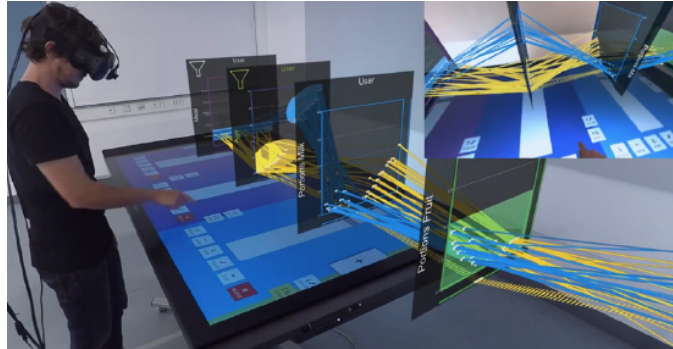


Figure 2.9 – 3D parallel coordinate plot (PCP) visualisation in an AR interface using HMD and touch screen [13].

Glyph visualisation [100] (Figure 2.10) displays multi-dimensional data points using complex symbols or icons where each aspect of the glyph's shape, size, colour, orientation, or texture represents a dimension of the data.

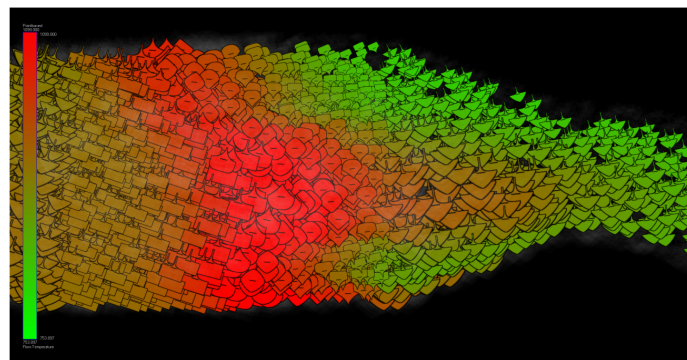


Figure 2.10 – An example of glyph visualisation: the image shows a diesel particle filter oxidising soot at over 1000 degrees Celsius. It uses colour to indicate *temperature* of the process, different shapes to show *soot quantity* and *change rate*, and rotation to represent *needed oxygen* [101].

Geographic visualisation, also known as cartographic visualisation [102], refers to the graphical representation of spatial and geographic data. It is typically used to display relationships and patterns across geographic locations and can be found in various forms such as maps and globes (Figure 2.11).

Volume visualisation [103] allows to transform multi-dimensional datasets into visually interpretable forms using techniques like ray casting [104] or iso-surface extraction [105], facilitating the detailed analysis of internal structures (Figure 2.12).



Figure 2.11 – Geographic visualisation using 3D Globe: the participants exploring migration flows between countries [14].

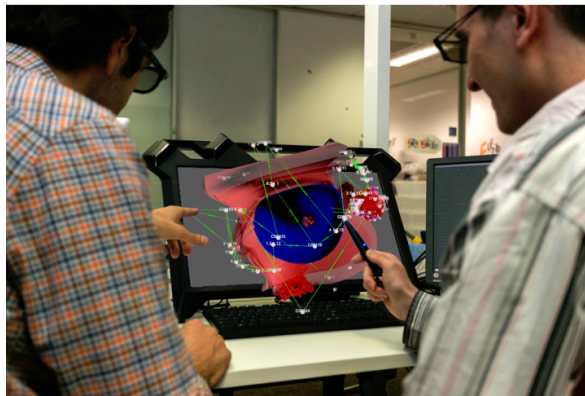


Figure 2.12 – Example of volume visualisation: users visualising cell model in 3D [15].

Finally, flow visualisation [106] is a technique that used dyes, smoke, or particles to trace and map the flow patterns of computational simulations, applicable in fields such as aerodynamics, meteorology, and medical research (Figure 2.13).

2.2.2. Interaction with Data

According to Brehmer and Munzner's [17] taxonomy (Figure 2.14), IA manipulation can be organised into tasks: *Select*, *Navigate*, *Arrange*, *Change*, *Filter*, and *Aggregate*.

Select refers to the interaction technique used to identify and choose specific data points. It allows users to trigger actions like displaying detailed information, applying filters, or modifying visualisation properties of the selected data points. The selection can be classified into single-point selection using raycasting [107, 108, 109] or virtual cursor [110, 9], and multi-object selection using brushing [111, 112, 113] or box selection [114, 115, 116].

Navigate enables the users to change their viewpoint or move through a virtual and/or real environment. Different modalities have been proposed to facilitate

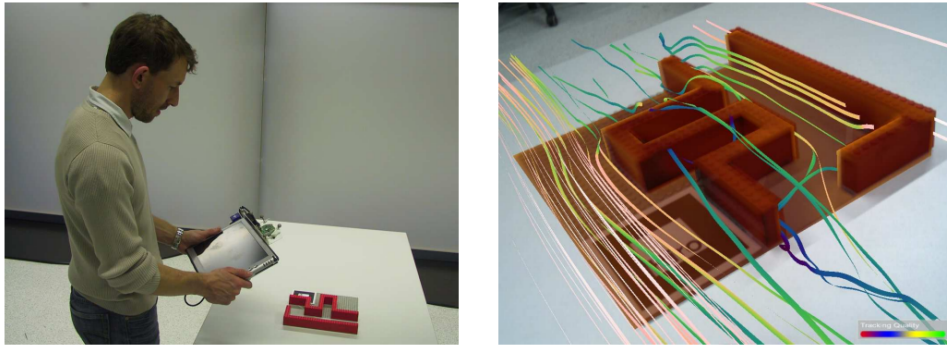


Figure 2.13 – Example of flow visualisation: a user visualising the air flow [16].

navigation such as natural walking, redirected walking, or ‘flying’ through environments using controllers [108, 117], zooming [118, 119, 120], and manipulating the visualisation space itself (e.g., through scaled world grabbing [121, 122] or world-in-miniature technique [122, 123]).

Arrange refers to the interaction techniques that allow the users to organise or reposition data within a visualisation environment. This involves moving, rotating, or re-scaling objects to enhance visibility and comprehension or to reveal hidden patterns within the data. According to Fonnet and Prié [124] different techniques can be categorised into arranging data points [125, 126], view components [127, 128], and entire view [117, 129, 130].

Change is a functionality that allows the users to modify the visual encoding of data points. Key aspects include changing visual mapping of data attributes [131, 132] (e.g., colour, shape, or size), switching between different data visualisations [133, 134, 135] (e.g., graphs or scatter plots), and adjusting visual properties (e.g., opacity or scale [136, 137]). This capability is used for dynamically exploring data by adapting the visual presentation to highlight trends, patterns, or anomalies, making it easier for the users to derive insights from complex datasets.

Filter refers to the techniques that enable the users to selectively control the display of data within a visualisation setting based on specified criteria. According to Fonnet and Prié [124], the users can use direct selection-based filtering to interact directly with the data. Filtering is done by the direct result of selection using box [114], voice command [118], or slice [138]. Alternatively, abstract layer manipulation [108, 139] uses menu elements, allowing for the application of filters through a structured interface.

Aggregate involves different techniques for changing the granularity of visual data representations. An example can be found in the work of Hurter *et al.* [134] when they mapped the users’ movements to data exploration tools in a mixed reality data sphere. This capability allows the users to adjust the level of detail in their analysis, facilitating both overview and in-depth exploration of the data.

The other manipulation interactions can come from combining different tasks

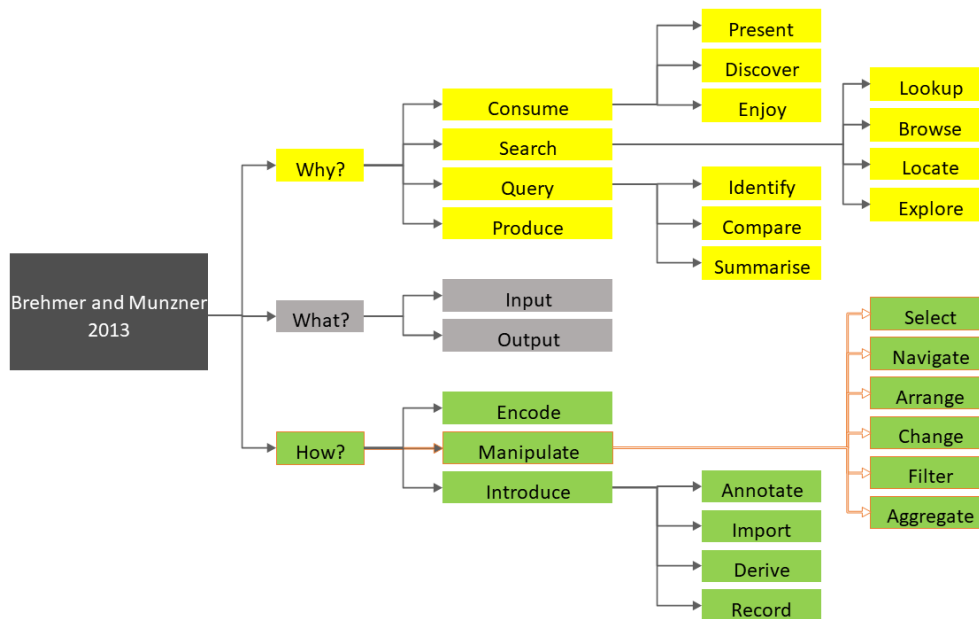


Figure 2.14 – The Immersive Analytic manipulation interaction, according to Brehmer and Munzner [17]

listed above. For instance, details-on-demand is closely linked to *Navigate* and *Select*. It allows the users to request and view additional, detailed information about specific data points. This technique helps the users explore complex datasets by providing insights into data points without overwhelming them with excessive information upfront. This is in line with the *Overview+Detail (O+D)* design paradigm, which provides a high-level view of the dataset (the overview) while allowing users to zoom in on specific areas to retrieve more granular information (the detail). This approach enables users to manage and navigate large datasets effectively by balancing the need for context with the ability to focus on specifics [140, 141].

In immersive environments, details-on-demand can be activated by selecting a data point (the activation can be reactive [107, 142] or predictive [143]), typically through gestures, raycasting, or controller inputs. Once activated, it can display textual descriptions, data attributes, linked metadata, or more detailed visual representations such as charts, graphs, or even multimedia content.

2.2.3. Immersive Analytic Toolkits

In order to facilitate the usability of IA to the large public, many IA frameworks or toolkits have been proposed with a high-level, friendly user interface and grammar language appropriate for both novice and expert users. For instance, *ImAxes* [133] is one of the first systems that provides a flexible set of axes to be manipulated and combined to create different plots for adaptive visualisation of data in both VR and AR. The two following toolkits *DXR* [144] and *IATK* [12] were developed for a wide range of users for rapid prototyping. *DXR* [144]’s declar-

ative visualisation grammar allows the users with no experience in 3D graphs or immersive technologies to easily create 3D data visualisation in immersive environments. IATK [12], on the other hand, supports interactive data visualisation using scatterplots, bar charts, and parallel coordinates plots with manual data-linking capabilities. Later, another framework called U2VIS was proposed by Reipschlagner *et al.* [30] to support 2D and 3D bar charts, scatter plots, line charts, parallel coordinates, and pie charts using AR. To facilitate the usability evaluation of MR applications, Nebeling *et al.* [145] introduced the Mixed Reality Analytics Toolkit (MRAT), designed as an integrable Unity plugin, enabling the collection, analysis, and visualisation of user interaction data.

For *in-situ* data analytics, some toolkits have been also proposed. For instance, MIRIA [146] has been designed for *in-situ* visualisation and analysis of spatio-temporal user interaction data in mixed reality and multi-display environments. It supports various visualisations like 3D movement trajectories, position heatmaps, scatter plots. It also integrates AR visualisations of spatial interaction data into the physical locations where it was recorded, facilitating a comprehensive and immersive analysis of complex spatial interaction data. A more recent toolkit is RagRug [147], designed for situated analytics for context-aware, adaptive visualisations with AR, facilitating the integration of AR visualisations with Internet of Things (IoT) data streams through distributed dataflow and reactive programming patterns. It allows developers to describe and link physical and virtual elements with data flows.

A completely different approach for web-based IA was introduced in Saifee's work [148] through VR-Viz, which facilitates quick exploration and prototyping. Additionally, Butcher *et al.* [149] present VRIA, which, akin to AR.js within this process, provides data visualisation capabilities in AR across desktop and mobile browsers.

To the best of our knowledge, existing IA toolkits (Figure 2.15) are still limited in their ability to manage big and complex datasets. Most of them use CSV/JSON files or SQL databases to store and query data. For instance, the users of IATK or DXR can import CSV or JSON files into Unity scenes to visualise using VR or AR headsets. Similarly, MRAT uses SQL databases for storing and managing the interaction data collected during user sessions. However, these methods of managing data are limited in terms of reasoning and inference capabilities, and therefore, may not support many types of queries.

2.2.4. Meteorology and Climatology Data Analysis

Meteorological and climatological data analysis often requires the visualisation and manipulation of large amount of data. In practice, the analysis process relies heavily on visualisation methods using weather maps and different types of diagrams and graphs to represent the data. Most researchers in meteorology and climatology use desktop-based 3D open-source software (e.g., Met.3D [150], VAPOR [151], ParaView [152]), the commercial software (e.g., Iris Explorer [153],

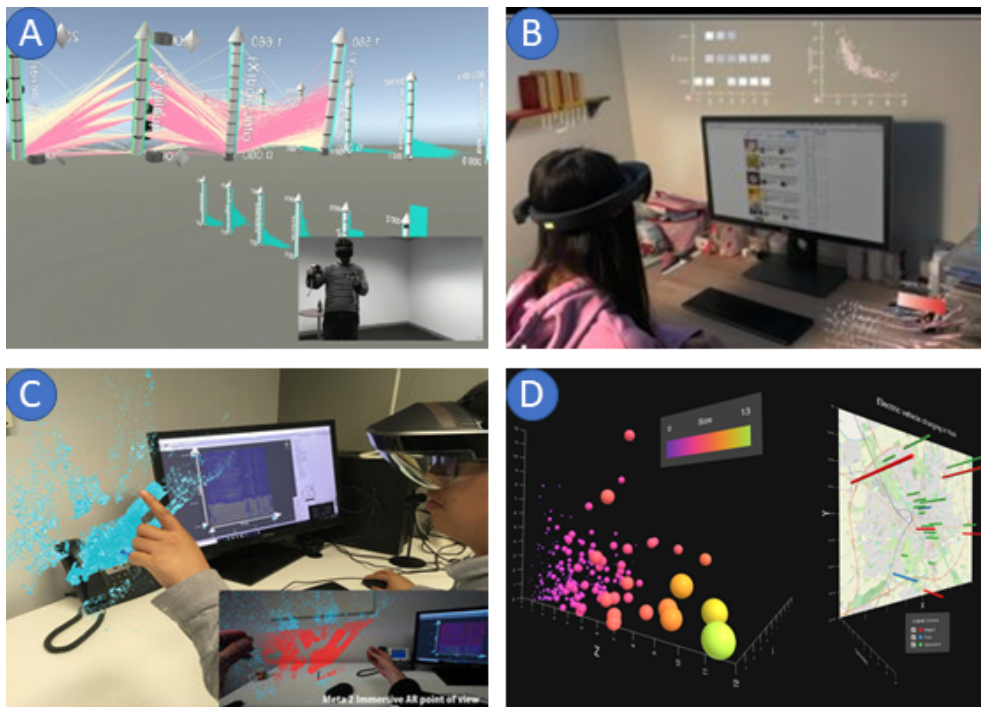


Figure 2.15 – Examples of Immersive Analytics Toolkits: A) ImAXes enables dynamic manipulation and combination of axes for flexible data representations. B) DXR and C) IATK facilitate the creation of 3D visualisations within immersive environments, offering advanced data exploration capabilities. D) VRIA is a comprehensive web framework, supporting immersive 3D data visualisation, allowing for accessible and interactive data analysis across platforms.

Amira-Avizo [154]) are rarely employed [155] or scripts based on Python or different programming languages by using libraries, for example, MetPy [156].

These tools can be classified into two categories according to their utility: in a research context and in an operational forecasting setting [157]. According to Koppert *et al.* in [158], the research tools are mostly used to explore data from observations or simulations to find correlations between numerical variables and real meteorological phenomena. Therefore, ideally those systems must be complex but flexible enough to adapt to different exploration and analysis tasks as well as various data formats, and be configurable by different types of users (novices and experts). On the other hand, forecasting tools have to be designed with few parameters and be usable in the most efficient way possible.

Many studies have been conducted to determine the potential of AR in these fields. In the research context, AR interfaces have often been used in weather simulation. For instance, [159] is one of the earliest studies on augmented video for cloud and sky simulation. Later, an AR simulator was proposed to visualise precipitation data (rain, snow, and hail) [160]. Recently, Ritterbusch *et al.* [161], through the simulation of urban wind flow, demonstrate the advantages of mobile

AR in facilitating the access to simulation results. Besides the simulation, for scientific data analysis, there are different IA tools designed to plot different graphs of meteorological and climatological data. Sicat *et al.* [144] show that their toolkit can be used to visualise weather data and how it can be helpful for collaborative tasks. Their system was designed for hurricane data, but it was limited to only few thousands of data points. IATK [12] asserts to be able to visualise to a much larger number of data points. For the weather forecasting, few works were done (e.g., [162, 163]), and most of them were based on mobile AR because of their promoted accessibility to the large public.

Apart from scientific and weather forecast context, the AR interfaces have been used for others applications. For instance, regarding environmental monitoring, some works have combined Internet of Things with AR interfaces [164, 165]. They are used to overlay information (e.g., air temperature, oxygen rate in the air), informing the user about the surrounding environment in real-time. Training about meteorological concepts through AR-based serious games is another application. Murrell *et al.* [166] show that AR can increase students' engagement to learn the basics of meteorology in large lecture class. Meister *et al.* [167] confirm that AR technology can improve the training of aviation students on weather conditions.

2.3. Semantic-based Approach in Meteorology and Climatology using Extended Reality

This section begins by introducing some common terms, then provides an overview of the application of semantic-based approaches for meteorology and climatology. It also explore how ontology and linked data have been implemented in extended reality.

2.3.1. Ontology and Linked Data

In computer science, an ontology is “a formal, explicit specification of a shared conceptualisation” [168]. The principal components of an ontology are classes (or concepts), properties (or attributes), instances (or class members), and relations. It can be built using different ontology languages such as KIF (Knowledge Interchange Format) [169], DAML+OIL [170], RDF (Resource Description Framework) [171], RDFS (RDF Schema) [172], and OWL (Web Ontology Language) [173]. The RDF, RDFS, and OWL are the standard languages developed by the World Wide Web Consortium (W3C). These languages are then manipulated using syntaxes such as XML, JSON, or N3. W3C has recommended an architecture of semantic web, an extended version of the current World Wide Web by incorporating semantic metadata into information and data, enabling systems to better understand and process content. The architecture of semantic web includes:

- **Representation** layer: it structures and describes the data (RDF/XML) and allows for uniquely identifying resources based on their namespace (URI/IRI).

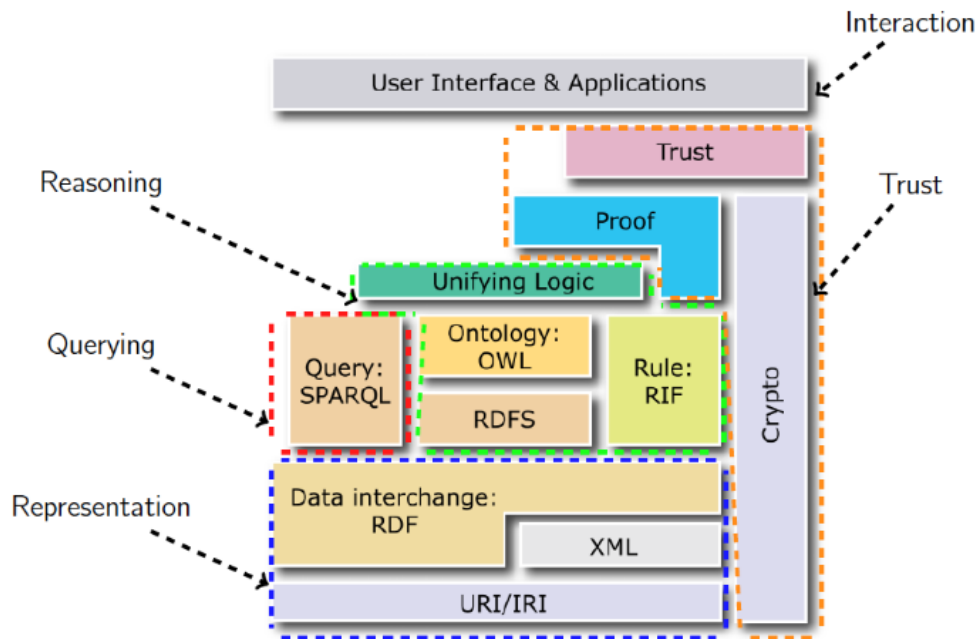


Figure 2.16 – Architecture of semantic web recommended by W3C.

- **Query** layer: it enables the expression of queries on documents in RDF format. The dedicated query language is SPARQL.
- **Reasoning** layer: it sets interpretations on the data through the definition of axioms inspired by the family of description logics.
- **Trust** layer: it ensures the protection of data and resources from unauthorised access and attacks, providing mechanisms such as authentication, authorisation, and encryption.
- **Interaction** layer: it provides mechanisms for user interaction with the system, allowing users to view, manipulate, and query data effectively.

I will detail next two main ontology languages that I used in this thesis: RDF and OWL.

RDF

RDF is a framework of information representation in the semantic web [171] (Figure 2.17). Its statement is in the form of a triplet: a subject, a predicate (property), and an object. RDF Schema (RDFS) is an extension of RDF. It provides basic elements for the description of ontologies. RDF structures data as a model of directed graphs, which formally describe resources and their properties or relationships:

- **Subject** is the resource to describe,
- **Predicate** is the property of the subject, and
- **Object** can be either the final information (literal) or another resource.

A resource can be a URI (Uniform Resource Identifier), a literal, or identity-

less. In the latter case, it is referred to as a “blank node” or anonymous node. This is an important concept that enables the definition of multi-component structures to describe the provenance of information or to represent complex information. These are containers used for the aggregation of data.

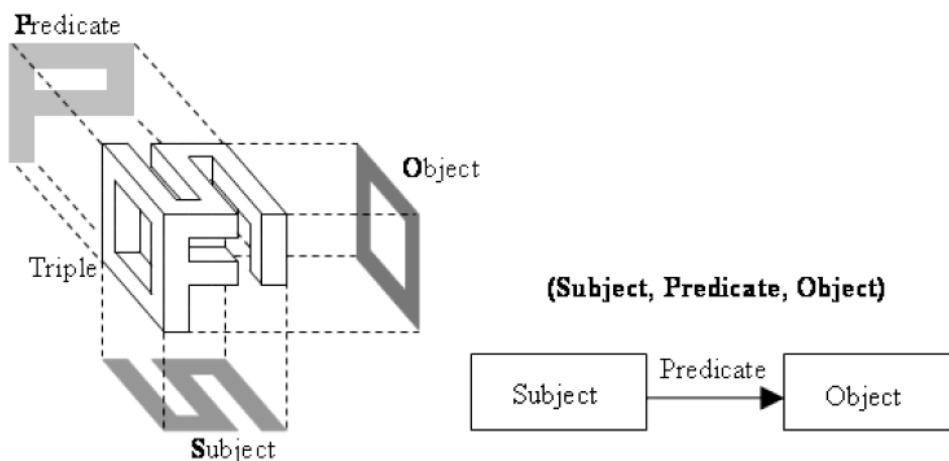


Figure 2.17 – Illustration of the basic decomposition of a triple in RDF language: Subject, Predicate, Object.

Example of RDF Triple

```

1 @prefix foaf: <http://xmlns.com/foaf/0.1/>.
2
3 <http://example.org/#Alice> foaf:knows <http://example.org/#Bob> .

```

This RDF triple illustrates a simple relationship:

Subject *<http://example.org/Alice>* represents a person named Alice.

Predicate *foaf:knows*, used from the FOAF vocabulary [174], denotes a relational link to another person.

Object *<http://example.org/Bob>* identifies the person known by Alice, namely Bob.

OWL

OWL is an extension of the RDF Schema that allows rich and complex knowledge representation. This language uses the family of description logics for the definition of axioms, enabling the verification of the consistency of a description schema and the automatic verification of a resource based on its properties. OWL also enables the inclusion of relationships between objects with assertions provided by RDFS, and allows properties to link classes through relations such as symmetry, equivalence, and cardinality.

Example of RDF Schema (RDFS)

```
1 @prefix rdfs: <http://www.w3.org/2000/01/rdf-schema#> .
2 @prefix ex: <http://example.org/> .
3
4 ex:Person rdfs:Class .
5 ex:Employee rdfs:subClassOf ex:Person .
```

This RDF Schema example defines **Person** as a class and **Employee** as a subclass of **Person**, illustrating a simple class hierarchy.

Example of Web Ontology Language (OWL)

```
1 @prefix owl: <http://www.w3.org/2002/07/owl#> .
2 @prefix ex: <http://example.org/> .
3
4 ex:Person a owl:Class .
5 ex:Employee a owl:Class ;
6     owl:equivalentClass [ owl:intersectionOf (ex:
7     Person ex:FullTime) ] .
8
9 ex:manages a owl:ObjectProperty ;
10    owl:domain ex:Employee ;
11    owl:range ex:Employee .
```

This OWL example showcases more complex definitions, including equivalent classes and object properties with specific domain and range restrictions. **ex:Employee** is equivalent to the intersection of **ex:Person** and **ex:FullTime**, meaning that an individual must satisfy both conditions (being **Person** and **FullTime**) to be classified as an **Employee**. **ex:manages** property is an **object property** where only **ex:Employee** instances can manage other **ex:Employee** instances, as specified by its domain and range.

2.3.2. Ontology and Linked Data for Meteorology and Climatology

To link and share meteorology and climatology data easily without restriction, different ontologies have been created. SWEET (Semantic Web for Earth and Environmental Terminology) is one of the early projects on weather conceptualisation into ontology and linked data [175, 176]. It is a set of 200 ontologies containing about 6,000 concepts developed by NASA's Jet Propulsion Laboratory [177]. Its initial version was based on DAML+OIL [170] and the current version (SWEET 2.3) on OWL 2. Built on top of SWEET ontology, NNEW (Next Generation Network Enabled Weather) [178] was promoted in the NextGen (Next Generation Air Transport System [179]) project. It especially introduces additional weather phenomena and concepts as well as relations to develop a 4-dimension weather data cube (4-D Wx Data Cube). Both SWEET and NNEW contain concepts describing complex meteorological phenomena to be used as core ontology. However, they are partitioned into several ontologies and there are dependencies between them. Using an ontology requires importing all of its dependencies. It can overload the database and thus affect its response time, an important factor for smooth and

real-time AR interaction.

Sensor Web Enablement (SWE) [180] proposed by Open Geospatial Consortium (OGC) [181] was set up to describe sensors, sensor observations, and sensor interface definitions. It is based on seven top-level concepts (i.e. Feature, Observation, ObservationCollection, Process, PropertyType, ResultData, and UnitOfMeasurement), excluding the location and time concept which are imported from other sources. Inspired by SWE, an ontology based on OWL 2 was created by W3C Semantic Sensor Network Incubator group. It is called SSN (Semantic Sensor Network) ontology [182]. It uses DUL (DOLCE-UltraLite) [183] as an upper-level ontology and adds additional concepts to describe sensors. Since SSN is the standard ontology of semantic sensor web, we used it as the main core of our own meteorological ontology.

Several ontologies emerged later which extends the SSN with new concepts describing time, location, or measurements: AEMET [184], SMEAR [185] and ACORN-SAT [186]. AEMET ontology was designed to publish dataset of the Spanish Meteorological Office in the form of linked data. It consists of four modules: measurements, sensors, time, and location. This ontology, however, does not define classes for complex meteorological phenomena. On the other hand, SMEAR ontology has been designed to describe environmental phenomena dataset. It was set up as a software framework (called Wavellite) to organise and interpret sensor data for atmospheric monitoring. It is based on four ontologies (WURVOC, SSN, QB, and STO) to structure information according to four layers (measurement, observation, derivation, and situation). Finally, ACORN-SAT is the ontology proposed to publish the Australian Bureau of Meteorology (BOM) dataset (daily temperature records over the last 100 years) as linked data. It focuses on the description of temperature and rainfall data. Moreover, it does not contain classes for complex meteorological phenomena such as hurricane, storm, or sea and wind characteristics.

The proposed ontology in Chapter 4 does not use ACORN-SAT as it does not describe the meteorological phenomena necessary for our application. Additionally, the SMEAR ontology is too software-dependent to be reused in IA context. Regarding AEMET, the aim is to use a more simplified version by not including the location and measurement unit classes. Instead, we propose to use only some basic ontologies (SSN, WGS84_pos [187], time [188], and units [189]) and add new classes to describe complex weather phenomena which are currently missing in SSN.

2.3.3. Ontology and Linked Data in Extended Reality

Domain-specific ontologies are used to semantically describe and model existing concepts and knowledge. For instance, they help to tackle the explosion of information ([190, 191, 192]), to facilitate the interconnection of data sources (linked data) ([193, 194]), to solve the problems of data integration ([195, 196]) and interoperability [197], to target the issue of spatial-temporal dimensions and

heterogeneous environmental data visualisation [198].

In VR, ontology is often used in many types of applications. For example, Pellens *et al.* [199] used an ontology to define how objects behave in the virtual environment, while Aubry *et al.* [200] proposed to structure and organise the knowledge model associated with annotations using ontology. Edward *et al.* [201] used the ontological approach to manage a virtual environment for risk prevention. Additionally, Moreno *et al.* [202] employed this technique to enhance simulation realism and integrate different data sources. Another example is Trellet *et al.* [203]'s work which unifies the interaction between 3D structures and 2D data analysis of molecules with ontology. Youcef *et al.* [204] utilised ontology to normalise terminology in cataract surgery training in VR. Lastly, Chokwitthaya *et al.* [205] used ontology to standardise VR experiments on human-building interactions.

In AR applications, ontology and linked data can be used to increase dynamic context-awareness of the physical world. For instance, they have been used to display the contextual information about cultural heritage sites [206, 207, 208], to specify geographic locations [206, 209], to support maintenance or training on complex systems [210, 211, 212, 213]. Such semantic-based approach for context-awareness in AR is also useful for healthcare and well-being: to support daily patients' needs [209, 214], or for elderly dependent users [215].

Besides context awareness, semantic-based approach in AR has been used for scientific data visualisation. An example is DatAR [216], an IA environment for the visualisation of neuroscientific concepts. However, regarding meteorological and climatological scientific data, I did not find any AR system based on ontology and linked data. Moreover, for other application fields, no user experiment has been conducted to study the impact of such approach in terms of usability, performance, and effort for the users to solve data analysis tasks.

2.4. Shared Workspace in Collaborative Immersive Analytics

This section introduces different frameworks and toolkits proposed for collaborative IA. It then explores various studies conducted on synchronous co-located collaboration for different user position arrangements. Finally, it examines different privacy management strategies in immersive collaboration.

2.4.1. Collaborative Immersive Analytics

One of the first IA collaborative platforms was designed for the CAVE [217]. Its benefits have been highlighted for collaborative data analysis [218], but it is still costly due to the high cost for infrastructure. Later, similar systems have been developed, improving resolution and tracking systems (e.g., [219, 220]). Cordeil *et al.* [221] compared CAVE2 with VR HMD in the visualisation of 3D graphs. They found that in both platforms, the pairs of participants achieved similar high accuracy. However, they were faster in the HMD condition, which means that CAVE environments are not necessarily required for collaborative IA.

Several IA platforms and frameworks have been proposed for scientific visualisation using HMDs. For instance, Szalavri *et al.* [51] developed a co-located collaborative AR system for scientific visualisation. Benko *et al.* [222] proposed a collaborative AR system that supported both remote and co-located work to explore an archaeological dig. Similarly, Kurillo *et al.* [223] proposed Telearch, a VR system for remote collaboration for archaeological research. Donalek *et al.* [37] explored the use of immersive collaborative VR platforms for both co-located and remote scientific data visualisations and showed that immersion led to a demonstrably better perception and understanding of the data. Nguyen *et al.* [224] designed a framework for collaborative IA in co-located as well as remote contexts, composed of four system's components: data management, analytics engine, query engine, and networking and communication. In [225], Royston *et al.* demonstrated a VR system for co-located collaborative interaction with social network (Twitter friend/follow network) data visualisation. Butscher *et al.* [13] proposed ART, a co-located collaborative analysis tool to visualize multidimensional data in AR. More recently, Seraji *et al.* [226] introduced XVCollab, a co-located IA tool that allows users to use different interfaces such as desktop environments and AR setups. Additionally, Friedl-Knirsch *et al.* [227] proposed a co-located IA prototype for collaborative data analysis using different AR technologies, including video see-through, optical see-through, and handheld devices.

The trend of using HMD-based AR for IA, especially for co-located collaboration, is significantly increasing. However, only some systems take into account the fact that visualising complex scientific data may require different profiles and thus intricate phases between cooperative and individual tasks. Moreover, to the best of my knowledge, there is no existing solution to structure the physical space so that collaborators can interact with each other and with the complex data without disturbing or invading each other's physical space, especially in daily limited workspaces such as offices and meeting rooms. This thesis explores different approaches to organise the users' position in a co-located situation and the division of private and public workspace when working collaboratively.

2.4.2. Users' Position Arrangement in Synchronous Co-located Collaboration

This subsection explores existing works on different approaches to organise users' position in a co-located scenario collaboration. In a synchronous system, the awareness of others in space is paramount to the collaborative working process. This awareness involves identifying the presence, location, actions, and activities of others at a particular moment [228]. Therefore, face-to-face interaction greatly facilitates communication cues via body language and gestures [229, 230]. Moreover, social protocols are often maintained during AR-based co-located interactions. For instance, the users do not interact with virtual content when it is outside of their personal workspace and thus perceive it as if it does not belong to them [231].

Examining synchronous co-located collaboration through an immersive inter-

face presents a challenge related to the arrangement of the users' positions. Numerous investigations into user behaviours during collaboration have centred around the F-formation [232]. This phenomenon, observed in face-to-face interactions, delineates how individuals unconsciously configure themselves spatially and socially during a conversation, often forming a structure resembling the letter 'F'. It often occurs in face-to-face, side-by-side, or corner-to-corner arrangements. A specific study by Marquardt *et al.* [233] delved into collaborators' behaviour using various F-formation configurations, asserting that spatial relationships and positioning of individuals significantly impact their performance and conduct during collaboration. This conclusion finds support in another study [38], which further explored the users' position arrangement through F-formation in the context of IA using VR.

In real-world context such as office environments or enclosed spaces, Lee *et al.* [231] conducted an exploratory study involving teams of three co-located users who were instructed to freely arrange their shared virtual workspace. They observed a natural inclination among participants to use walls for organising 2D items of personal charts/windows, while positioning 3D visualisations in the surrounding space. Recent work by Luo *et al.* [234] presents an empirical study focusing on the influence of the physical environment on spatial arrangement during collaborative tasks with paired users in AR. Their findings emphasise that the configuration of workspace furniture significantly impacts how users organise their virtual content. The recommendation arising from their research suggests incorporating furniture into AR workspaces within physical environments rather than opting for entirely empty rooms. These investigations highlight the critical role of effective spatial planning, considering factors such as line of sight, workspace furniture, and overall ergonomic design of collaborative (virtual and physical) workspace, to ensure seamless and efficient interaction among participants.

2.4.3. Privacy Management in Immersive Collaboration

In collaborative immersion, an important issue is to manage private and public content. To study the management of private and public content, I classified the proposed solution into two groups: visually oriented (a user can not see the private contents of others), and space-partition oriented (the user has their own personal space and can not interact or see the contents of other restricted spaces).

The visually oriented privacy approach enables personal or sensitive virtual content to be hidden so only authorised people can interact with or see it without any space restrictions. Some mechanics are required to allow the users to configure the privacy when they want to share the hidden content. For example, the work in [18] proposed "vampire mirrors" and "privacy and publicity lamps" in collaborative AR to manage the users' view. Using "vampire mirrors," all public objects are visible in the mirror; it reflects objects that are set as public, while those designated as private do not appear in the mirror (Figure 2.18). In "privacy and publicity lamps" metaphor, the privacy state of objects can be changed by shining a light on them,

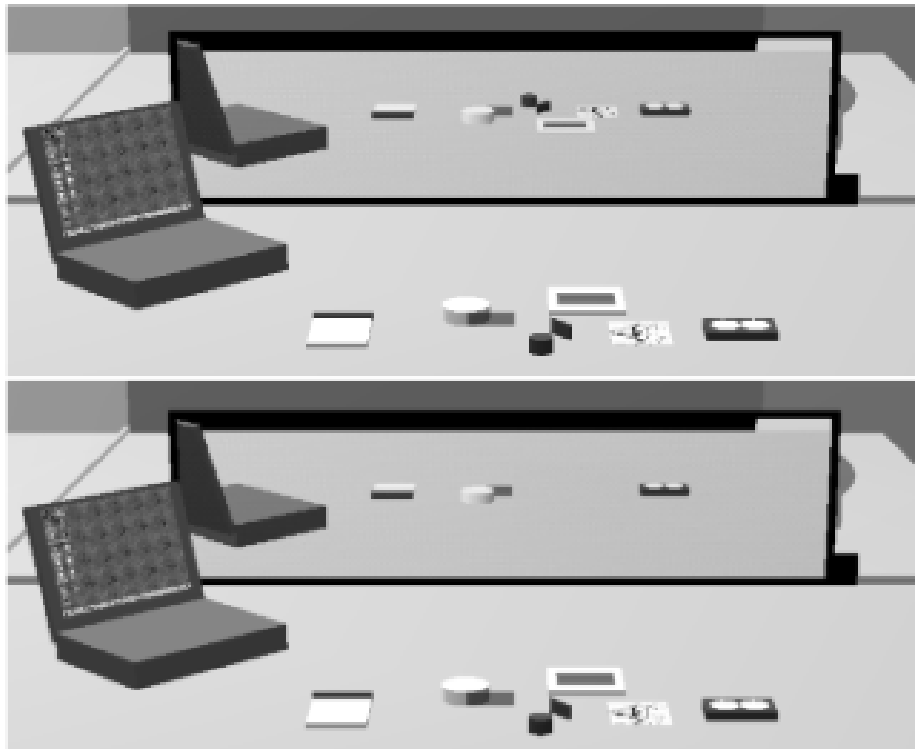


Figure 2.18 – Example of “vampire mirror” to visualise public and private objects [18]: Top - all public objects are visible in the mirror. Bottom - private objects are not visible anymore in the mirror.

marking them as either visible to all (public) or hidden from view (private). Thus, privacy lamps render objects private, whereas publicity lamps highlight objects to make them visible to all participants in the environment (Figure 2.19).

Regarding the space-partition oriented approach, 3D contents are dispatched, according to their privacy status, in different sub-spaces of the world dedicated to each user (private sub-spaces) or available for all users (public sub-space). Therefore, a user can interact with 3D contents, either if they are located in their private sub-space or are located in the public sub-space and not currently used by another. Bullock and Benford [235] early discussed on access control of 3D contents in collaborative virtual environments in proposing access restrictions based on sub-spaces of the virtual world. Later, Szalavári *et al.* [236] introduced the concept of privacy layers within co-located collaborative environments, specifically for gaming. They developed a system where specific spaces were assigned distinct privacy layers. Within this setup, all objects in a given region shares the same privacy level. Crucially, when objects were moved from one region to another, their privacy status would automatically change to match the new region’s privacy level. Recently, for AR-based remote immersive collaboration, Mahmood *et al.* [237] proposed space

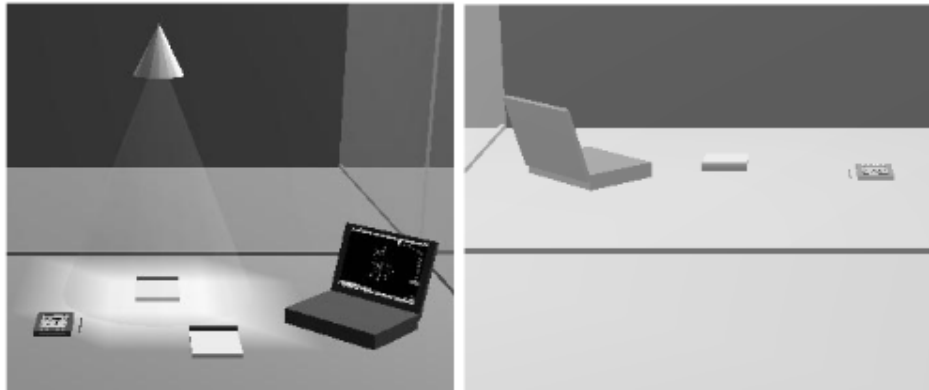


Figure 2.19 – Example of “privacy and publicity lamps” [18]: Left - a privacy lamp shines on an object, hiding it from other users. Right - the perspective of another user, where the objects illuminated by the lamp light are missing.

partition of each individual’s AR workspace in two sub-spaces, one to manage their private contents, and the other allocated to the public virtual space shared with all the users. James *et al.* [238], presented a study on a co-located collaborative system combining the use of wall displays with AR headsets. In the proposed hybrid system, public contents were accessible on some physical wall displays but also on shared virtual walls, visible with the AR headsets. Moreover, the AR headsets managed a private space located as close to the user as possible, with virtual objects dispatched in a semi-circle around the user, always facing and moving with them.

Existing space-partition based approaches often overlook physical workspace constraints and the spatial arrangement of collaborators when defining private or public sub-spaces. In my opinion, this is a significant limitation in existing co-located AR-based immersive collaborative systems. To address this, my proposal involves automatically dividing the physical workspace into dedicated sub-workspaces, considering factors such as physical constraints, number of collaborators and their positions. Furthermore, to evaluate the added value of this partitioning approach, we plan to assess its effectiveness in combination with view privacy policies. Additionally, we aim to explore the implications of private and public views within this co-located collaborative space. One of the most recent works and similar to this study is workspace guardian concept proposed in [239]. However, this work did not address the IA use case. Furthermore, their partitioning technique was manual (self-defined workspace boundary) and the boundary was not visualised on the floor.

2.5. Conclusion

This chapter begins with a brief introduction to existing interaction techniques which focus on selection for Head-Mounted Display (HMD)-based Augmented Reality (AR) interfaces. It also provides an introduction to Immersive Analytics, starting with data visualisation and interaction in Extended Reality. Additionally, I defined the notion of ontology and present an overview of relevant AR and Virtual Reality (VR) applications. Finally, I introduced existing collaborative IA frameworks and explore various user studies on user positioning in co-located collaboration, as well as different privacy management techniques in immersive collaboration.

Overall, existing IA toolkits do not fully support data management and selection interaction, two important processes especially when working with big and complex datasets. Additionally, working collaboratively in co-located settings can be challenging when visualising multidimensional data, such as meteorological data. The design of the proposed collaborative systems should be adapted to meet these requirements. In the upcoming chapters, I will first present, in Chapter 3, improvements to selection techniques by introducing expanded data points in IA and conducting a user study to identify the best selection methods in IA. Then, in Chapter 4, I will highlight the proposed IA system for meteorological visualisation and examine the benefits of a semantic approach for data management through a user study. Finally, in Chapter 5, I will showcase new techniques for workspace management to improve user position arrangements and study the effects of these proposed techniques.

3 - Selection Techniques in Augmented Reality for Immersive Analytics

This chapter presents the new selection technique based on expanded data points that I have designed to improve selection tasks in Augmented Reality (AR). This technique aims to help a user to select quickly and accurately data points during meteorological immersive analytics (IA) tasks using hand-mounted display (HMD)-based AR interface. However, it is relevant and applicable to all immersive systems that use this type of data-point visualisation. In this chapter, after the introduction, I will detail the technical aspects of the approach. Then, I will describe a user experiment conducted to investigate user performance and subjective evaluation of this selection technique. Lastly, several prospective approaches to further enhance this data-point selection will be outlined.

3.1. Introduction

The selection and manipulation of data are among the key operations (see Section 2.2.2) that are performed repetitively during a data analysis task. The ability to select specific data points within a dataset is crucial for inspection and comparison between them. A data point is a unit of data that contains several attributes. For example, in meteorology, a data point can include measurements such as pressure, wind speed, temperature, and other variables at a specific time. By selecting individual data points or groups of data points, the user can focus their attention on specific regions, uncover hidden patterns, and gain a better understanding of the underlying data distribution. The effectiveness of the selection depends not only on the pointing and selection confirmation technique, but also on the target size according to Fitts' law [240]. The pointing technique (e.g., ray casting, virtual hand) allows the user to indicate one or several objects to be selected for manipulation, and the confirmation selection technique (e.g., dwelling, clicking, voice, and hand gesture) triggers the selection. In case of the ray-casting technique for the pointing, this method depends on the ray's origin (head, hand, or eye) and its direction. The air-tap and voice confirmation techniques combined with hand or head pointing have been largely used in Microsoft HoloLens headsets. However, selecting distant and small objects is often challenging, which can greatly affect the user experience.

To overcome this limitation, I proposed a solution which facilitates the selection operation via the expansion of a data point when the cursor of the ray or the virtual hand hovers over it. Moreover, I consider that the data visualisation on a 2D plan is an important aspect to be studied when designing an IA system due to the fact that many real datasets from geophysics, meteorology, or climatology domains are

actually visualised in 2D based on the geographic coordinates of the data itself. Despite this constraint, it is relevant to assert the usefulness of the Fitts' law and its application in expanding data points for selection in working with 2D datasets on a 3D HMD-based AR interface. My main contribution in this aspect was to propose, design, and evaluate this new selection technique using a headset-based AR interface. The research question addressed in this chapter is:

RQ2: Will the selection technique based on expanded data points improve the performance and user experience of data selection in HMD-based AR interfaces?

The expanding data point technique was presented as a poster at the ACM Symposium on Virtual Reality Software and Technology (VRST) in November 2022 [241].

3.2. Fitts' Law and Expanding Interacting Widgets

In this section, I will present some background on Fitts' law, a predictive model of human movement on which I based my design for the selection technique by expanding 3D data points.

Indeed, most of the comparative selection techniques [74, 93, 83] used Fitts' law design in Human-Computer Interaction (HCI) given by equation formulated by MacKenzie [240].

$$MovementTime(MT) = a + b \times ID \quad (3.1)$$

$$ID = a + b \times \log_2\left(\frac{A}{W} + 1\right) \quad (3.2)$$

where a and b are empirically determined via linear regression, and A and W represent the target distance and size. ID (logarithmic term in Fitts' law) is the index of difficulty, which represents the task difficulty. From this law, it is known that the larger the target, the less time it takes to reach it. The earliest study [240] involves the target with a constant size (meaning no expanding target).

The concept of expanding interacting widgets during selection has been largely used in interface design. The widgets are expanded when being pointed at. For instance, in Mac OS X, the icons in the dock bar expand when the mouse cursor hovers over them. Many experiments were conducted to determine the factors that affect the selection of expanding targets. For instance, McGuffin and Balakrishnan [242] concluded that the isolated expanding item selection is faster and easier than a non-expanding item. Moreover, they found that the improvement in the user performance does not depend on the initial target size but on the final one. Later, Zhai et al. [243] investigated the expanding items by testing more conditions. For

example, they add the condition that participants did not always know whether expansion would occur. They did not get full evidence that the expanding target facilitates pointing (due to the increase of error rate depending on ID), as concluded by McGuffin and Balakrishnan [242]. However, they found that the performance was further improved when the users did not know whether the expansion was going to occur. In 2005, McGuffin and Balakrishnan [244] conducted another experiment in which they considered the error rate, besides different designs of multiple expanding targets. However, unlike Zhai et al. [243], they did not observe a clearly increasing error rate when the difficulty index of target acquisition was increasing.

3.3. Selection Technique

Inspired by the studies on expanding widgets by McGuffin and Balakrishnan [242, 244], I have developed a technique for selecting data points in interactive applications (IA) by expanding their size during interaction. The selection mechanism activates when the cursor intersects with a data point, causing its visual representation to expand.

Our proposed approach is, given a data point P_i where the cursor is located at a certain time, we propose to enlarge its size (w_i) and also those of its eight neighboring points in a linear way based on a ratio A . Initially, we have:

$$w_i = w_{i+1} = w$$

where w_i represents the size of P_i , w_{i+1} represents the size of the neighboring points of P_i , and w is the common value of their sizes.

$$I_0 = D - w$$

Where I_0 is the initial distance between the two points from side to side, and D is the distance between the two points from center to center (with D being invariant) (Fig 3.2).

Following the enlargement, the new interspacing is given by:

$$I_1 = D - \frac{w_i + w_{i+1}}{2}$$

Where I_1 becomes the new distance between the two points from side to side.

Basically, we want a linear distribution of the enlargement limited to P_i and P_{i+1} , thus:

$$w_i = Aw, \quad w_{i+1} = \frac{A+1}{2}w \quad \text{and} \quad w_{i+2} = w$$

Consequently, we have:

$$I_1 = D - \frac{3A+1}{4}w \tag{3.3}$$

To prevent overlapping of data points, it is necessary that:

$$I_1 > 0 \Rightarrow D > \frac{3A+1}{4}w$$

In our experimental setup, as illustrated in Fig. 3.1 with $D = 2w$, it follows that:

$$A < \frac{7}{3}$$

Thus, we choose $A = 2$. Thanks to this:

$$I_1 = \frac{1}{4}w \quad \text{and} \quad I_2 = \frac{3}{4}w$$

\Rightarrow no overlap between the enlarged data points P_i and P_{i+1} .

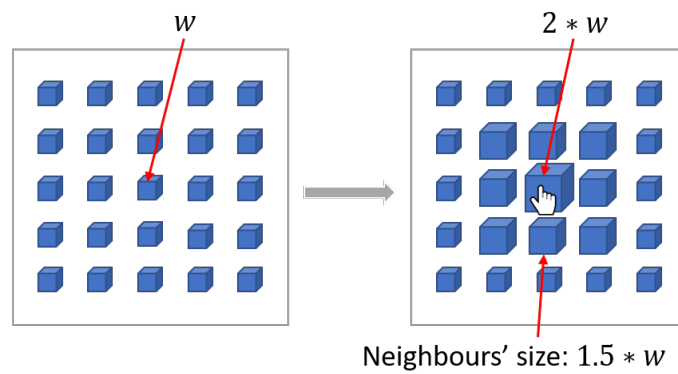


Figure 3.1 – Design of expandable data points.

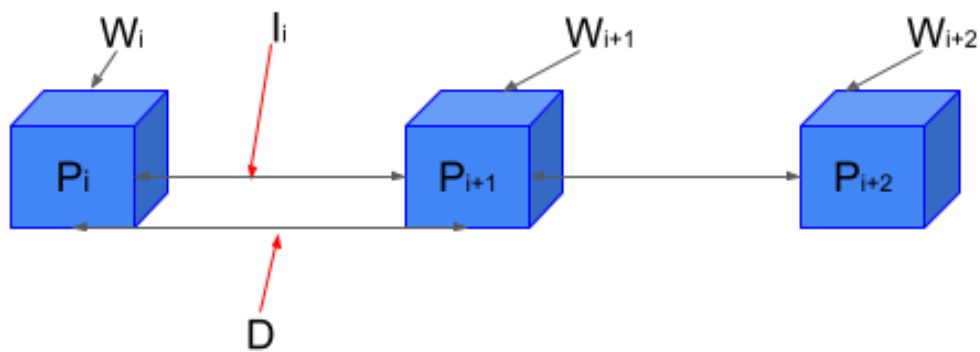


Figure 3.2 – Representation of three data points and the distance between them.

3.4. User Study

This experiment aimed to evaluate the benefits of the expanding technique of data points when the user selects 3D data points regularly tiled on 2D data board with a Microsoft HoloLens 2 headset. I compared it with the baseline condition which was without the expanded point model. I also considered their usage within the combination of different approaches for ray-casting and selection confirmation technique commonly used with this headset. In summary, I considered three following factors:

- POINTING is the ray-casting technique to control the interacting cursor using *Head* or *Hand* as the origin of the ray and to give its direction.
- SELECTION CONFIRMATION is the interactive mode used to confirm the selection provided by the ray-casting. It can be either *Voice* or *Air-Tap*. To avoid using the HoloLens 2 system command's "Select", the word "Point" was used for the *Voice*.
- POINT DESIGN indicates whether to use expanded point model (*Expanded*) or not (*NoExpanded*).

The experiment was conducted with eight conditions (see Table 3.1) following a within-subjects experimental design.

ID	Pointing	Selection Confirmation	Point Design	Abbreviation
C1	Head	Voice	Expanded	He-V-E
C2	Head	Air-Tap	Expanded	He-AT-E
C3	Hand	Voice	Expanded	Ha-V-E
C4	Hand	Air-Tap	Expanded	Ha-AT-E
C5	Head	Voice	NoExpanded	He-V-noE
C6	Head	Air-Tap	NoExpanded	He-AT-noE
C7	Hand	Voice	NoExpanded	Ha-V-noE
C8	Hand	Air-Tap	NoExpanded	Ha-AT-noE

Table 3.1 – Eight conditions of the Exp. 1 with three factors.

3.4.1. Hypotheses

I expected that the *Expanded* approach would help the user select more easily the data points within the scene. Therefore, I formulated the following hypotheses:

- H1.1** *Expanded* point design will help the user finish their task faster compared to *NoExpanded* despite different POINTING and SELECTION CONFIRMATION techniques.
- H1.2** *Expanded* results less error compared to *NoExpanded* despite different POINTING and SELECTION CONFIRMATION techniques.

3.4.2. Participants

In this study, there were 9 male and 7 female participants whose age ranged from 22 to 30 ($\mu = 26.25, \sigma = 3.66$). Five of them (one male and four females) have never used an immersive system before.

3.4.3. Apparatus

The system was running Unity3D on a computer with a Intel[®] Xeon[®] W-2135 processor, 32 GB RAM, and Nvidia Quadro 4000 graphics card. A Microsoft HoloLens 2 was used for rendering and interaction.

3.4.4. Experimental Task

In each condition (C1-C8), the participant had to select nine target red points out of $36 * 36$ points in total regularly arranged on a $1m \times 1m$ data board (the remaining points were in blue) (see Fig. 3.3 - left). Each point is represented as a cube of 0.8 cm of each dimension. This data board was placed directly $1.5m$ away in front of the participant at the beginning of the task. The target points were randomly distributed in nine zones of the data board (see Fig. 3.3 - right). When the participant selected a target, its colour turned to white to indicate the successful selection. The task for each condition was completed when all the targets were selected.

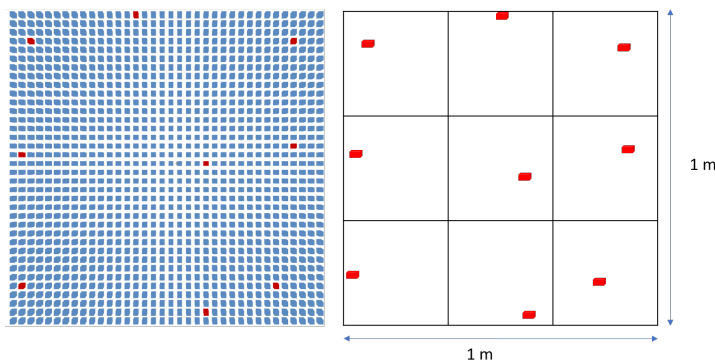


Figure 3.3 – *Left*: Random distribution of red targets in nine zones of a data board which includes in total $36*36$ 3D points regularly tiled. *Right*: Blue points are removed, targets are accentuated for visibility, and dividing lines are added.

3.4.5. Procedure

This experiment took approximately 50 minutes. At the beginning, each participant was welcomed and received instructions on the task, and signed a consent form. They also filled a pre-experimental questionnaire for demographic data and their VR/AR experience. Next, they were equipped with a Microsoft HoloLens 2 headset and followed a tutorial to learn how to use it.

The eight conditions were randomly ordered for each participant. Before starting each condition, there was a training trial during which they were asked to use its

corresponding combination technique of the three factors to select the four cubes of different sizes (1 cm, 3 cm, 6 cm, and 9 cm) arranged on the horizontal line. There was no time limit in the training until the participant felt ready to start the task. Once the task is completed, they filled out NASA-TLX questionnaire. At the end of the experiment, I asked the participant to rank the eight conditions according to their preferences.

3.4.6. Data Collection

I registered 1152 trials: 2 POINTING techniques \times 2 SELECTION CONFIRMATION techniques \times 2 POINT DESIGN modes \times 9 targets \times 16 participants. For each trial, I collected the following measures:

- *Task Completion Time (TCT)*: the time needed to complete the task in each condition. It started when the participant began to perform the task and ended once the nine targets were correctly selected.
- *Total Error Distance (TED)*: the distance between the badly selected points to the intended target in the same zone. The final value was accumulated for all the targets.
- *Total Distance of Cursor Movement (TDCM)*: the accumulated distance that the pointer covered before reaching a target. For each trial, I obtained nine values for nine targets as follows:

$$d(CP_{t_i}, CP_{t_{i+1}}) = \|CP_{t_i} CP_{t_{i+1}}\| \quad (3.4)$$

$$TDCM_k = \begin{cases} \sum d(CP_{t_i}, CP_{t_{i+1}}) - d(CP_{t_0}, TP_k) & \text{if } k = 0 \\ \sum d(CP_{t_i}, CP_{t_{i+1}}) - d(TP_k, TP_{k-1}) & \text{if not.} \end{cases} \quad k \in \{0, 8\} \quad (3.5)$$

with **CP**: the cursor's position, **TP**: target point's position, **t**: time at instance *t*, and **i**: time index, **k**: index of the targetting point. Since the order to select one of 9 targeted points was random during the task, the first targeted point selected index is 0 ($k = 0$), and the last targeted point index is 8 ($k = 8$).

- *NASA-TLX*: the subjective evaluation of cognitive load of each condition at the end of the corresponding task.
- *Overall ranking*: the preference ranking of eight conditions from 1 to 8 (1 is the best and 8 is the least preferred) at the end of the experiment.

3.4.7. Statistical Results

For the *Task Completion Time (TCT)*, I used normal QQ-plots and Shapiro-Wilk tests to analyse the normality of the data and it was not normally distributed. I then calculated its asymmetry and found that the distribution was positively asymmetric. Therefore, I applied a log-transformation ($\log_{10}(x)$ for positive asymmetric data). The average *TCT* for each technique and its 95% confidence intervals (CI) are presented in Fig. 3.4.

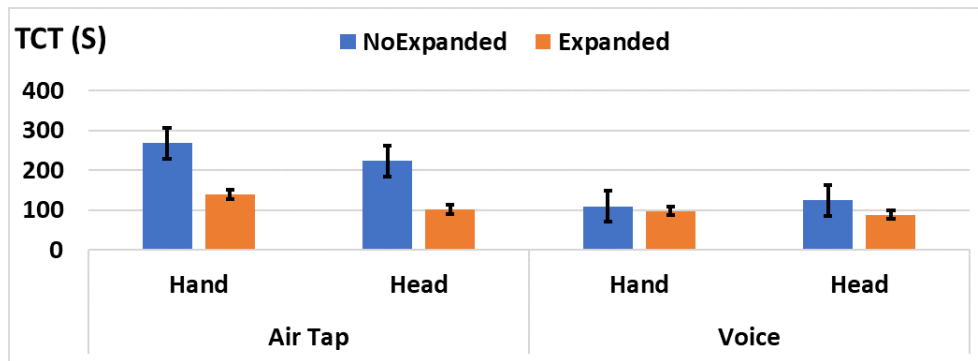


Figure 3.4 – Task Completion Time (TCT) firstly grouped into two conditions of Pointing technique. Error bars show 95% confidence intervals (CI).

Using multi-way repeated-measures ANOVA test with the three factors, I did not find any significant three-way interaction between them ($F_{1,120} = 0.01 * 10^{-3}$, $p = 0.99$). There were no interaction effects between POINTING and SELECTION CONFIRMATION ($F_{1,120} = 1.13$, $p = 0.30$), or between POINTING and POINT DESIGN ($F_{1,120} = 0.40$, $p = 0.53$). However, there was a significant interaction effect between SELECTION CONFIRMATION and POINT DESIGN ($F_{1,120} = 7.85$, $p < 0.001$). Further analysis showed that the main effect of POINT DESIGN on TCT was statistically significant for the *Air-Tap* confirmation ($F_{1,124} = 27.60$, $p < 0.001$), but was not significant for the *Voice* command ($F_{1,124} = 1.69$, $p = 0.20$). I also investigated the main effect of each factor separately on TCT. The result shows a significantly independent effect of POINT DESIGN on TCT ($F_{1,120} = 21.57$, $p < 0.001$) and of SELECTION CONFIRMATION on TCT ($F_{1,120} = 19.61$, $p < 0.001$). However, there was no significantly independent effect of POINTING on TCT.

Regarding *Total Error Distance (TED)* (see Fig. 3.5), the QQ-plots and Shapiro-Wilk tests showed that the data were not normally distributed. I applied a log-transformation as previously mentioned in TCT analysis. The results of multi-way ANOVA revealed no statistically significant interaction between the three factors ($F_{1,120} = 0.19$, $p = 0.66$), and no significant interaction effect neither between POINT DESIGN and SELECTION CONFIRMATION ($F_{1,120} = 0.01$, $p = 0.90$), nor between POINTING and POINT DESIGN ($F_{1,120} = 0.70$, $p = 0.40$). However, there was a significant interaction effect between POINTING and SELECTION CONFIRMATION ($F_{1,120} = 6.72$, $p < 0.05$). The simple main effect of SELECTION CONFIRMATION on TED was statistically significant for *Head* pointing technique ($F_{1,124} = 16$, $p < 0.001$), but was not statistically significant for *Hand* pointing ($F_{1,124} = 0.07$, $p = 0.79$). The main effect analysis has been conducted to investigate the effect of each factor on TED. The result revealed a significant effect of SELECTION CONFIRMATION ($F_{1,120} = 9.2$, $p < 0.001$). However, there were no significantly independent effect of POINT DESIGN ($F_{1,120} = 1.78$, $p = 0.18$) or

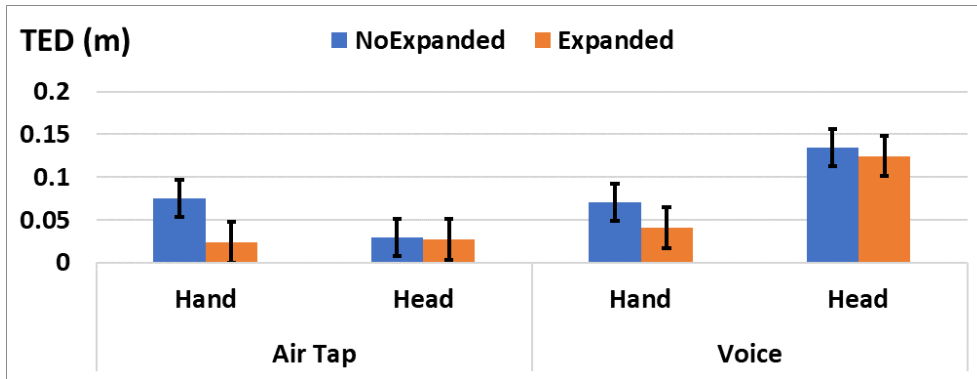


Figure 3.5 – Means and 95% CI of Total Error Distance (TED) results grouped according to Selection Confirmation.

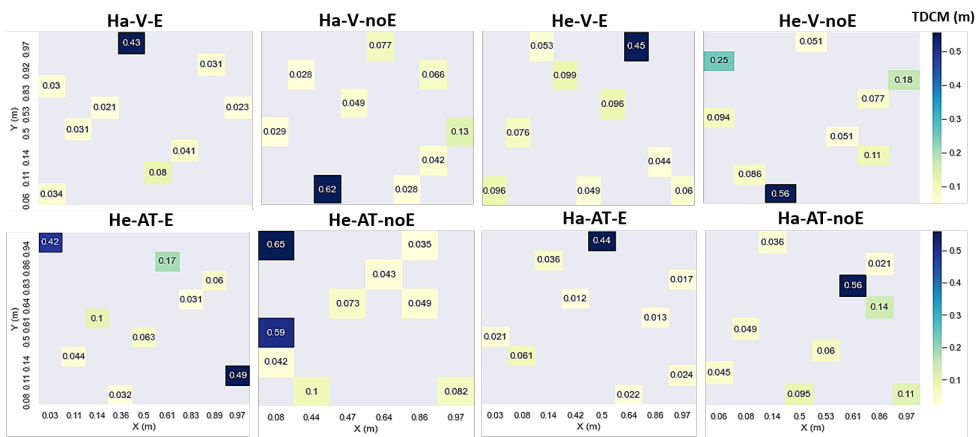


Figure 3.6 – Heatmaps of the participant P04's Total Distance of Cursor Movement (TDCM) of the eight conditions mapped on the data board in their order of execution (left to right, top to bottom).

POINTING ($F_{1,120} = 2, p = 0.16$).

Using the *Total Distance of Cursor Movement (TDCM)* data collected, I analysed the tendency of the participants' cursor movements on the data board during their tasks. I found that they followed a similar fashion and for illustration, the TDCM heatmaps of the participant P04 is showed in Fig. 3.6.

Regarding the answers from NASA-TLX questionnaire (see Fig. 3.7), to analyse non-normal and ordinal-scale data, it is recommended to apply non-parametric statistical tests. However, in my case the variance homogeneity test with Levene's test was not significant. Moreover, the Shapiro-Wilk's test of normality revealed that data of all the NASA subscales was normally distributed. Therefore, I used the parametric multiple-way ANOVA. The test showed that there was no statistically significant interaction between the three factors on subscales of the cognitive load. mental demand ($F_{1,120} = 0.70, p = 0.41$), physical demand ($F_{1,120} = 0.70, p =$

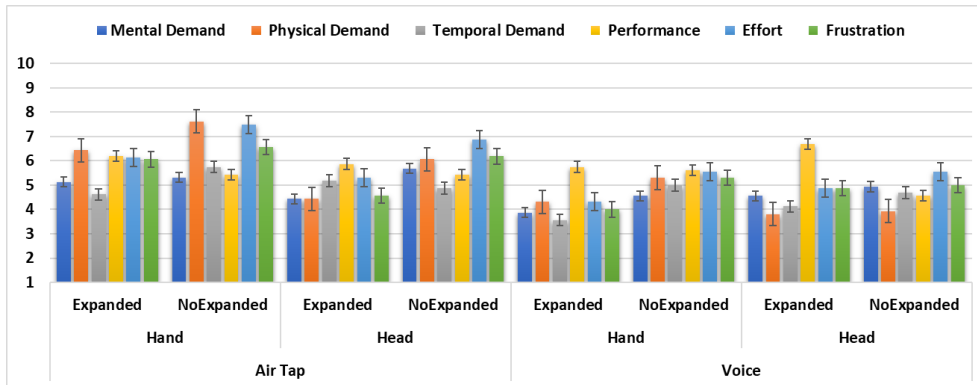


Figure 3.7 – The NASA-Task Load Index (NASA-TLX) results mainly grouped into two conditions of Selection Confirmation.

0.40), temporal demand ($F_{1,120} = 0.16, p = 0.70$), performance ($F_{1,120} = 1.80, p = 0.18$), effort ($F_{1,120} = 0.30, p = 0.58$), and frustration ($F_{1,120} = 1.70, p = 0.19$). In addition, there was no significant interaction between any pair of factors. The results of the two-way ANOVA are in the Table 3.2. An analysis has been conducted to investigate the three factors' main effect on the NASA subscales. The result showed a significant independent effect of POINT DESIGN on all the subscales. It was similar in the case of SELECTION CONFIRMATION on all the subscales except performance. There was a significant main effect of POINTING on mental demand.

	Pointing X Confirmation	Pointing X Point Design	Confirmation X Point Design
Mental Demand	$F(1,120) = 0.66, p = 0.41$	$F(1,120) = 0.2, p = 0.6$	$F(1,120) = 0.05, p = 0.8$
Physical Demand	$F(1,120) = 1.14, p = 0.28$	$F(1,120) = 0.07, p = 0.8$	$F(1,120) = 1.14, p = 0.3$
Temporal Demand	$F(1,120) = 0.16, p = 0.7$	$F(1,120) = 2.7, p = 0.1$	$F(1,120) = 0.7, p = 0.4$
Performance	$F(1,120) = 0.01, p = 0.9$	$F(1,120) = 0.9, p = 0.33$	$F(1,120) = 0.37, p = 0.53$
Effort	$F(1,120) = 1.77, p = 0.19$	$F(1,120) = 0.02, p = 0.88$	$F(1,120) = 0.39, p = 0.53$
Frustration	$F(1,120) = 1.58, p = 0.21$	$F(1,120) = 0.01, p = 0.91$	$F(1,120) = 0.09, p = 0.76$

Table 3.2 – Two-way ANOVA results between different factors on the NASA-TLX subscale.

Concerning *Overall ranking* (see Fig. 3.8), the combined *Head-Voice-Expanded*

condition ($\mu = 2.44, \sigma = 1.88$) was rated the best, while the *Hand-Air-Tap-NoExpanded* condition was the least preferred ($\mu = 7.11, \sigma = 1.69$).

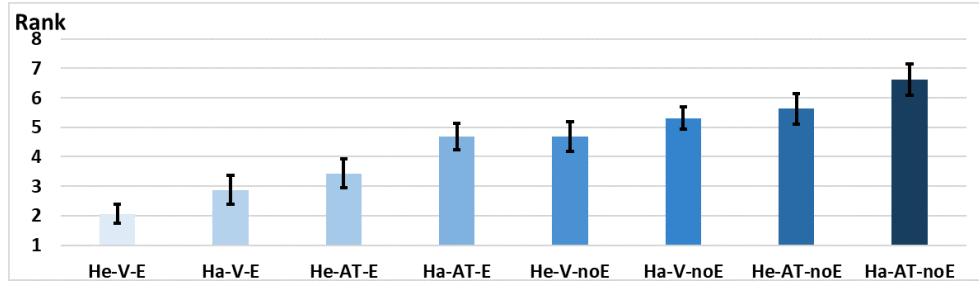


Figure 3.8 – Ranking of the eight methods according to user preference. The 1st rank indicates the most preferred and the 8th the least.

3.4.8. Discussion

Overall, if only the POINT DESIGN mode was considered, this experiment showed that selection using *Expanded* points was faster than *No-Expanded* ones. However, expanding the data points significantly improved TCT using *Air-Tap* confirmation technique but not in the case of *Voice* command. Therefore, this result could not confirm **H1.1**.

I found that using *Voice* to activate selection was faster than *Air-Tap* gesture. This can be explained by the gesture recognition performance mentioned in [83]. There was no significant difference between *Head* and *Hand* pointing techniques in terms of TCT or TED. However, due to the interaction between POINTING and SELECTION CONFIRMATION, *Head* pointing technique could affect the TED based on the SELECTION CONFIRMATION. In this case, *Air-Tap* could produce less TED than *Voice* technique. From the results of TED, contrary to my expectations, I did not find any significant difference between *Expanded* and *No-Expanded* points using different selection techniques, which did not support **H1.2**.

The heatmaps of TDCM shows that the participants had two difficulties in selecting data points. The first is related to the relative position of data point to the central part of the data board. Points near the edges were difficult to select despite the point model (expanded or not). The second concerns the order with which the participant selects data points. The participants took more effort to select the first targets but they got better afterwards.

The results of the subscale cognitive load analysis of NASA-TLX showed that for all the subscales except mental demand, *Expanded* condition has been rated less demanding than *No-Expanded*. Amongst the two techniques for SELECTION CONFIRMATION, *Air-Tap* was rated more demanding than *Voice* with regard to physical demand, temporal demand, effort, and frustration. The participants preferred the condition with *Head* pointing and *Voice* confirmation command with *Expanded* points than the others.

3.5. Improvement of Proposed Technique

In this selection, I will elaborate some ideas for improving and adapting the technique to expand data point technique in IA on different types of data points. I also propose a new refinement technique to improve the selection technique on HMD-based AR interface.

3.5.1. Towards a Generalisation of Expanded-Data-Point Technique

This section introduces how expanded-data-point approach can be used on different data representations (e.g., arrows, spheres, cubes, glyphs) in 2D and 3D graphs with potential occlusion or overlapping in dense clusters. In the context of IA, when I refer to overlapping of data points, it means that multiple data points in a dataset occupy a small space or take up close positions in the feature space or on a graph. In other words, their values or coordinates are closely similar or identical. In order to detect the occlusion, the data can be easily pre-analysed before the visualisation using one of the classic data mining techniques for cluster analysis such as k-means [245], hierarchical clustering [246], and density-based clustering [247].

Non-overlapped Data Points

With non-overlapped data points, I propose an expanding technique of 3D data points that can be applied both in 2D plan and 3D plan. In the design of expanded data points displayed in the 2D plan, I use arrow shape to represent data points but my proposed approach is also pertinent for all types of data representation (sphere, cube, glyph, etc.). I choose arrows as they often represent vector data types, which are popular in geophysical, geospatial, or meteorological datasets. An arrow pointing in a particular direction in 3D can represent the direction of a vector (u, v, w) , while its length and/or colour can be used for other properties.

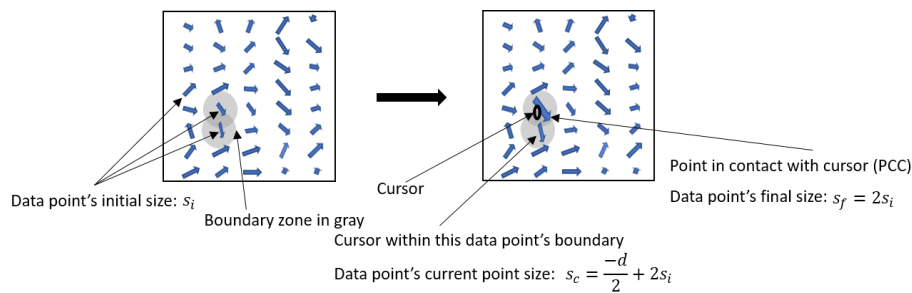


Figure 3.9 – Design of expanded data points visualised on a 2D plane. The visualisation shows wind direction as vectors and wind force simulated on a regular 2D grid with latitude and longitude coordinates.

In an example in Fig. 3.9, I present some data points of wind direction in 3D and wind force simulated on a regular 2D grid with latitude and longitude

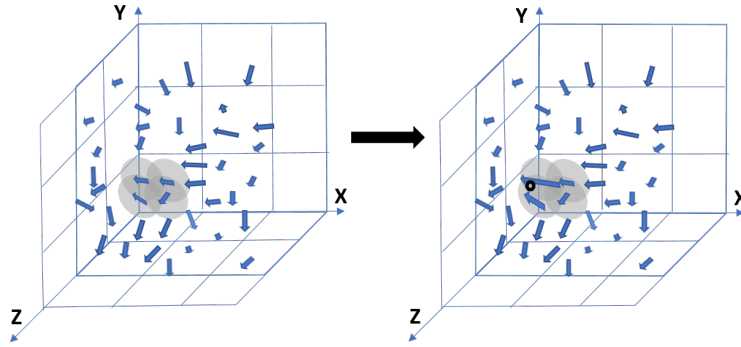


Figure 3.10 – Design of expanded 3D data points in a 3D space. The data includes 3D vectors visualising the wind (wind direction and wind force) simulated in 3D space with latitude, longitude, and elevation coordinates.

coordinates. Using the expanded-data-point approach, during the selection, the arrows can dynamically resized depending on their proximity to the user's cursor. We define an invisible boundary (a sphere in 3D) surrounding each data point. Given s_i the initial size of a data point, its boundary radius is $r = 2s_i$. When the cursor is within this boundary, the data point expands its size following the next equation:

$$s_c = \frac{-d}{2} + 2s_i \quad (3.6)$$

where s_c is current size, s_i is initial size, and d is the distance between the current cursor's position and the centre of boundary.

To avoid overlapping as in the first technique (Equation 3.3) when the points expand, I_i must be greater than 0.

$$I_i = D - \frac{s_i + s_{i+1}}{2} = D - \frac{3}{2}s_i. \quad (3.7)$$

Thus from Equation 3.7 we have: $I_i > 0 \Rightarrow D > \frac{3s_i}{2}$, where I_i is the distance between two data points (P_i and P_{i+1} in Fig. 3.2).

Once the cursor reaches the data point, its size is at the maximum value of $2s_i$. On the other hand, when the cursor moves away from the data point, its size gradually decreases until it goes back to the original size of s_i when the cursor goes beyond the boundary. If the boundaries of several data points are overlapped and the cursor is within the intersection, each of these data points will expand proportionally according to Equation 3.6. The same principles can be applied for the interaction between cursor and data points during the selection of the 3D data points in 3D space (see Fig. 3.10).

I apply the same principles for the interaction between cursor and data points during the selection of the 3D data points in 3D space (see Fig. 3.10).

Overlapped Data Points

To design expanded data points in overlapped data clusters, I propose the following approach of “exploding” the neighbourhood of the data point in focus with regard to its nearest data points (see Fig. 3.11). This algorithm will work with all the data points that have been pre-labelled as in the dense clusters using cluster analysis techniques as mentioned above. This algorithm looks at all the neighbourhood points within a predefined distance that surround the data point that has come in contact with the cursor (Point in Contact with Cursor - PCC). By creating a spatial buffer between the PCC and its neighbours, it allows sufficient space for the data points to expand their size.

Specifically, when the cursor hovers over in the boundary zone of a data point (PCC) with its initial size s_i :

1. The first step consists in determining the PCC's neighbourhood by considering all data points of the same cluster that the PCC belongs to. Two radii (r and R with $r < R$) from the PCC centre are defined. The distances between PCC and all the points of the same cluster are calculated. If the distance is inferior to r , the data point is considered as in the immediate neighbourhood. If the distance is between r and R , the data point is a distant neighbour. If it is out of range of R , the data point will not be taken into account for the next step.
2. This step consists in adding space between the data points in the immediate and distant neighbourhood and PCC. For the immediate neighbourhood, the distance between each data point in this zone and PCC will be increased an r value. And for the ones in distant neighbourhood, their respective distance to PCC will be added an R value.
3. The final step consists in changing the size of CCP to $2s_i$ and the immediate neighbourhood to $3s_i/2$.

When the cursor is at the intersection of several boundary zones, only the data point that is closest to the cursor will be considered as PCC. In this design, I used a cube representation; but the technique can be used with other representations (sphere, line, glyph, etc.).

3.5.2. Refinement for Selection Technique

I propose a new approach for accurate pointing by following a paradigm that combines a primary point method and a refinement technique. My approach uses the user's head for ray-casting in normal cases and when the accuracy to select the target is needed, the user can activate the refinement mode by using their hand gesture. The flowchart of the whole process of the algorithm is illustrated in Fig. 3.12.

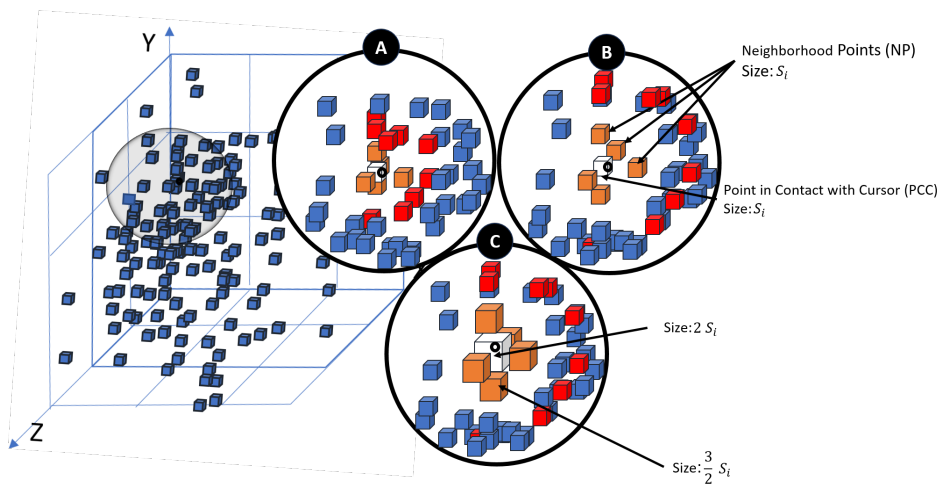


Figure 3.11 – Algorithm of expanding data points by adding distance between the data point in contact with the cursor (PCC) and its neighbouring data points. A) Immediate neighbourhood is detected, represented by orange data points, while the distant neighbouring points are in red. B) Space is added between these data points and the PCC to create a buffer for expansion. C) PCC and the data points in the immediate neighbourhood are expanded.

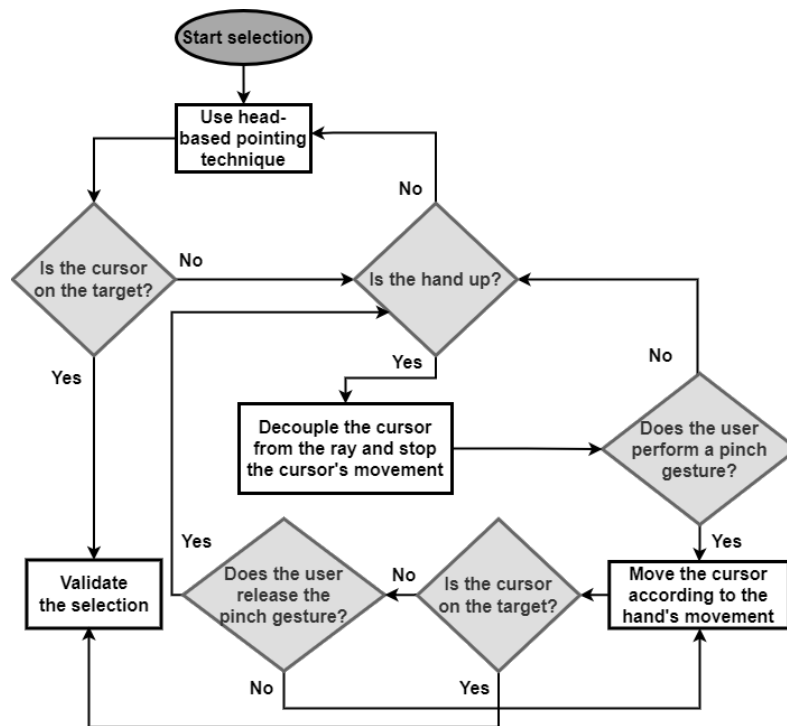


Figure 3.12 – Flowchart of the process of the head-pointing and hand-refining technique for selection.

Head-and-Hand Switching Technique for Pointing using Ray-casting

This algorithm is designed to be used during the selection process which involves mostly the head-based approach to control the ray and the cursor. It is triggered when the user's hand is raised and detected by the Microsoft HoloLens 2 headset. Once the trigger is recorded, the system will decouple the cursor's attachment from the ray and freeze its movement. A loop of checking the pinch gesture performed by the user and their hand movement is executed to control the position of the cursor accordingly (Fig. 3.13.A). The loop continues until either the cursor is on the target (which allows the user to validate it), or the user releases the pinch gesture (Fig. 3.13.B). The control of the cursor's position will go back to the ray (and thus controlled again by the user's head) once the headset cannot track the hand anymore (Fig. 3.13.C). This pointing technique can be easily integrated in the whole selection workflow with different techniques of selection confirmation using voice or other hand gestures.

During the control loop of the cursor's position by the pinch gesture and hand movement, the PRISM (Precise and Rapid Interaction through Scaled Manipulation) technique [248] is applied to improve the accuracy of the cursor's position in relation to the hand movement. Concretely, three velocity values are predefined: Min, Scaling Constant (SC), and Max. If the user's hand velocity is lower than

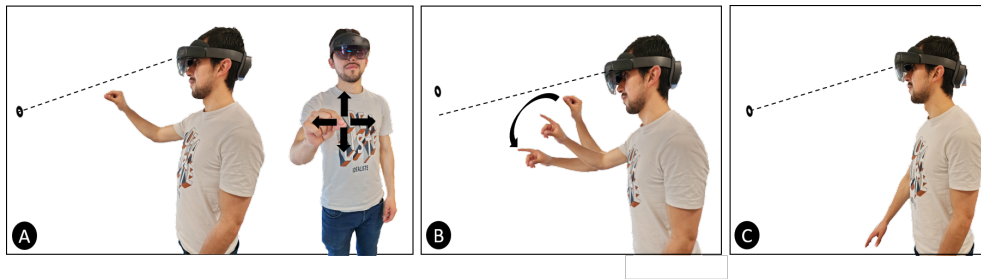


Figure 3.13 – Switching technique between head and hand to control the ray-casting attached to a cursor during pointing operation using an AR HMD device (Microsoft HoloLens 2). The ray and cursor follow the user's field of view based on the head's forward direction. A) When the user's hand is up (and the HMD can track the hand), the direct link between the ray and the cursor is decoupled, and the cursor stops moving. If the user makes a pinch gesture (pinching the thumb with the index), the cursor follows the hand and moves accordingly within a 2D plane. B) If the user releases the pinch while their hand is still tracked, the cursor becomes immobile again. The user can repeat the pinch gesture as in A) to adjust the cursor's position for better refinement. C) When the hand is down and untracked, the cursor reattaches to the ray and follows the head movement.

Min value, the cursor stays still. If it is between Min and SC, the cursor's motion is scaled down from the hand's motion. As soon as the user moves their hand at the velocity above SC, the cursor's velocity will match exactly to the hand's. And once the user's hand velocity exceeds Max value, besides the 1:1 matching between the velocity of the hand and cursor, a recovery procedure is applied to reduce offset (accumulated distance between the hand and the cursor) over time until the offset is eliminated or the hand speed falls below Max. The advantage of using PRISM for cursor movement is that it provides a fine-grained control over the cursor's movement, facilitating the user's precise adjustments and movements. This is especially useful for tasks requiring high accuracy levels such as data point selection. Additionally, using PRISM can reduce fatigue and strain, allowing the user to move the cursor using more natural hand movements.

Implementation

The technique was implemented in AR interfaces on Microsoft HoloLens 2 using Unity3D version 2021.3.31f1 and Mixed Reality Toolkit 2 (MRTK2). The algorithm of this technique can be found in Algorithm 1. Specifically, I used `IMixedRealityHandJointService` provided in MRTK2 for the hand-joint data. I obtained the origin (position and orientation) of the palm's centre using the `RequestJointTransform(param1,param2)` function, which is used as the origin of the hand pointing. The `param1` specifies which joint or part of the hand for tracking; in our case, it is set to `TrackedHandJoint.Palm`. The `param2` specifies which hand to track and I used `Handedness.Right`. I used the same function to get the finger data by changing the parameters using

Algorithm 1 Head-and-Hand Switching Approach for Selection Technique

```
procedure HeandPointingHandRefining
  jointPose  $\leftarrow$  TryGetJointPose(Palm, HandRight)
  while true do
    if jointPose then
      PalmjointTransform  $\leftarrow$  RequestJointTransform(Palm, HandRight)
      ThumbjointTransform  $\leftarrow$  RequestJointTransform(ThumbTip, HandRight)
      IndexjointTransform  $\leftarrow$  RequestJointTransform(IndexTip, HandRight)
      PalmHeadDist  $\leftarrow$  Distance(PalmjointTransform.position, Head.position)
      if PalmHeadDist  $\leq$  DeltaDistA then
        ThumbIndexDist  $\leftarrow$  Distance(ThumbjointTransform.position, IndexjointTransform.position)
        if ThumbIndexDist  $\leq$  DeltaDistB then
          CursorNextPosition  $\leftarrow$  PRISM(CursorLastPosition, PalmjointTransform.Position)
          MoveCursor(CursorNextPosition)
          CursorLastPosition  $\leftarrow$  CursorNextPosition
        else
          FreezeCursor(CursorLastPosition)
        end if
      end if
    else
      MoveCursor(HeadPostion, HeadForwardDirection)
    end if
  else
    MoveCursor(HeadPostion, HeadForwardDirection)
  end if
end while
end procedure
```

RequestJointTransform(TrackedHandJoint.ThumbTip, Handedness.Right) for the thumb tip and the RequestJointTransform(TrackedHandJoint.IndexTip, Handedness.Right) for the index tip.

In the pseudo-code (Algorithm 1), DeltaDistA and DeltaDistB are the thresholds to be set. DeltaDistA is the threshold distance between the user's hand and head. In the implementation, the DeltaDistA was set at 0.4m because with different values [0, 0.1, 0.2, ..., 1] tested, I found that 0.4m was the easiest to use. This parameter is important because it will let us know when to stop the cursor from moving. When the value is too large, the cursor may frequently stop involuntarily, affecting the user experience. DeltaDistB is the threshold used to determine if the finger has been pinched. It must be close to zero for good accuracy. Fig. 3.14 shows a sequence of hand gestures to activate the head-and-hand switching approach for selection.

3.6. Conclusion

In this chapter, I presented an expandable data representation model inspired by the study in [244]. I have conducted an experiment to assess this novel selection technique. The result showed that the selection using *Expanded* points was faster than *No-Expanded* ones considering only the POINT DESIGN mode. Moreover, *Voice* confirmation was rated as the best selection technique from subjective feedback. Consequently, the *Expanded* data point design received positive feedback in

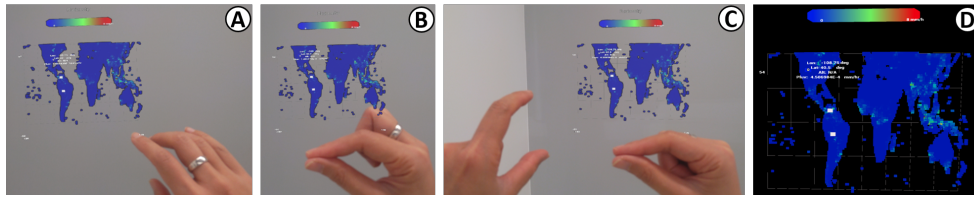


Figure 3.14 – Different hand gestures to activate the Head-and-Hand switching technique for pointing and selection. A) The user raises their hand to activate this technique from the default technique of cursor control by the head. The cursor stops moving. B) The user presses their index finger with the thumb, and the cursor starts following their hand movement. C) The user confirms the selection by using the Air-Tap gesture with either the right or left hand. D) A close-up view of the meteorological dataset with dense data points on the HMD-based AR interface.

regardless of the pointing and confirmation technique in use.

In summary, although **H1.1** and **H1.2** were not fully confirmed, the results show that *Expanded* data points improved performance and user experience, compared to *Non-Expanded* data points, answering the **RQ2**. Therefore, I decided to use the *Head-Voice-Expanded* combination as the selection technique for my proposed IA environment (Chapter 4) for three reasons. First, the experiment results showed that the *Expanded* points were easy and faster to select. Second, *Voice* command was less tiring and more preferred by the participants and *Head* pointing also received a lot of positive feedback. Finally, the combination of the three techniques was rated by most participants as their best technique for selection.

However, the experiment still had many limitations. In this study, the selection technique was considered only for visualising 3D data points regularly tiled on a 2D plane. Moreover, the multi-target selection was not evaluated.

To adapt this proposed technique to another type of data point, I proposed in Section 3.5.1 a solution to generalise this technique to overlapped and non-overlapped 3D data points displayed in a 3D space. Moreover, I designed and implemented a novel technique of decoupling head movement for pointing and hand gestures for pointing refinement to improve its accuracy. In the future, a user study must be conducted to confirm this enhancement.

4 - Immersive Analytics with Augmented Reality in Meteorology: An Exploratory Study on Ontology and Linked Data

This chapter addresses some multi-scale data visualisation challenges in Immersive Analytics (IA) through Augmented Reality (AR). To tackle these issues, I will present an ontological approach for handling multi-scale meteorological datasets. In a user study conducted to evaluate this approach, meteorology serves as the proof of concept, demonstrating the approach's effectiveness with inherently multi-scale data. Nonetheless, this methodology can be applied to other IA systems utilising AR. The chapter concludes with a discussion of open problems related to this contribution.

4.1. Introduction

In Section 2.2.4, I have discussed how the AR technology could bring great benefits to meteorological data analytics. However, the limited field of view of AR Head-Mounted Displays (HMD) may hinder the analysis process when there is too much data to visualise all at once, which often happens in the context of complex data analytics tasks with large datasets. In addition, most Virtual Reality (VR) and AR applications in IA use NoSQL databases to store and query data [249, 250, 251], and to handle large volumes of unstructured or semi-structured data [252, 253, 254]. However, NoSQL databases are sometimes limited in terms of reasoning and inference capabilities, and therefore, may not support some range of queries.

One approach to help reduce the complexity of the datasets and to accelerate the analytical reasoning process is to rely on the previous knowledge of the related domain(s) in the form of ontology and linked data. Essentially, an ontology, as defined by Thomas Gruber, is "a specification of a representational vocabulary for a shared domain of discourse - definitions of classes, relations, functions, and other objects" [255]. Over the last decades, we have witnessed a colossal effort of many experts in different scientific fields who aimed to build and share their own ontologies (e.g., life sciences [256], climatology [186], biomedicine [257]). In semantic web technologies, ontologies are utilised to aid in the comprehension and manipulation of data. By linking structured data, linked data can enhance its utility through semantic queries [258]. Despite the fact that ontology and linked data are field-dependent, once the domain knowledge has been formulated, it can be easily reused in many applications.

This chapter proposes an exploratory study on the use of a semantic approach in AR-based IA and addresses the following research question:

RQ1: Can the semantic-based approach facilitate visualisation and analysis in immersive analytics for meteorological data?

My case study uses meteorological datasets collected from different sources of real measurements and simulations. These datasets include heterogeneous and multi-scale big data on temperature, heat flux, precipitation, humidity, wind velocity, amongst others. I consider this a typical example to demonstrate the interest of the semantic based approach in a real-world IA application. I will present next the design and the development of a proof of concept of an AR interface using an ontology to demonstrate how such approach enables the user to display appropriate data during the interaction and to enhance their performance in the data analytics process. To bring forth the advantages of ontology and linked data in this IA application, I examined different ontologies in meteorology and climatology and design an ontology based on the existing ones. Indeed, the meteorological and climatological ontologies in the literature are often large or complex in terms of concepts and dependencies on other ontologies, which reduces the query performance in AR-based systems. Moreover, they also lack certain rules and concepts to allow the user to accurately formulate queries to some specific part of the datasets. Finally, I evaluated the potential of my AR-based IA system in conducting an experiment that aims to demonstrate the relevance of my semantic approach compared to a conventional non-ontological one. This chapter is based on work accepted for publication at Virtual Reality Springer [259].

4.2. Semantic Immersive Analytics Framework

I present in this section my semantic IA framework which follows the ontology and linked data approach to support the AR-based IA process to analyse meteorological data.

4.2.1. Design Overview

The semantic IA pipeline consists of four processes (*Data*, *Models*, *Knowledge*, and *Visualisation*) proposed by Keim *et al.* [2] with some modifications (Fig. 4.1).

Data process is an essential step in the framework (cf. **Data Processing and Concept Modelling** component in Fig. 4.1). It aims to transform heterogeneous data to homogeneous one. Indeed, meteorological data is mainly spatial-temporal, but is collected from different sources (e.g., satellites, radar, weather balloons, etc.). It must be transformed to be used for querying and visualising. Therefore, our first concern was to set up our own ontology model in this specific domain. I then instantiated ontological individuals (via Resource Description Framework (RDF) triples) to semantically link raw data to some of the classes of our ontology.

Visualisation process allows the user to explore the data interactively. This process is managed by Visualisation Engine via User Interface modules of **Interacting**

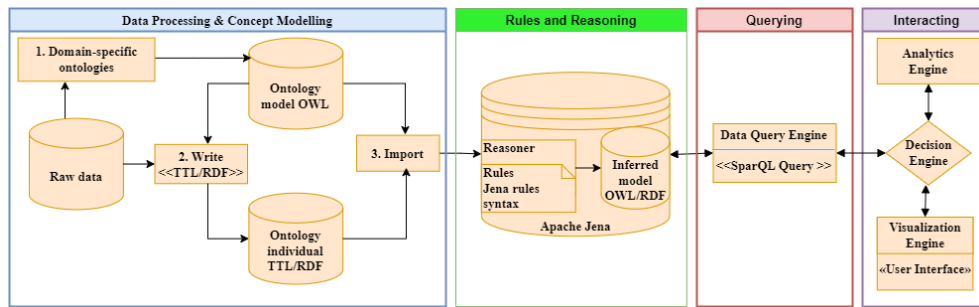


Figure 4.1 – Overview of our semantic immersive analytics approach.

component in order to gain *Knowledge* from data. However, in some cases, *Visualisation* process alone is not enough to extract domain knowledge via **Querying** component, and it must be coupled with an analysis step (cf. Analytics Engine) which is characterised by the *Models* process. This process allows users to automatically extract information from data, targeting the *Knowledge* process. It is managed within **Rules and Reasoning** component, which infers the model via a reasoning engine (cf. Reasoner). I will detail next the design and implementation of each component.

4.2.2. Data Processing and Concept Modelling

As highlighted in Section 2.3, the existing ontologies for meteorology and climatology are often very large or complex in terms of concepts/classes and dependencies (e.g., SWEET, NNEW described in Section 2.3.2). Some ontologies also lack some of the concepts that are needed in our application (e.g., SSN, AEMET, SMEAR, ACORN-SAT), or are designed for very specific datasets (e.g., AEMET, ACORN-SAT). To avoid overloading of RDF database which stores the data in the form of linked data, I propose an ontology using SSN as a core, extend it by other specific ontologies such as units and time, and add more classes and rules for the system.

To design the domain-specific ontology, there are different approaches (e.g., [260, 261, 262, 263]) which helps to avoid common pitfalls. I built the ontology (Fig. 4.2) following “Ontology development 101” approach [263]. It provides an intuitive and iterative tool to build ontologies with basic knowledge of their design process. This approach is divided into sequential steps as follows:

- Step 1: Identifying the domain and scope of the ontology. In this step, questions related to expertise (also called competency questions) were formulated with the meteorologists I collaborated with at LATMOS (Laboratoire Atmosphères, Observations Spatiales), and the ontology must be able to answer them. Some examples of the formulated competency questions are:

Q1: What is the wind state according to the Beaufort scale Table [264]?

- Q2: Is there a depression/anticyclone?
- Q3: When/Where does the cyclone phenomenon start/ends?
- Q4: Where is the eye of the cyclone phenomenon?
- Q5: What is the temperature, humidity, precipitation, wind speed, and other recorded values at a specific place, time and date?
- Q6: What is the minimum/maximum temperature, humidity, wind speed, and other recorded values at a specific place, time and date?
- Q7: Is there sunshine at a specific place, time and date?
- Q8: When/Where does the temperature drop/stay below 0° Celsius?
- Q9: Over a period of time, what is the highest/lowest temperature, pressure, precipitation, pressure and other values recorded, and at which specific place, time and date?
- Step 2: Considering the reuse of existing ontologies in the context of IA, the chosen ones should be understandable for future extension with classes, properties, and rules to facilitate data integration and resampling. Moreover, to support real-time interaction required in AR and VR applications, the existing ontologies to be selected must have only few dependencies with others, to avoid overloading the RDF database in favour of query response time, an important factor for fluid interaction in IA. Therefore, I chose to reuse in a modular structure the four following ontologies (Fig. 4.2):
 - SSN** [182] describes sensors and observations. It is composed of 41 concepts and 39 object properties organised into ten modules, inheriting directly from DUL 11 concepts and 14 object properties [183].
 - OWL Time** [188] describes temporal concepts and expresses the relationship between temporal entities.
 - WGS84_pos** [265] is used to describe the coordinates (latitude, longitude, and altitude) and other related information about spatially-located objects (e.g., size, shape, etc.).
 - Units** [189] represents different units of measurement and the relation between them.
 - Step 3: Enumerating domain-dependent terms. This step consists in defining the terms of the ontology glossary. This glossary is extracted from competency questions (formulated in Step 1). In this case, it contains terms such as: Wind state, Light winds, Light breeze, Gentle breeze, Fresh breeze, Strong breeze, Storm, Hurricane, Pressure, Average pressure, Depression, Anticyclone, Cyclone, Phenomenon, Cyclone eye, Temperature, Cold, Dew point, Precipitation, Humidity, Wind, Sunshine, Cloud, etc.
 - Step 4: Identifying concepts amongst all the terms defined in Step 3. The class of a concept either already exists in the reused ontologies and if not, this concept is added as a new class in the ontology. Following this process, I introduced 28 new classes (Fig. 4.2). They are then linked together to create a class hierarchy through the relationship of *subclass-of*

or *is-a* (Fig. 4.3).

- Step 5: Iterating over all the classes and determining the terms in the set of terminology that are properties. The properties are used to connect two individuals (object properties) or to connect a subject with an attribute and to define data types (data properties). Following this process, I identified 21 object properties. Some exist in the reused ontologies such as: Location, Longitude, Latitude, Altitude, etc. Some others have been added as new ones such as: hasTemperature, hasHeat, hasPressure, hasWindForce/hasWindVelocity, hasHumidity, hasDirection, hasWindState, belongsObservation, hasDewPoint, hasWeather, hasCloud, etc. I also identified 16 data properties. Existing ones are, for instance: hour, resultTime, hasSimpleResult, hasXSDDuration, etc. I also added others such as: hasMin, hasMax, hasTemperatureValue, hasPressureValue, heatRate, hasDirectionU, hasDirectionV, hasHeatValue, hasSource, hasDewPointValue, etc.
- Step 6: Specifying possible domains and ranges of values for the new properties defined in Step 5. The domain states that any resource that has a given property is an instance of one or more classes. The range states that the values of a property are instances of one or more classes [266].
- Step 7: Defining instances of the classes and adding them into the ontology. This step transforms the data into RDF triples based on the ontology.

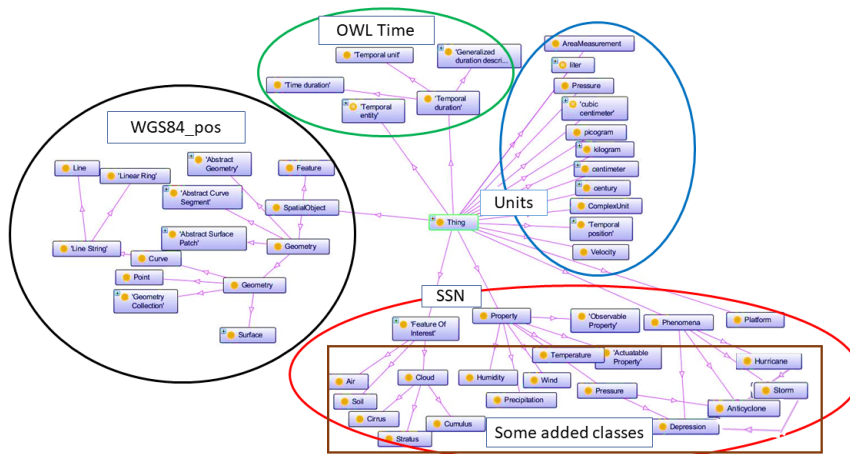


Figure 4.2 – A representative part of our ontology model. Different modules are represented with specific colours: black, green, blue, and red, representing respectively the WGS84_pos, Time, Units, and SSN ontologies (along with our additional classes).

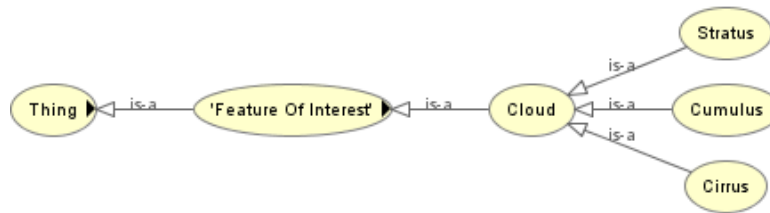


Figure 4.3 – Using *subclass-of* or *is-a* to specify class inheritance.

4.2.3. Rules and Reasoning

The inferred model (cf. **Rules and Reasoning** in Fig. 4.1) allows the sampling and feature extraction of data. To perform reasoning process (i.e. deducing knowledge), I need reasoners and syntactic rules. Reasoners are used to compute or derive new facts from existing knowledge. Many reasoners exist (e.g., OWLIM-lite [267], Jena [268], Fuxi [269], EYE [270]) with their pros and cons [271]. Amongst them, Jena is a Java-based open-source application framework for semantic web applications. I selected this framework because of its predefined reasoners, and especially its generic rule reasoner. This latter provides human-readable syntax with short rules to simplify notation. It also supports user-defined rules written in Jena format.

The ontology model was defined using basic rules between classes such as transitivity, disjunction, and equivalence. Moreover, as mentioned above, the ontologies I reused do not address specifically meteorological phenomena and I thus added concepts and properties to target them. I also introduced in the inferred model a number of rules enabling the extraction of data that must be classified as an instance of specific phenomena (e.g., storm, hurricane). Some of these rules have been used to help the users perform tasks in the experiment (Section 4.3).

For example, rule R1 (cf. Listing 4.1) determining the set of data points of a depression is based on pressure property (in Hectopascal (hPa)). As a Storm *is-a* Depression, to determine if this same set of data points describes also a storm, rule R2 (cf. Listing 4.2) only needs to analyse the wind speed property (in m/s). Listings 4.1 & 4.2 present these rules written in Jena generic.

```

1 [isDepressionPoint:
2 (?p rdf:type local:Pressure)
3 (?p local:hasPressure ?pressure)
4 le(?pressure,1013.2)
5 (?p geo:location ?coordinate)
6 ->( ?coordinate rdf:type local:Depression)]

```

Listing 4.1 – Depression Rule (R1).

```

1 [isThePointInSTorm:
2 (?w rdf:type local:Wind)
3 (?w local:hasWindForce ?force)
4 ge(?force,17.43)le(?force, 32.63)
5 (?w geo:location ?coordinate)

```

```

6 (?coordinate rdf:type local:Depression)
7 ->(?w rdf:type local:Storm )]

```

Listing 4.2 – Storm Rule (R2).

4.2.4. Data Query Engine

Once the RDF database is established, it is crucial to set up a data query engine that can extract and process the data for visualisation in response to real-time interaction events from the user interface. Our system relies on the use of SPARQL query language, which is based on different query forms such as: SELECT, CONSTRUCT, ASK and DESCRIBE [272]. To support the interaction, I set up different manipulation and voice commands on the AR interface using Microsoft HoloLens 2: to trigger generic actions (e.g., show the main menu "Main menu", to select a button "Select"), or to make queries on field-dependent information (e.g., to display data of "Wind Velocity", "Pressure", "Depression", "Storm Zone", etc.). The querying process (cf. **Querying** in Fig. 4.1) allows the user to filter the data or a part of the data.

For example, via a SELECT operation automatically generated by a simple voice command, the user can request part of data which satisfies the specific rule R2 about the storm to highlight the related data points in the immersive environment (see Fig. 4.4).

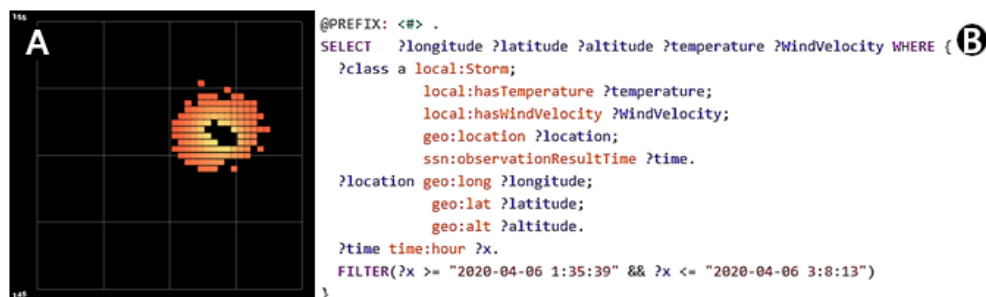


Figure 4.4 – Left: Data points resulting from the "Storm Zone" voice command. Right: The corresponding SPARQL query to find all data points (individuals) belonging to the inference class Storm during a specific interval of time.

The user can also trigger an ASK operator to check whether an instance belongs to a specific class or satisfies some criteria. Some examples of ASK command include:

- To check if a class belongs to another class.

```

1 ASK {local: Strabus
2     rdfs: subClassOf local: Cloud
3 }

```

The response is true for this case.

- To check if an individual of a specific class satisfies some criteria:

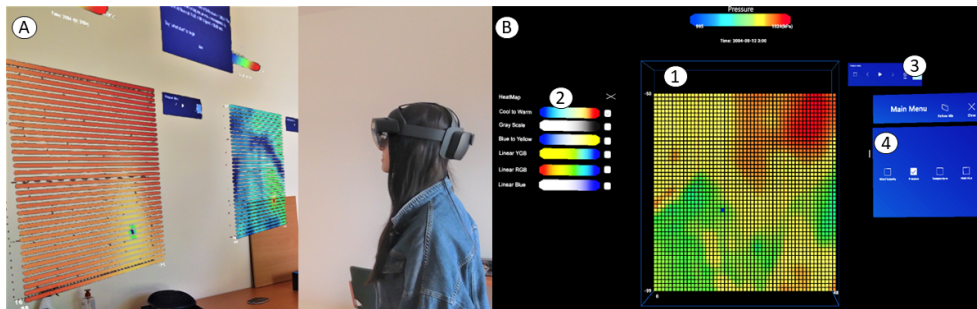


Figure 4.5 – A) A user performs meteorological data exploration and analysis tasks using an Augmented Reality headset. The data is linked between graphs, facilitating the analysis of associated variables of a phenomenon. B) Some features implemented for spatial-temporal data exploration: (1) Bounding box for data manipulation, (2) Toolbox offering different colour maps for data visualisation, (3) Toolbox for animations of spatio-temporal data, and (4) Main menu to choose the weather observation(s) to visualise. Thanks to ontology and linked data, it is possible to animate different variables in the same temporal context.

```

1 ASK {
2   ?class a local:Storm;
3     geo:location ?location.
4   ?location geo:lat "150"^^unit:deg;
5     geo:long "-20"^^unit:deg.
6 }

```

This request checks whether the data point with latitude of 150 degrees and longitude of -20 degrees in the database is situated in a storm area.

— To perform some reasoning by automatically using SPARQL queries.

```

1 ASK {ssn: 'Feature of interest'
2   rdfs: subclassOf local: Cirrus
3 }

```

The response will be true despite the absence of an explicit direct link between the two concepts.

The data resampling based on this querying process allows the user to visualise only the data of interest. In the context of AR-based IA, it is beneficial from two main aspects. First, in terms of visualisation and interaction, the limited field of view of some AR headsets makes their use tiring for the user, which can affect user experience. The resampling helps to filter the data to show only relevant part of it. Second, concerning computational power, this process will help to save the GPU calculation to facilitate the big and complex data rendering. Moreover, ASK commands allow the user to check relevant information before displaying it.

4.2.5. Analytics Engine and Interaction

The IA environment has been designed based on the features and limitations of the AR headset (Microsoft HoloLens 2) I used in this study (see Fig. 4.5). The

system follows a client-server architecture that separates database management and interaction components.

The AR interface allows the user to integrate data from different sources and to understand the relationship between the data thanks to the semantic links. It can be used by both novice and advanced users. I focus on AR technology for immersive analytics because it provides the user with a large workspace and its potential for co-localised immersive collaboration.

I implemented different interaction techniques following the O+D design paradigm for interactive data exploration at various levels of detail [140, 141]. For instance, with Context-on-demand, the user can see all the details of a particular point by selecting it (Fig. 4.6). The system also supports voice commands and air-tap gestures to confirm the selection. The touch interaction was implemented, but due to a tracking issue and the large number of data points in the experiment (Section 4.3), it was not accurate for selection and is not considered in the user study. Moreover, the Microsoft HoloLens 2 headset's existing pointing techniques (see Section 2.1) do not help to avoid the Eisenberg effect [86] when selecting distant and small objects. To overcome this issue, based on the result of an experiment in Chapter 3, I chose to use the Expanded Data Points selection technique proposed in Section 3.3 with the head pointing and voice validation technique. Since I also deal with temporal datasets, I implemented both automated and manual animation control to visualise the data that changes over time.

The user can make queries of different types of data (e.g., pressure, temperature, humidity, wind) and visualise it in graphs or scatter plots. Thanks to the links created between them in the ontology, when the user selects a data point in one representation, its corresponding points are also selected in others (Fig. 4.6.B). In addition, they can display a world map to pinpoint the source of the data based on the real spatial coordinates (Fig. 4.6.A). They can use two types of data representation: a pixel-based board for 2D data based on its longitude and latitude, and a voxel-based volume for 3D data with its 3D coordinates. The pixel-based board is a graph in which each cell is colour encoded. It illustrates meteorological data in conventional way by using colour maps to indicate the value of physical quantities (e.g., wind speed, pressure, humidity, etc.). Similarly, the voxel-based volume provides an overview of the multi-dimensional data in 3D space. For smooth rendering and performance management on Microsoft HoloLens 2, I used graphical shaders for data visualisations.

4.3. Use Case Study

I conducted an experiment to compare my ontological approach with the non-ontological baseline using an AR Microsoft HoloLens 2 headset. The experiment follows a counter-balanced within-subjects design with repeated measures and two independent factors considered as follows:

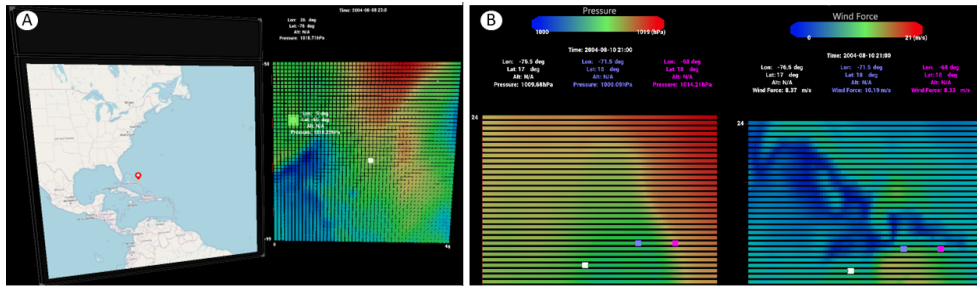


Figure 4.6 – A) The user interacts with the graph and the map: when they select a data point, it is highlighted on the map. B) The user can display multiple graphs together (e.g., pressure, temperature, wind velocity, etc.): when a point is selected on one graph, the corresponding points are automatically selected on the others.

- APPROACH (A) indicates whether the user uses *computer-assisted* (A1) or *non-computer-assisted* method (A2). Using A1, the user can get help from the underlying architecture of ontology and linked data (Fig. 4.7). For example, for task T2 (see Sec. 4.3.4), they can trigger a SPARQL query via voice command “Storm Zone” to automatically select all the data points belonging to a storm zone instead of manually looking for them. With A2, the data is stored in a MongoDB database under the document format. The user solves the tasks themselves based on given rules (e.g., Rule 1: a storm occurs when a depression area is accompanied by circular wind flow and wind speed between 17.43 and 32.63 m/s). Such rules was explained to participant during the training phase.

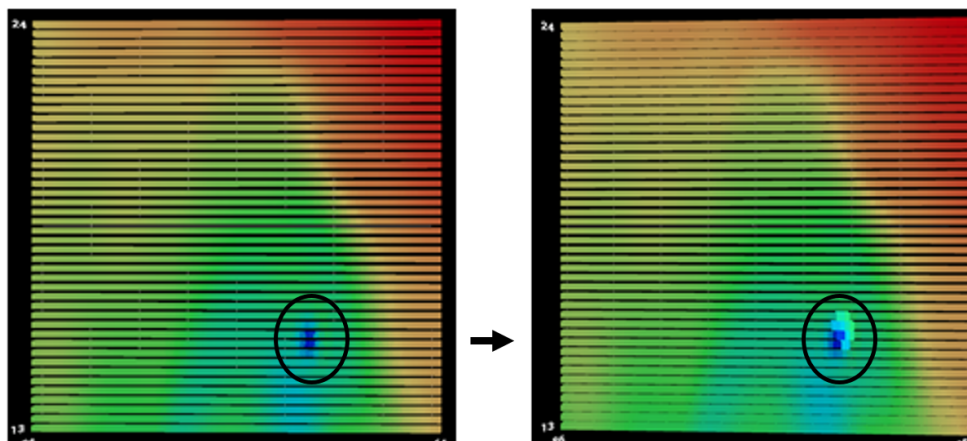


Figure 4.7 – When the user focuses their cursor on the graph and says “Storm Zone”, all the data points belonging to a storm zone that satisfy rule R2 (Listing 2) are highlighted in a more vivid colour. This region of interest is outlined by a black circle in the two figures for readability purposes.

- TASK (T) consists of three types of tasks (see Sec. 4.3.4) selected in the context of meteorological data analysis. Since I conducted this experiment

during the Covid pandemic with the participants from my university who are novice in this specific domain, the tasks were simplified. In this experiment, I used the data which includes surface pressure and wind speed from 09/08/2004 to 16/08/2004 simulating Hurricane Charley given by Alex Crosby *et al.* [273]. Nine separate subsets of the data were picked for training and evaluation tasks.

4.3.1. Hypotheses

I assumed that as the *computer-assisted* data analysis approach provided the user with an intelligent heterogeneous data integration and analysis in the IA environment, it would improve the analysis task performance. I formulated the following hypotheses:

- H2.1** It takes less time and effort for the user to solve data analysis tasks with the *computer-assisted* approach than with a *non-computer-assisted* one.
- H2.2** The *computer-assisted* will produce the least amount of errors and increase the user's confidence in their answers to the tasks.

4.3.2. Participants

Sixteen participants participated in this experiment, including 4 females and 12 males aged between 19 and 30 years old ($\mu = 24.25$, $\sigma = 3.66$) from my university. 14 were computer scientists, 13 had previously used an AR headset, and seven had used 3D visualisation software (e.g., CAD, 3D modelling, 3D data visualisation). None of them was working with meteorological data before. As the meteorologists of the Atmospheres, Space Observations Laboratory (LATMOS), have contributed in designing and evaluating the first prototype, we recruited non-experts in meteorology in this study in order to get a more generalised understanding of the ontological approach's performance with basic data analytics tasks. They could also provide valuable feedback for refining the system and making it applicable to a wider range of users and immersive analytics scenarios in domain applications.

4.3.3. Apparatus

The system was developed in Unity3D and ran on a Windows computer of Intel Xeon w-2135 processor, 32 GB RAM, and RTX 4000 graphics card. Microsoft HoloLens 2 was used for rendering and interaction. The 5 GHz Wi-Fi connected the desktop to the headset. Regarding the databases, I used Apache Jena Fuseki server for ontology and linked data for A1, and MongoDB for document data for A2 on Windows 10.

A comparison between these two databases was performed in terms of query response time according to the number of queried data points (see Fig. 4.8). The test was run on the same dataset using the same hardware for the experiment. It shows the disadvantage of Apache Jena Fuseki when the number of queried data points at one time increases over 1 million. Therefore, I did not consider the response times of the two databases for queries in the final task completion time

of the experiment.

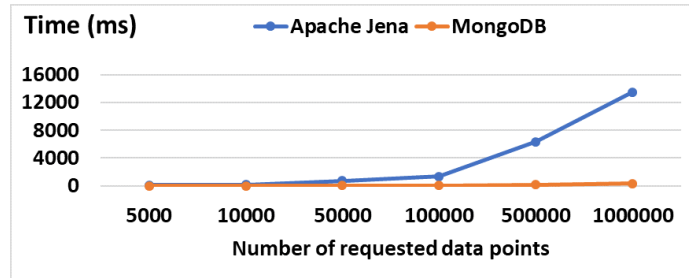


Figure 4.8 – Query response time according to the number of queried data points using two types of database server.

4.3.4. Experimental Tasks

There were three tasks T1 to T3 with increasing complexity (see Table 4.1) chosen according to the meteorological data analysis task process. Each task was solved within the two conditions (A1 and A2) on different datasets to limit the learning effect. T1 and T3 have two equivalent sub-tasks, X and Y, using two separate datasets. For example, if the T1X was used for A1 then T1Y was used for A2, and vice versa. There were 2450 data points for each graph in T1 and 3872 in T2. In T3, there were 3872 data points for each graph in each timestamp.

During T1, the participants must find the three lowest/highest pressure data points and their corresponding wind velocity. With T1 in A1 condition, thanks to the linked data, when the participant selected a data point in Pressure graph, its corresponding point was automatically highlighted in Wind Velocity graph (Fig. 4.6.B). With T1 in A2, they had to identify manually the corresponding wind velocity.

With T2 in A1, the participant could use the voice command “Storm Zone” (not mandatory), which triggered a SPARQL query to select all the data points for the specific date satisfying the rule R2 (Fig. 4.7). The user had to check before validating their choices. With T2 in A2, in order to balance the average time between the two conditions A1 and A2, the user had to find only four points in the storm areas.

Finally, in T3, they performed the task similar to T2 at three different timestamps.

4.3.5. Procedure

Each session lasted about 75 minutes. At the beginning, each participant was welcomed, signed a consent form, and received introduction of the system. Next, they filled out a pre-experimental questionnaire on demographic information. Afterwards, they were equipped with the AR headset. A pre-training session was conducted to familiarise the participant with the use of the headset, the user interface, its functions and interactions.

ID	Task
T1X	1. Find three lowest pressure points in Pressure graph. 2. Validate the corresponding points with the same coordinates in Wind Velocity graph.
T1Y	1. Find three highest pressure points in Pressure graph. 2. Validate the corresponding points with the same coordinates in Wind Velocity graph.
T2	Find four points in the storm area in both the Pressure graph and Wind Velocity graph.
T3X	Find the points in the storm area in both Pressure and Wind Velocity graph on 12/08/2004 at 02:00 & 17:00, and on 13/08/2004 at 11:00.
T3Y	Find the points in the storm area on both Pressure and Wind Velocity graph on 10/08/2004 at 21:00, 22:00 & 23:00.

Table 4.1 – Three types of tasks in the experiment.

There was a training phase before each task when the meteorological concepts and task instructions were explained on a training dataset. Subsequently, the participant started a task in A1 and A2 condition in a counter-balanced order on two different datasets.

After each condition, they filled out two questionnaires: NASA-TLX for cognitive load and SUS for system usability. At the end of each task, the participant also ranked the two conditions according to their preference and rated their confidence on the answers. The same process was repeated for all of the three tasks.

4.3.6. Data Collection

I collected data from 96 trials: 2 APPROACHES \times 3 TASKS \times 16 participants. For each trial, I registered the following measures.

Quantitative data:

- *Task Completion Time (TCT)*: the time needed to complete the task in each condition. It started when the participant initiated the task and ended once it was done. This time did not include the response time of queries to the databases.
- *Number of attempts*: the number of times the participant tried to reach requested data points during the task. It was calculated based on the number of times the cursor passes over them.
- *Answers to tasks*: the number of data points correctly selected. It was used to evaluate the correctness of the answers.

Subjective data:

- *System Usability Scale (SUS)*: the usability of each approach (A1 and A2) estimated after the task.
- *NASA-TLX*: the cognitive load of each approach estimated after the task.
- *Overall ranking*: the ranking of the two approaches according to the preference of the participant for each task.
- *Confidence score*: the degree of confidence in the participant's answer from 1 (not at all confident) to 7 (very confident) after having solved the task.

4.3.7. Statistical Results

Quantitative data: I used normal QQ-plots and Shapiro-Wilk tests to analyse the normality of all the data from the three quantitative measurements. Since none was normally distributed, I applied a log-transformation after an asymmetry test.

Regarding *Task Completion Time (TCT)* (see Fig. 4.9), a two-way repeated-measures ANOVA was used to evaluate the interaction of the two factors APPROACH and TASK. The result revealed that there was no significant interaction between them ($F_{2,90} = 0.80, p = 0.41$). The main effect test was performed and the result showed a significantly independent effect of TCT on APPROACH ($F_{1,90} = 44, p < 0.001$) as well as on TASK ($F_{2,90} = 20.7, p < 0.001$).

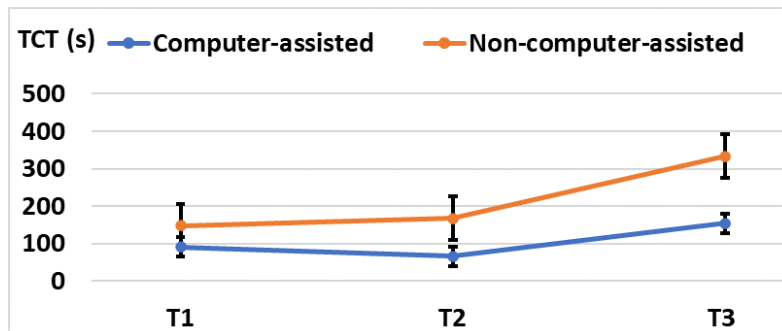


Figure 4.9 – Means and 95% CIs of Task Completion Time (TCT) in seconds for both of the approaches and the three tasks.

From *Number of attempts* (see Fig. 4.10), I analysed the interaction of the two factors using two-way repeated-measures ANOVA. I did not find any significant interaction effect between them ($F_{2,90} = 0.09, p = 0.91$). The main effect test showed that there was a significantly independent effect of this factor on APPROACH ($F_{2,90} = 8.60, p < 0.001$) and TASK ($F_{2,90} = 11, p < 0.001$).

To evaluate the correctness of *Answers to tasks*, the participants' responses were transformed into numerical data. I converted correct answers into 1 while the false ones into 0. The final result showed that there were only two wrong answers in the data.

Subjective data: With the answers from *System Usability Scale (SUS)* questionnaire, I used its score calculation method to compute *usability score*. The pair-

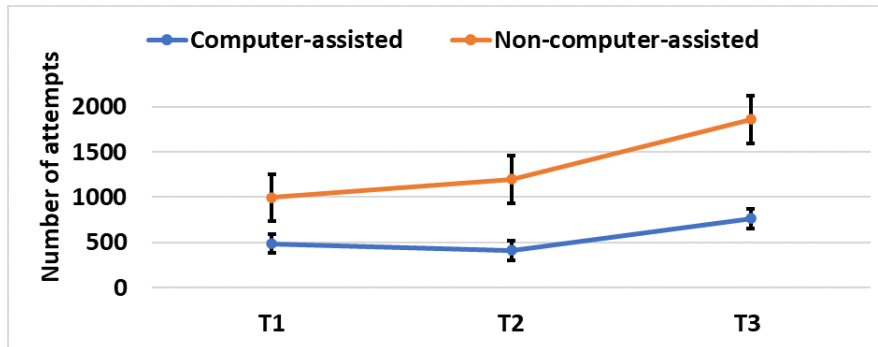


Figure 4.10 – Means and 95% CIs of *Number of attempts* for both of the approaches and the three tasks.

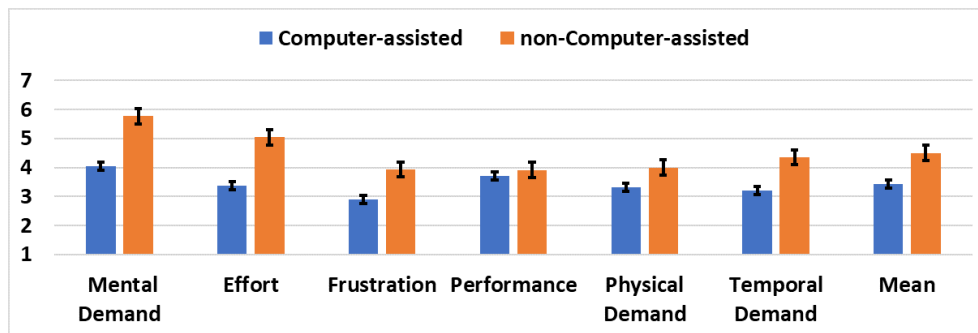


Figure 4.11 – NASA-TLX results are detailed in subscales for the two approaches.

sample t-test was used to compare the mean SUS scale values in *computer-assisted* ($\mu = 81.30, \sigma = 13.14$) and *non-computer-assisted* ($\mu = 71.77, \sigma = 16.60$). I found that there was a significant difference in the score ($p < 0.05$).

Concerning *NASA-TLX* (see Fig. 4.11), I used Wilcoxon signed-rank tests to analyse the overall workload. There was a significant difference between *computer-assisted* ($\mu = 24.24, \sigma = 17.02$) and *non-computer-assisted* ($\mu = 35.04, \sigma = 14.58$) workload ($p < 0.001$).

The answers from *Overall ranking* showed that all the participants preferred *computer-assisted* approach for *T1*, and 15 of them preferred the same approach for *T2* and *T3*.

I used Wilcoxon signed-rank tests for crossed comparison of *Confidence score*. The result showed that there was no significant difference between *computer-assisted* ($\mu = 6.06, \sigma = 1.04$) and *non-computer-assisted* ($\mu = 5.83, \sigma = 0.16$) on the score of confidence.

4.3.8. Discussion

The statistical analysis showed that *computer-assisted* approach based on ontology outperformed *non-computer-assisted* by means of *Task Completion Time (TCT)*. I also found that *computer-assisted* task required significant fewer number

of attempts made by the participants to solve the tasks. These two results support **H2.1**.

The answers to the tasks the participants gave were mostly correct for both conditions. The confidence score was also similarly rated. Therefore, I could not confirm **H2.2**. Both of these measurements can be explained by the fact that each participant was very well trained in different interaction techniques employed in the tasks and performed well with the minimum meteorological concepts required.

In terms of *usability score*, both of the approaches were rated positively in all the tasks even though *computer-assisted* was significantly rated higher on average than *non-computer-assisted*. Moreover, the participants perceived that solving the tasks using *computer-assisted* significantly reduced the cognitive load compared to *non-computer-assisted*. Overall, they preferred *computer-assisted* based on ontological approach to *non-computer-assisted* according to the questionnaires' answers. In general, *computer-assisted* approach received overwhelmingly positive feedback from all the participants.

The high *usability score* of the semantic approach confirms that it can be used to visualise and analyse complex data for meteorology. Using the same methodology can help to get this approach go beyond the meteorology domain. Specifically, considering an application field using immersive analytics, we can first analyse the concepts and knowledge required in the related domain to determine if some existing ontologies can be combined and/or extended to target the application. The second step is to establish domain-dependent inference rules to help users manage large datasets and, more specifically, to facilitate data queries in an immersive context. The third step is to tune these ontologies and rules according to the technical limitations of the chosen XR technologies. The final step is to experiment with the system using application scenarios and end-users to validate and enhance the inference rules and their related interactive paradigms.

4.4. Conclusion

Recently, Immersive Analytics (IA) using Augmented Reality (AR) technology has gained its popularity. Although AR facilitates data exploration and user experience, it is still challenging to visualise and interact with heterogeneous and big data from different sources. It is due to computational limits and the lack of appropriate methods to integrate such data in the same immersive environment.

To fill this gap, I proposed an approach based on semantic-knowledge representation using ontology and linked data. I explored its benefits in the context of meteorological data analysis. I designed and developed an AR-based IA environment for novices and experts to work on such diverse data sources, which are conceptualised and linked within an ontology.

In the first part of the chapter, I proposed a design of an ontology for meteorological data in AR-based IA. Following the "Ontology development 101" methodol-

ogy [263], the main features of this design process are: (i) identifying the domain and scope of the ontology, (ii) considering the reuse of existing ontologies, (iii) building the glossary of terms by enumerating domain dependent terms in meteorology with the end-users, (iv) identifying concepts among all this glossary, (v) iterating over all the classes to find the terms in the set of terminology that are properties, (vi) specifying the possible domains and ranges of values for each property previously defined, (vii) defining instances of the classes and adding them within the ontology. With this ontology set up, I designed and implemented an ontology-based AR system on Microsoft HoloLens 2 device for IA tasks on meteorological data. The second part of this chapter, I described the use case study I conducted to evaluate the interest of such ontological approach for an AR-based IA. The results show that the semantic-based approach does facilitate visualisation and analysis process in IA for meteorological data, answering the **RQ1**.

In the next chapter, I aim to assess the performance of this IA system using AR technology in a collaborative context.

5 - Physical Space Partitioning and View Privacy in AR-based Co-located Collaboration for Immersive Analytics

This chapter presents my new proposal on the automatic physical space partitioning technique, which also includes three generated virtual boundaries to highlight the workspace limit, and the co-located collaboration system using Augmented Reality (AR) technology. The physical space partitioning technique was designed by considering the available physical space and the various users' positions during their COLLABORATIVE IMMERSIVE ANALYTICS (IA) tasks. Although it has been constructed for IA, it can be applied to all generic co-located AR collaboration that involves both individual and shared tasks. In this chapter, after an introduction, I will detail the design and implementation of the physical space partitioning technique. Then, I will describe two experiments carried out to evaluate it. The first was a study on the different types of visual representations that can be used to visualise the physical space boundaries. The second experiment focused on the effect of workspace management techniques and view privacy when combined with the physical space partitioning technique. This chapter will be concluded with some guidelines in applying physical space partitioning technique and a discussion of several open problems.

5.1. Introduction

In many immersive collaborative systems, people with different expertise and skills can work collaboratively to interact with and analyse data for decision-making. Each person may focus on some particular aspects that are crucial for addressing a common question or a shared task. On the one hand, in co-located collaboration, displaying data when its quantity becomes significantly large everywhere in the physical space can be disturbing or distracting for other collaborators when some parts of the data itself may not be relevant for all of them. On the other hand, nearby individuals' spatial relationships and positioning can significantly affect user performance and behaviour during collaboration [233]. Regarding collaborative tasks, which often consist of a sequence of several sub-tasks alternating between individual and cooperative steps intertwined, this becomes particularly critical.

This work aims to help the users to be aware of their personal and public workspace in the physical space to perform collaborative tasks better. To achieve this goal, my proposed solution focuses on partitioning physical space, with consideration for the available area and the various configurations of public and private workspaces needed. Moreover, to effectively split the workspace in AR, it is important to use visual cues to display boundaries. These cues should help the users

understand their own workspace, their partners', and the shared (or public) one. By ensuring clear delimitation and aiding in the maintenance of spatial awareness within the physical environment, I suppose that smoother collaboration and interaction is facilitated. However, it is important that these boundary cues (*Line*, *Opaque*, and *Semi-transparent* boundary cues) do not overly alter the perception of real and virtual objects within the users' field of view. This leads to two following research questions :

RQ3.1: Which of the three visualisation modes: *Line*, *Opaque*, and *Semi-transparent* is the most appropriate method of displaying the users' workspace boundaries?

RQ3.2: Will the automatic partitioning with a separation of public and private view for each user facilitate the workflow of the immersive analytics work on meteorological data?

To address these questions, the proposed system for IA of meteorological data analysis presented in Chapter 4 was extended to a co-located collaborative setup in this work. Using this collaborative AR-based IA system, I first studied various techniques for visualising the boundaries of the physical environment, including *Line*, *Opaque*, and *Semi-transparent* boundary. I conducted a study to compare them in terms of task performance, usability, and cognitive load. Following the outcomes of the initial experiment, a second experiment was undertaken to investigate the impact of the physical space partitioning technique when it is combined with different view privacy configurations. This user study involved pairs of co-located users engaging in collaborative tasks on complex datasets. From the results obtained, an analysis was conducted, leading to discussions on the merits and limitations of workspace partitioning in AR co-located collaboration.

The first study in this chapter is currently under review for the EuroXR 2024 conference, while the second study has been accepted for publication at Spatial User Interaction (SUI) 2024 [274].

5.2. Automatic Physical Space Partitioning & View Privacy

When designing a co-located immersive system for multiple users involved in collaborative tasks, it is critical to consider the limitations of physical space. In typical work settings, such as offices or meeting rooms cluttered with cumbersome furniture, the users might find themselves needing to negotiate the occupied space to enable spatial interactions in AR. This aspect gains particular importance during the handling of complex task that include the transitions between individual and cooperative phases. The absence of established, agreed-upon individual and collective workspaces can result in confusion, reduced productivity, and disruptions in workflow, as the users may inadvertently obstruct each other or cause visual occlusions. Moreover, I believe that the arrangement of collaborators within the

physical workspace not only affects individual performance but also shapes collective behavior and collaboration patterns.

This section introduces the automatic technique for partitioning the available physical space amongst the co-located users utilising a Head-Mounted Display (HMD)-based AR interface. This technique calculates and allocates a designated subspace for each collaborator, catering to both individual and collaborative tasks. My method for determining a set of suitable physical workspaces encompasses the following key steps:

- Step 1: Scan the physical space to understand the scene, obtain the environment mesh data, and remove the ceiling and walls from the mesh.
- Step 2: Partition the space into $n + 1$ spaces, where n is the number of collaborators.
- Step 3: Compute new meshes to define the boundaries of different workspaces.
- Step 4: Assign to each user a private workspace, and indicate the public workspace.

These steps are detailed in the following:

In the initial step, the Scene Understanding package from the Mixed Reality Toolkit (MRTK) is used to scan the environment. This process generates a mesh of the physical space, capturing its main structures, including walls, floors, and ceilings. The mesh's vertex coordinates are subsequently used as input for the partitioning algorithm.

Following this, the partitioning algorithm divides the environment in the second phase. Given our scenario, the environment is partitioned into $n + 1$ spaces, accounting for the number of collaborators n in addition to a public/joint space. Various algorithms exist for space partitioning, each with its advantages and drawbacks, as noted in the literature [275]. The k -means clustering algorithm was selected for its simplicity, efficiency, and quick convergence, attributes that render it ideal for real-time or iterative clustering tasks [276].

The third step involves generating new textured meshes for each cluster, using the results from the k -means algorithm.

In the final stage, the system identifies the joint space by analysing the room's mesh data. The subspace nearest to the room's centre is earmarked as the public workspace. The system then calculates the distance from each user's current position to the other subspaces, assigning them to the nearest available subspace accordingly. The pseudo-code of the algorithm is found in Algorithm 2.

To allow content privacy in the different subspaces, I also implemented a privacy policy for the digital content corresponding to each user. In essence, when a user operates within their designated individual workspace, all associated objects are private. Consequently, these private objects are only visible and implicitly modifiable by their owner. The owners are provided with the flexibility to alter privacy settings, enabling either sharing functionality explicitly or transferring objects to the public workspace. By default, all the objects located in the public space are

Algorithm 2 Automatic Physical Space Partitioning Technique

Input: MeshVerticesList, MeshPosition, UsrNumB**Output:** MeshList

```
1: procedure SpacePartition(MeshVertices, UsrNumB)
2:    $N \leftarrow \text{UsrNumB} + 1$ 
3:   if  $N < 3$  then
4:     MeshList.Add(MeshGenerate(MeshVerticesList))
5:     return MeshList
6:   else
7:     clusters  $\leftarrow$  KMeans(MeshVerticesList,  $N$ )
8:     for  $k \leftarrow 0$  to  $N - 1$  do
9:       MeshList.Add(MeshGenerate(clusters[ $k$ ]))
10:    end for
11:    return MeshList
12:  end if
13: end procedure
```

visible and interactable by all the users. In this use case, interactions with these objects include modifications to their position, orientation, and size.

5.3. Boundary Visual Representations for Space Partitioning

To communicate the workspace boundary established by the above space partitioning technique to the users, I proposed three visualisation modes. These visual representation use varying opacity levels to mark the boundary: opaque, semi-transparent, and line mesh textures.

In the cases of opaque and semi-transparent boundaries, as illustrated in Fig. 5.1.C and Fig. 5.1.D respectively, the *MeshGenerate* function from Algorithm 2 takes the result of the k -means algorithm as input. The Delaunay triangulation algorithm [277] is subsequently used to identify all the triangles that form the new mesh, with each cluster derived from the k -means output delineating a distinct workspace. These meshes are then rendered with the appropriate materials. Specifically, for the opaque boundary, Unity's default materials are employed, setting their opacity to 'opaque'. In contrast, for the semi-transparent boundary, materials from the MRTK toolkit are used, which feature an option for near-fading. This functionality allows for the configuration of the system such that the areas in close proximity to the user appear transparent, and gradually transition to full opacity as the distance increases.

For the line boundary (Fig. 5.1.B), after clustering with the k -means algorithm, the focus shifts towards identifying the border vertices for each subspace. Once these vertices are determined, the subsequent step involves connecting them to form the line mesh that delineates the boundaries of each subspace.

Meticulous design underpins each boundary visualisation technique, with a keen consideration of its advantages and limitations aimed at informing users about the distinct limits of workspaces. This approach enhances user interaction and awareness during collaboration. Specifically, the implementation of an opaque boundary responds to the critical need for unmistakable differentiation not only between the

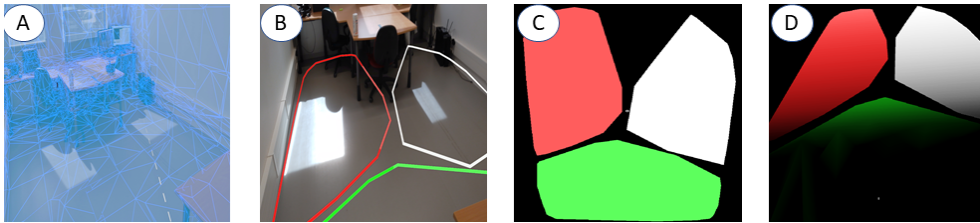


Figure 5.1 – A) The room mesh is obtained by scanning the physical environment using Microsoft HoloLens 2. The space is then partitioned using three types of boundaries generated on the floor to indicate different workspaces (green is public, red and white are private): B) Line on real floor, C) Opaque, and D) Semi-transparent in Unity3D.

physical floor and the workspaces but also amongst various virtual workspaces. Conversely, semi-transparent boundaries present a notable advantage by allowing users to perceive the physical floor below, a feature essential for circumventing real-world obstacles that might lie on the ground in the user’s proximity. Providing a visual cue for the physical floor, while simultaneously delineating virtual workspace boundaries, serves to bolster safety and situational awareness amongst users. Finally, opting for the line boundary technique, known for its simplicity and minimal visual intrusion, provides a discreet demarcation of workspace limits, thus minimising visual distraction from the workspace boundaries for the users.

5.4. Experiment 1: Evaluation of Boundary Visualisation Techniques for Physical Space Partitioning

To choose amongst the three boundary visualisation techniques for physical space partitioning, meaning opaque, semi-transparent, and line mesh textures (Section 5.3) for the collaborative IA system. The first experiment was conducted to evaluate them independently following within-subjects experimental design. There was one factor *TECHNIQUE* which includes three conditions (Fig. 5.1):

- *Opaque boundary* technique allows the users to view workspace floors covered by an opaque virtual material.
- *Semi-transparent boundary* places a virtual material over the real floor, enabling the users to see the floor beneath them within a certain radius, beyond which the view becomes progressively opaque.
- *Line boundary* technique outlines the workspace boundary with a virtual line on the real floor.

During the experiment, the order of the techniques was counterbalanced across all participants based on a balanced Latin square.

5.4.1. Hypotheses

Given the impact of different boundary visualisation techniques on user performance, it was assumed that while all boundary visualisation techniques would de-

lineate the virtual limits of different workplaces, they would not significantly affect user performance. However, the *Line Boundary* technique could be more subjectively favoured by participants due to the minimal visual distractions it presents, allowing clear visibility of the boundaries. I thus formulated the following hypotheses:

- **H3.1.0:** A similar amount of time will be needed to complete the required tasks under any of the three conditions: *Opaque boundary*, *Semi-transparent boundary*, and *Line boundary*.
- **H3.1.1:** *Line boundary* technique will be rated higher in usability, demand less task load, and be preferred by participants over the other conditions.

5.4.2. Participants

Six pairs of participants, ranging in age from 18 to 32 (nine men and three women), participated in the experiment, having been recruited from our Department and University. Amongst these participants, ten were working in the field of computer science, while the remaining two were involved in mechanics and language processing, respectively. In terms of academic qualifications, two participants held a Ph.D., eight had a Master's degree, and two possessed a Bachelor's degree. Additionally, seven participants had previous experience with virtual and augmented reality systems, with two regarding themselves as experts.

5.4.3. Experiment Setup

The entire system, including its components (two clients and a server), was developed using Unity3D 2021.3.15f1. The server application was executed on a Windows computer equipped with an Intel Xeon W-2135 processor, 32GB of RAM, and an RTX 4000 graphics card. Microsoft HoloLens 2 devices were employed for rendering and interaction, serving as the client hosts. A local network utilising 5-GHz WiFi facilitated the connection of the headsets (clients) to the desktop (server). The experimental room was set up to mimic a real office space for two people, with dimensions of $5m \times 3.5m$, and was furnished with tables and chairs.

5.4.4. Experimental Task

Given that the experiment aimed to evaluate the three boundary visualisation techniques, it could be considered independently from conventional data analytics tasks. Therefore, I designed an entertaining, collaborative scenario for pairs of participants. The task for the experiment involved decorating an apartment, where each participant was assigned a different kind of its interior furniture to process. Initially, participants engaged in a discussion to understand the apartment's design plan, which was based on a 2D image (Fig. 5.2.B). This discussion aimed to clarify their individual responsibilities in collecting various objects from their own workspaces to furnish the 3D model of the apartment situated in the common area. Three 3D models of apartments were randomly linked to the three conditions of the boundary visualization technique, with the specific objects to be collected by

each participant varying according to the apartment models. For each condition, participants were tasked with finding and bringing six particular types of objects from a shelf in their workspace. One participant focused on decorative items such as flowers, plants, and lamps (Fig. 5.2.A), while the other concentrated on furniture and appliances like chairs, tables, and fridges (Fig. 5.2.C). The allocation of roles was predetermined randomly at the beginning of each condition's task.

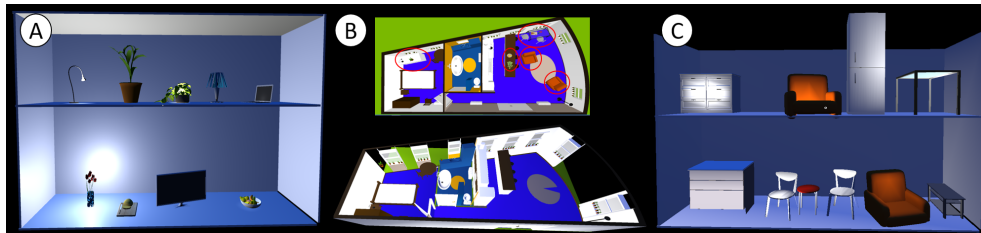


Figure 5.2 – Example of a task in experiment 1: A) User A's shelf contains decorative items such as lamps, flowers, plants, a TV, and a laptop. B) A 3D apartment model and a 2D image highlight missing objects with red circles indicating where they should be placed in the 3D space. C) User B's shelf contains furniture items such as chairs, tables, fridges, and cabinets.

5.4.5. Procedure

The duration of the experiment was approximately 40 minutes. Upon arrival at our laboratory, each pair of participants received a warm welcome, were provided with task instructions, and signed an informed consent form. Subsequently, they completed a demographic information questionnaire. Each participant was then equipped with a Microsoft HoloLens 2 headset. A training session ensued to familiarise the participants with the headset usage, user interface, its functionalities, and interaction modalities. Following this, the participants undertook three tasks aligned with the three conditions, with the sequence of these conditions being counterbalanced.

To begin each task, the participants were required to position themselves in the public workspace (denoted as the green workspace in Fig. 5.1) to review the task instructions and observe the boundaries demarcating the different workspaces. Upon readiness, they initiated the task by pressing the start button on the menu.

At the end of each task, the participants were asked to complete the NASA-TLX questionnaire and the System Usability Scale (SUS) form. At the end of the entire experiment, they were requested to rank the three techniques based on their preference. An open-ended interview was conducted to collect their feedback on the three visualisation modes.

5.4.6. Data Collection

I registered 36 trials: 3 TECHNIQUES \times 12 participants and collected the following measures:

Quantitative data:

- *Task Completion Time (TCT)*: the time needed to complete a task under different conditions. This duration commenced from the moment the participants initiated the task and finished with the placement of the last objects in the 3D model. Given that six objects were to be identified and positioned within each task, the average TCT across these six trials was utilised for statistical analysis.

Subjective data:

- *System Usability Scale (SUS)*: usability of each technique estimated after the task.
- *NASA-TLX*: a cognitive load of each approach estimated after the task.
- *Overall ranking*: The participants ranked the three techniques according to their preferences, with 1 being their top choice, 2 being their second choice, and 3 being their least preferred.

5.4.7. Statistical Results

Regarding *TCT*, the Shapiro-Wilk test was used to test the normality. The *TCT* data was found to be normally distributed. Subsequently, a one-way repeated-measures ANOVA test was conducted. The results of this test revealed no significant difference between the various techniques in terms of *TCT*: $F_{2,22} = 0.36$, $p = 0.7$ (*Line*: $\mu = 35.72s$, $\sigma = 8.2$, *Opaque*: $\mu = 38.31s$, $\sigma = 10.54$, *Semi-transparent*: $\mu = 34.93s$, $\sigma = 12.65$).

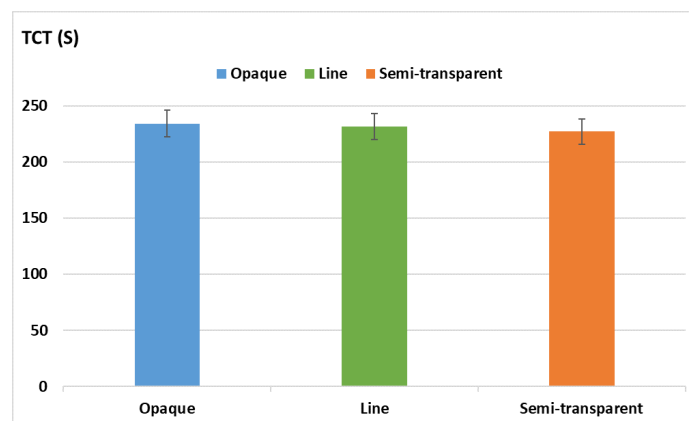


Figure 5.3 - Mean TCT by technique with error bars showing 95% confidence intervals (CI).

The subjective questionnaires were analyzed using the Friedman test. For the cognitive load, as measured by the NASA-TLX, the Friedman test showed no significant effect ($\chi^2(2) = 3.5$, $p = 0.17$), with all conditions presenting a low cognitive load (*Line*: $\mu = 25.83$, $\sigma = 13.3$, *Opaque*: $\mu = 35.13$, $\sigma = 16.39$, *Semi-transparent*: $\mu = 23.75$, $\sigma = 9.26$).

The SUS questionnaire and its score calculation method were used to calculate the usability score. The Friedman test indicated no significant effect ($\chi^2(2) = 0.12$, $p = 0.94$). However, amongst the conditions evaluated, only the *Line* condition achieved a mean score above 68, suggesting it was considered above average in usability (*Line*: $\mu = 68.33$, $\sigma = 24.38$). Conversely, the mean values for the *Opaque* and *Semi-transparent* conditions were below this threshold, indicating lower usability scores (*Opaque*: $\mu = 63.54$, $\sigma = 17.03$, *Semi-transparent*: $\mu = 62.92$, $\sigma = 17.28$).

In terms of overall ranking (Fig. 5.4), the Friedman test on the mean rankings revealed a significant effect ($\chi^2(2) = 8.66$, $p = 0.013$). A post-hoc analysis for paired conditions was performed using the Wilcoxon Signed Rank test with Bonferroni correction. This analysis indicated a significant difference between the *Line* and *Semi-transparent* conditions ($p = 0.014$), no significant difference between *Opaque* and *Line* ($p = 0.27$), and no significant difference between *Opaque* and *Semi-transparent* ($p = 1$). Considering only the number of participants who ranked a technique as their preferred choice (1), nine participants favored the *Line* technique as the best, in contrast to three for the *Opaque* and none for the *Semi-transparent*.

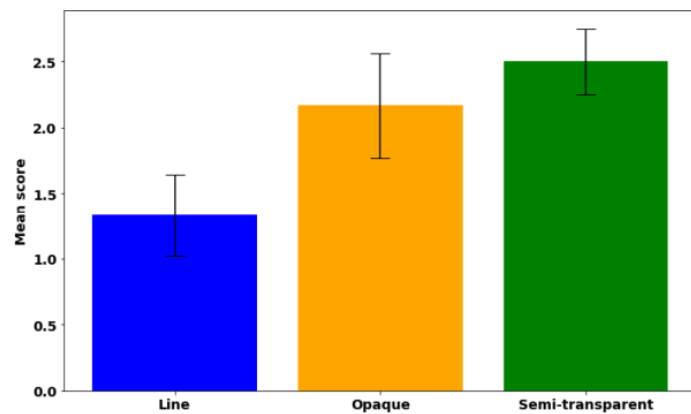


Figure 5.4 – Mean of overall user ranking of the three boundary visualisation techniques (1 indicating the best, 3 the worst), with error bars showing 95% confidence intervals (CI).

5.4.8. Discussion

This study investigated the effects of three different boundary visualisation techniques on Task Completion Time (TCT), cognitive load, and system usability. Initial hypotheses posited that there would be no significant differences amongst the conditions concerning TCT, which was corroborated by the statistical analysis. This outcome indicates that the selection of a boundary visualisation technique does not significantly impact task efficiency, thereby supporting the null hypothesis H3.1.0.

The absence of significant differences in cognitive load and SUS scores suggests that participants did not perceive any notable differences in usability or cognitive load amongst the techniques. However, the *Line* technique's higher SUS score, surpassing the average usability threshold, unlike the *Opaque* and *Semi-transparent* conditions. This could imply that the participant's subjective preference is higher for the *Line* condition regarding its usability, aligning partially with **H3.1.1**.

Furthermore, the overall ranking data, indicating a frequent preference for and positive feedback towards the *Line* technique, corroborates the SUS findings. For example, the P4 noted that the *Line* borders were easy to identify and did not interfere as much as the *Opaque* ones did. The P7 said "It's better when there are no colours on the floor." By comparing the *Line* condition to the *Opaque* and *Semi-Opaque* conditions, the P9 mentioned that "The opaque surfaces were too visually overwhelming, so it was somewhat headache-inducing", and the P8 said "If I use opaque, it hurts my eyes, and with transparent, I won't get all the details without outlines". Interestingly, the P12 commented "I didn't like the transparency of the floor; I preferred it to be completely opaque or just with Line on the borders. I found the transparency somewhat bothersome."

In response to **RQ3.1**, although the participants' preferences did not manifest as significant differences in performance or cognitive load, the *Line* technique was the most appropriate for displaying the users' workspace boundary because of its good usability, cognitive load score, and user preference. It was thus selected for the next experimentation.

5.5. Experiment 2: Evaluation of Physical Space Partitioning and View Privacy

This ultimate experiment investigated the effect of physical space partitioning techniques, as detailed in Section 5.2, along with view privacy policy on co-located collaboration in IA. Pairs of participants performed both collaborative and individual data analysis tasks on meteorological datasets. More specifically, I compared the efficacy of partitioned collaborative spaces against the baseline scenario where no partitioning was applied. Furthermore, the dynamics between private and public views and their influence on the collaborative workflow amongst the participants were examined. This experiment was designed as a $[2 \times 2]$ balanced within-subjects study, incorporating the following factors:

- **WORKSPACE**: *Non-partitioning* and *Partitioning*,
- **VIEW-PRIVACY**: *Private* and *Public*.

The two variables of the **WORKSPACE** factor are as follows:

- *Non-partitioning* serves as the default configuration for co-located collaborative workspaces in IA (Fig. 5.6). This setup allows the users to place their data anywhere in the real environment. In the context of this case study, for collaborative tasks, the participants stand side-by-side at a location of

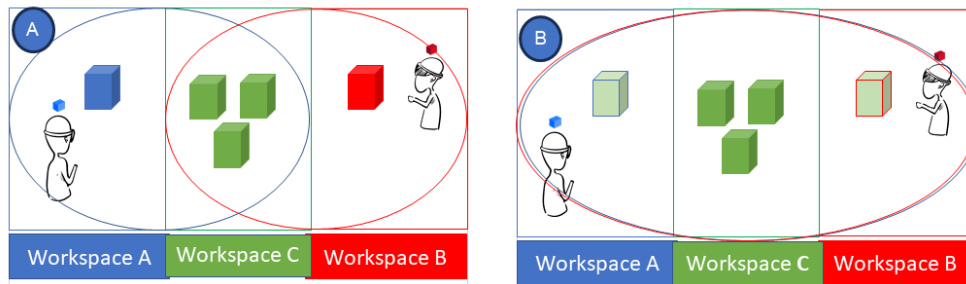


Figure 5.5 – The user’s view is represented by blue and red circles, while the space is divided into three workspaces, denoted by blue, green, and red rectangles: one public (green space) and two private areas. In condition (A), each user can see and edit only the objects within their designated space, in addition to those in the public area. In condition (B), all objects are visible to all users; however, editing rights are restricted such that only the owner can modify their objects, except for objects in the public space, which are editable by everyone.

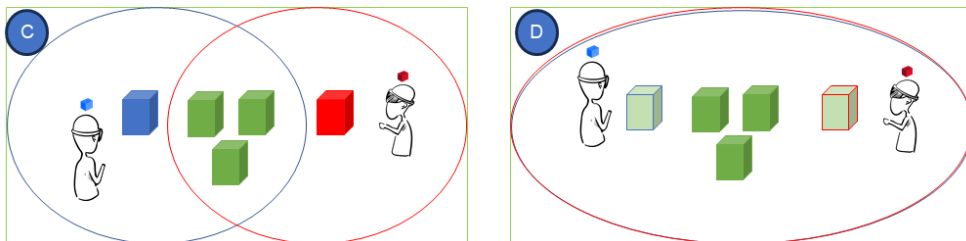


Figure 5.6 – The workspace is not partitioned: In condition (C), an object is visible and modifiable only by its owner, while public/shared (green) objects are visible and modifiable by everyone. In condition (D), every user can see all objects, but only the owner can edit them, while anyone can edit the public/shared objects.

their choosing within the real environment. When engaging in individual tasks, each participant selects their preferred position anywhere within the physical room.

- *Partitioning* (Fig. 5.5) describes the condition where the proposed partitioning technique is applied to segment the physical space into three distinct workspaces using a virtual line boundary on the floor: a public workspace (shared space) and two private workspaces (individual spaces). The public workspace is designated for collaborative tasks, whereas the two private workspaces are assigned to each pair of participants for individual tasks. The shared space remains accessible during individual tasks due to the availability of shared data that needs to be analyzed within this workspace.

For *VIEW-PRIVACY*, two different privacy policies are considered:

- *Private view privacy* (see Fig 5.5 A and Fig 5.6 C) is the condition in which there are two types of data: personal data belonging to its owner unless explicitly shared, and public data visible to all the users.
- *Public view privacy* (see Fig 5.5 B and Fig 5.6 D) implies that all the data

for individual and collaborative tasks is visible to all the users. Combining these two factors with each two variables, I obtained four conditions summarised in Table 5.1.

Table 5.1 – Four conditions in Experiment 2

Condition	Workspace	View-Privacy
A	Partitioning	Private
B	Partitioning	Public
C	Non-partitioning	Private
D	Non-partitioning	Public

5.5.1. Hypotheses

I assumed that *Partitioning*, with *Private* view for each user, would facilitate the workflow of collaborative work, increase the performance of individual and collective tasks, and improve overall user experience. Consequently, the following hypotheses were formulated:

- **H3.2.1:** Despite the privacy of the view, it takes less time and effort for the users to set up the workspace with *Partitioning* approach than with *Non-Partitioning* one during collaborative and individual tasks.
- **H3.2.2:** Regardless of the workspace's *Partitioning* or *Non-Partitioning* condition, sharing complete information all the time in *Public* view may negatively affects user performance and experience.

5.5.2. Participants

In this experiment, 16 people (8 pairs) were recruited, with ages ranging from 19 to 37 (12 men and four women). The majority had a background in computer science, with the exception of four who studied sociology. Regarding educational qualifications, three participants held a Ph.D., nine possessed a Master's degree, two had a Bachelor's degree, and two had completed high school. Experience with VR and/or AR technology varied among participants: six had basic knowledge, six had intermediate experience, and two considered themselves experts. In terms of data analysis skills, half of the participants had basic skills, though only one had prior experience with meteorological data.

5.5.3. Overview of the IA System

For this experiment, I have extended the previous AR-based IA system for collaborative data analytics tasks. This IA system was based on the client-server architecture, where the server enables a shared virtual space and facilitated real-time collaboration. The users are able to access both shared and private digital content by connecting their Microsoft HoloLens 2 devices to the server through a wireless network.

For data analytics tasks, I used the meteorological data collected from two NASA weather data sources: MERRA-2 [278] and GLDAS_NOAH [279]. The Modern-Era Retrospective Analysis for Research and Applications 2 (MERRA-2) provides estimates of atmospheric variables such as temperature, humidity, winds, and other parameters across the globe. The dataset features a latitude resolution of 0.5° , a longitude resolution of 0.625° , and a time step of 1 hour. On the other hand, the GLDAS_NOAH (Global Land Data Assimilation System with Noah Land Surface Model) represents a land surface modelling system. It merges satellite and ground-based observational data with land surface modelling techniques to produce a detailed representation of global land surface conditions. The GLDAS-2.0 format features a three-hourly time step and spatial resolutions of 0.25×0.25 . To synchronise both data types to the same time step, the GLDAS_NOAH data was converted into three-hour time steps by averaging the data across each spatial coordinate over 3 hours.

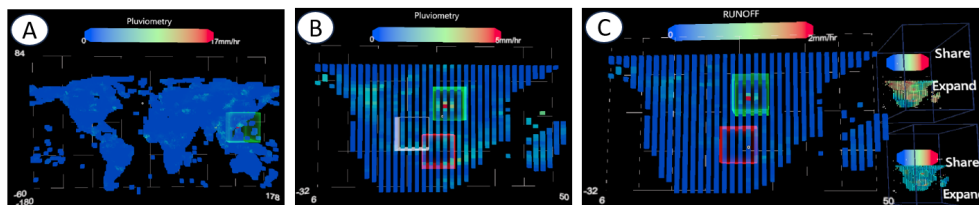


Figure 5.7 – Snapshots of our IA system: A) Overview: Pluviometry data of the world is publicly visualised to all users. They can narrow down to a specific area through a semi-transparent, modifiable green box that acts as a filtering tool. B) Filtering: The data filtered by the green box allows users to inspect the zone of interest in more detail. C) Private view: Different users have access to various sets of data in a private view and interact with them using their own tools. The interactions in both the public (B) and private (C) views are automatically reflected in the corresponding data visualisation to support the mutual decision-making process. In this example, two users manipulate two tools separately (red and white) in their own view to redefine the area with interesting meteorological phenomena based on different parameters (e.g., pluviometry, water runoff, temperature).

To support the analytics tasks of these datasets, I implemented the three main features following Shneiderman’s Visual Information-Seeking Mantra [280]:

- **Overview** enables the users to have a global overview of different types of datasets available in the public (Fig. 5.7.A & B) and private space (Fig. 5.7.C). Since there are many parameters of the datasets (e.g., wind velocity, pluviometry, water runoff) to be inspected (together or separately) as it is typical in the real-world scenarios, I also implemented functionalities for expanding and shrinking sections in the data visualisation, allowing the users to tidy up the workspace swiftly as needed, and sharing when necessary (Fig. 5.7.C).
- **Filtering and resampling** allow the users to dynamically refine and manipulate data representations based on specific criteria or parameters. They

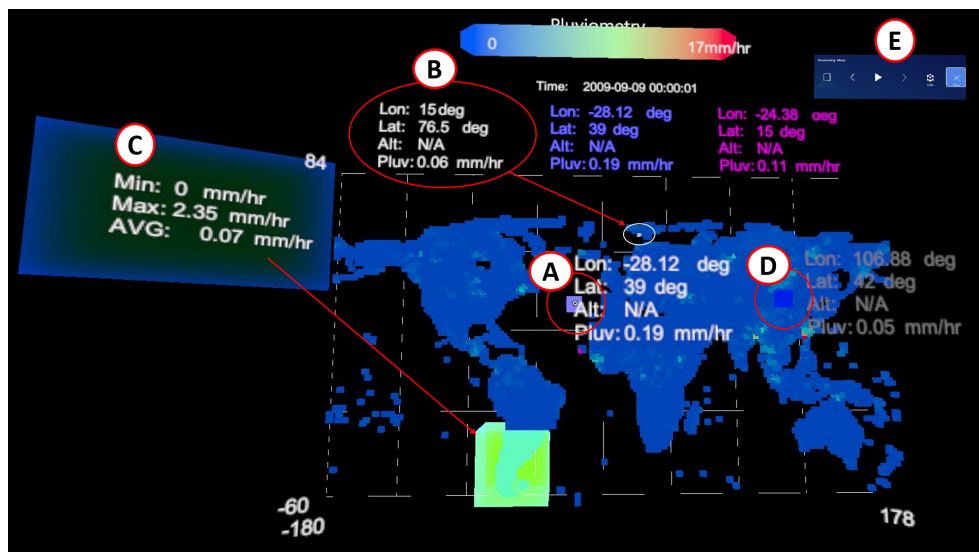


Figure 5.8 – A) When the user’s cursor hovers over a data point, it is automatically expanded, and its related details are shown. B) The information related to a data point is also displayed when the user selects it. Different colours are used to associate the information with a small subset of selected data points. C) A semi-transparent box can be used to select a specific area, and the label displays averaged information about the selected area. D) The user can also see the partner’s current interaction (e.g., a data point and its associated data), but this feature can be activated or deactivated to avoid visual clustering. E) A toolbox for playing animations of spatio-temporal data. The red lines and circles are used to highlight each corresponding item.

can apply filters to the displayed dataset, focusing on particular aspects, subsets, or categories of the data. These filters also include data sources, date and time ranges, geographic locations, meteorological parameters, or any other relevant data attributes. For instance, using an expandable 3D green box (Fig. 5.7.A), the users can select a specific area and trigger a data query to the database to select and display all the data belonging to this zone from different data sources (collected by various satellites or instruments). The result of the filtering is shown in Fig. 5.7.B. Alternatively, they can specify parameters for filtering directly on the interface using a 2D toolbox.

- **Details-on-demand** is a feature that enables the users to access specific information about particular data points by making a selection. The users can either hover the cursor on top of each data point for quick access of the information (Fig. 5.8.A) or select it explicitly for later comparison. If it is the latter, its details will be visualised in the neighbourhood of the graph (Fig. 5.8.B). Furthermore, they can select a subset of multiple data points by selecting several individual data points or by using a 3D semi-transparent modifiable box for zone selection (Fig. 5.8.C). It can be particularly helpful for comparing different values of these data points. Other users can see the

details of the data points under the user's cursor if this option is activated (Fig. 5.8.D).

5.5.4. Experiment Setup

The setup was the same as in Experiment 1.

5.5.5. Experimental Task

Based on the results of several interviews with meteorologists at LATMOS and Mahmood *et al.*'s study [237], it was determined that a typical collaborative scenario for meteorological and geo-spatial data analysis entails three principal stages. Initially, the collaborators discuss and explore a set of data together to identify a zone of interest and develop hypotheses of its meteorological phenomenon. The second stage involves evaluating additional parameters (such as rainfall, runoff, wind velocity, temperature variation) or consulting alternative data sources (like satellite imagery, radar, or weather balloons) related to the same area. This is a crucial activity, given the potential for data anomalies due to instrument errors under various setup conditions. Consequently, the collaborators must verify the consistency of their chosen area across different datasets, a process that may be undertaken individually as each person may be interested in other parameters or other data sources. In the final step, they gather their findings and discuss them together to make a final decision when it is possible.

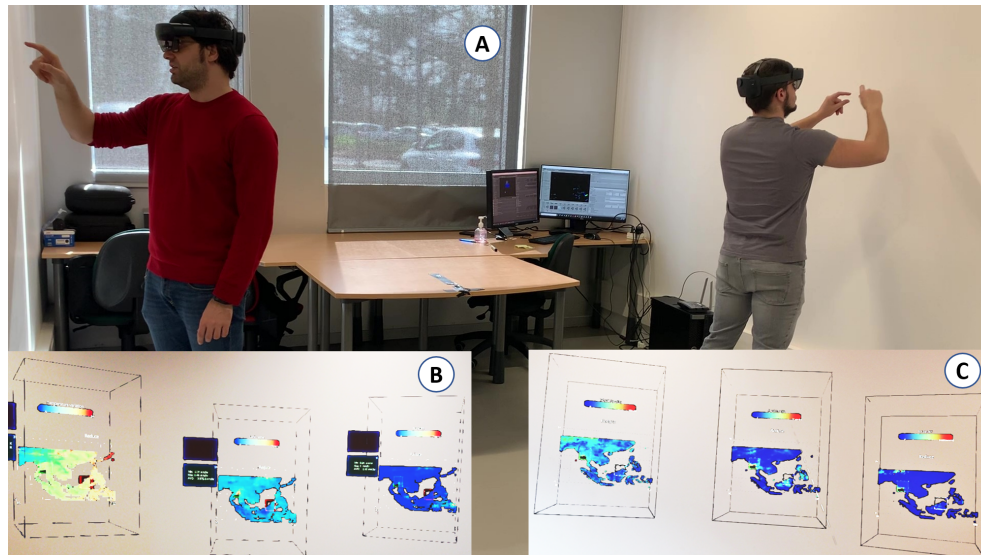


Figure 5.9 – A) Two participants worked together in the co-located AR environment during an individual sub-task. B) User 1 visualises temperature variation, land-water, and runoff data. C) Meanwhile, User 2 works on pluviometry, wind-velocity, and runoff data.

Therefore, the experiment was designed as follows: the pair of participants performed a data analysis task, which was segmented into three sub-tasks. The

initial collaborative sub-task (*collab-subtask-1*) involved collaboratively identifying a zone of interest - specifically, an area with the highest rainfall in the first dataset (data A). The individual sub-task (called *ind-subtask*) followed to check whether the selected zone of interest of the first sub-task was consistent with other information in other databases or the same database but using different parameters. For instance, the first participant (P1) used data A but inspected other meteorological parameters (*rate of change of total land water, temperature variations, and the runoff*), while their partner, the second participant (P2) visualised data B of another source, using three meteorological parameters (*rainfall, runoff, wind velocity*) (Fig. 5.9). Then, they moved on to the final collaborative sub-task (called *collab-subtask-2*) to confirm or refute that the area of interest corresponds to their selected area in the *collab-subtask-1*.

For the four conditions (Table 5.1), the pair of participants performed four main tasks with similar collaborative and individual sub-tasks. Each main task was carried out using different sets of data. Five data sets were used, one for training and four for evaluation; each data was from a specific day when a hurricane occurred. For the training task, the participants used the data from Hurricane Dorian (2009-08-26, 3 pm to 6 pm). For the experimental tasks, they used the data from Hurricane Katrina (2005-08-29, 6 pm to 9 pm), Monica (2006-04-23, 12 am to 3 am), Nargis (2008-05-02, 3 am to 6 am), and Marakot (2009-08-08, 9 pm to 12 am). The different data sets were collected from MERRA-2 and GLDAS_NOAH (Sec. 5.5.3). To simplify the experiment, although the whole database contained temporal data, certain timeframes were pre-selected for the participants to work with.

5.5.6. Procedure

Each experimental session lasted about 60 minutes and its main procedure was similar to Experiment 1. However, the difference was the training before the tasks to explain some meteorological concepts and the task instructions on a training dataset. Both participants performed the training as long as they needed and could ask questions any time. Then, the participants started a task for the condition in a random order (A, B, C, or D) on a random dataset. After each condition, they filled two questionnaires: NASA-TLX and SUS. They could also take a break between tasks if they wished to. When they finished the experiment, the participants ranked the four conditions according to their preferences and participated in an open-ended interview.

5.5.7. Data Collection

I collected data from 64 trials: 2 WORKSPACE \times 2 VIEW-PRIVACY \times 16 participants. For each trial, I recorded the following measures:

Quantitative data:

- The *Task Completion Time (TCT)*: is the total duration required to finish the task under different conditions. It started to be recorded when the

participants began the first collaborative sub-task and ended when they finished the last collaborative sub-task.

- The *Time to Arrange the Workspace (TAW)*: refers to the duration the participants needed to arrange the objects (public, private data) in the workspace under different conditions. Exceptionally, it was collected from 256 data points: 64 trials \times 4 data charts (three private and one public).
- The *Time for Positioning (TP)*: is the time the participants took to find a workplace for their individual sub-task. It started when they finished the first collaborative sub-task and stopped when the participant began their individual sub-task.
- *User Position*: This represents the spatial coordinates of an individual within the physical environment, which were recorded every second throughout each task.

Subjective data:

- *NASA-TLX*: the cognitive workload of each condition estimated after its corresponding task.
- *System Usability Scale (SUS)*: the usability of each condition estimated after each task.
- *Overall ranking*: is the score (from 1 the best to 4 the worst) participants given to the four conditions.

5.5.8. Statistical Results

Quantitative data: The normality of three types of time-related data was assessed using the Shapiro-Wilk test, and the ANOVA test was used to analyse the interaction between the two factors. The Shapiro-Wilk test determined that all time-related data did not follow a normal distribution. Upon calculating skewness, it was found that the distribution of the data was positively skewed. To address this, a logarithmic transformation was applied to *TCT*, *TAW*, and *TP*. Nonetheless, *TTC* remained non-normally distributed, so I used the Box-Cox transformation on this data.

In terms of *Task Completion Time (TCT)*, the two-way repeated-measures ANOVA indicated no significant interaction between the factors *WORKSPACE* and *VIEW-PRIVACY* ($F_{1,28} = 0.28$, $p = 0.59$). Moreover, the main effects of *WORKSPACE* ($F_{1,28} = 0.003$, $p = 0.96$) and *VIEW-PRIVACY* ($F_{1,28} = 0.008$, $p = 0.93$) on *TCT* were found to be statistically insignificant.

For deeper analysis, *TCT* was segmented into three phases: *collab-subtask-1*, *ind-subtask*, and *collab-subtask-2* (refer to Sec. 5.5.5 and Fig. 5.10). The *TCT* for both *collab-subtask-1* and *collab-subtask-2* demonstrated non-normal distribution. Following the results of the skewness test, a logarithmic transformation was applied. The two-way repeated-measures ANOVA test indicated no significant two-way interaction between *WORKSPACE* and *VIEW-PRIVACY* across *collab-subtask-1* ($F_{1,28} = 1.79$, $p = 0.19$), *ind-subtask* ($F_{1,60} = 0.001$, $p = 0.98$), and *collab-subtask-2* ($F_{1,28} = 1.07$, $p = 0.31$). Additionally, there were no significant inde-

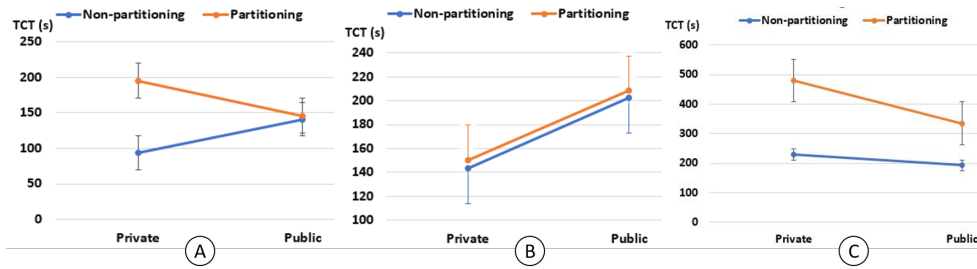


Figure 5.10 – Mean of Task Completion Time (TCT) divided into three phases: A) *collab-subtask-1*, B) *ind-subtask*, and C) *collab-subtask-2*.

pendent effects of either *WORKSPACE* or *VIEW-PRIVACY* on *collab-subtask-1* and *collab-subtask-2*. However, a significant independent effect of *VIEW-PRIVACY* on *ind-subtask* was observed ($F_{1,60} = 7.7, p = 0.007$), prompting a grouping of the data according to this variable. For the *PRIVATE* view condition, the mean and standard deviation were $\mu = 146.82s, \sigma = 42.98$, while for the *PUBLIC* view condition, these were $\mu = 205.31s, \sigma = 109.24$.

The analysis of the *Time to Arrange the Workspace (TAW)*, no significant interaction was detected between the two factors ($F_{1,252} = 0.49, p = 0.48$), and neither of the independent variables, *WORKSPACE* ($F_{1,252} = 0.1, p = 0.91$) nor *VIEW-PRIVACY* ($F_{1,252} = 0.14, p = 0.48$), exhibited a statistically significant main effect on *TAW*.

For further investigation, *TAW* was segmented into two phases: the Time to Arrange the Public Workspace (*Public TAW*) and the Time to Arrange the Individual Workspace (*Individual TAW*).

In terms of *Public TAW*, a statistically significant interaction was observed between *VIEW-PRIVACY* and *WORKSPACE* ($F_{1,60} = 5.75, p = 0.02$). The simple main effect of *WORKSPACE* on *Public TAW* was significant under the *Private* view condition ($F_{1,60} = 7.35, p = 0.009$) but not under the *Public* view ($F_{1,60} = 0.46, p = 0.5$). Within the *Private* view condition, the mean *TAW* for *Partitioning* ($\mu = 6.75, \sigma = 7.02$) exceeded that for *Non-partitioning* ($\mu = 2.25, \sigma = 2.59$). Additionally, the simple main effect of *VIEW-PRIVACY* on *Public TAW* was significantly apparent for *Partitioning* ($F_{1,60} = 6.56, p = 0.01$) but not for *Non-Partitioning* ($F_{1,60} = 0.68, p = 0.41$). The mean *TAW* for *Partitioning* in the *Private* view condition ($\mu = 6.75, \sigma = 7.02$) was higher than that in the *Public* view ($\mu = 2.5, \sigma = 3.18$). Despite the application of various statistical normalisation techniques, the distribution of the time taken to arrange the individual workspace (*Individual TAW*) remained non-normal. Consequently, a non-parametric test, specifically the Friedman test, was used to assess the differences across the four conditions. The results of this test revealed that there was no significant difference in *Individual TAW* among the conditions.

Concerning *Time for Positioning (TP)*, the two-way ANOVA indicated no significant two-way interactions between the factors ($F_{1,60} = 0.29, p = 0.58$).

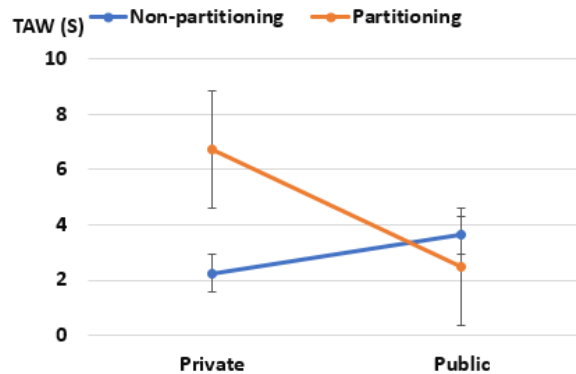


Figure 5.11 – Time to Arrange the Public Workspace (TAW) grouped into two conditions of Workspace.

Additionally, there were no significant independent main effects of *WORKSPACE* ($F_{1,60} = 0.3, p = 0.56$) or *VIEW-PRIVACY* ($F_{1,60} = 0.4, p = 0.52$) on *TP*.

The recording of user position data involved plotting their trajectories to examine the movement patterns of different participants throughout the experiment. Fig. 5.12 illustrates typical examples of participants P1 and P2's movements. The sequence in which conditions were experienced began with B, followed by C, D, and finally A. It was noted that, generally, the same workspace configuration was preserved by the participants. This pattern of behaviour was consistent across all the pairs. Notably, after experiencing a partitioning condition and then moving to a non-partitioning condition, participants tended to remain within the space previously assigned to them during the partitioning phase, despite having the option to occupy different areas.

Subjective data: The Friedman test was used to analyse the subjective questionnaires. In terms of cognitive load, the test did not find statistically significant differences in the means across the four conditions (A, B, C, D). Nevertheless, it was observed that the average workload was low across all conditions: A ($\mu = 37.02, \sigma = 14.59$), B ($\mu = 34.52, \sigma = 13.87$), C ($\mu = 35.85, \sigma = 18.17$), and D ($\mu = 42.65, \sigma = 17.16$).

Regarding the System Usability Scale (SUS) data, the Friedman test indicated no statistically significant variation in means across the different conditions ($p = 0.61$). However, each of the four conditions scored SUS score above 68, suggesting generally favorable usability perceptions: A ($\mu = 69.68, \sigma = 13.9$), B ($\mu = 72.34, \sigma = 13.31$), C ($\mu = 74.84, \sigma = 12.86$), and D ($\mu = 72.03, \sigma = 18.78$).

In the Overall ranking (Fig 5.13), the preferences of participants were as follows: condition C was favoured by seven participants, B by four, D by three, and A by two. Additionally, at the end of the experiment, 12 participants agreed to partake in open-ended interviews. Regarding the method of data sharing between collaborators in the *Private* view conditions (Q: *Which one do you prefer? Using the button to share the information with your partner or dragging the data to the*

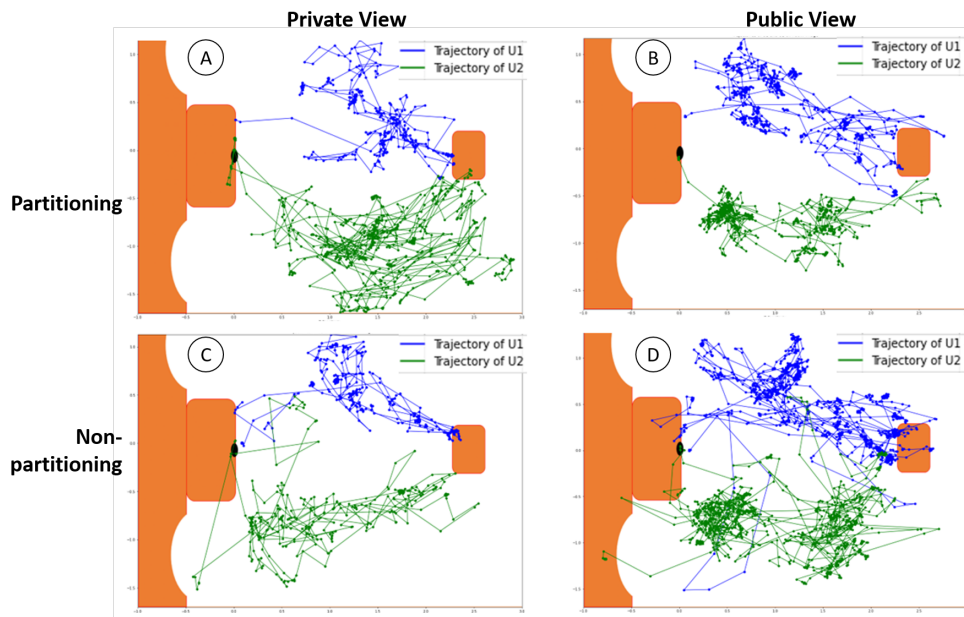


Figure 5.12 – Trajectories made by Participant 1 (in blue) and 2 (in green) during the task across the four conditions.

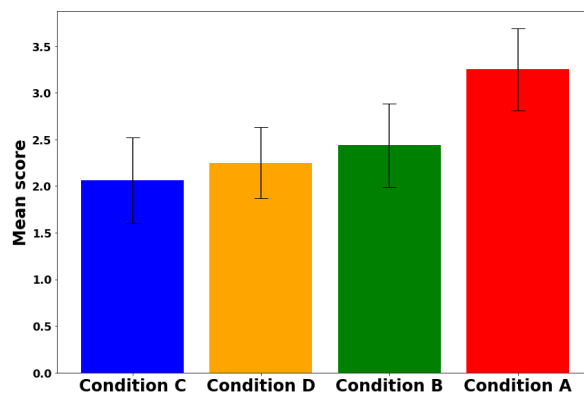


Figure 5.13 – Mean of overall user ranking of the four conditions (1 indicating the best, 4 the worst), with error bars showing 95% confidence intervals (CI).

shared workspace?), eight participants expressed a preference for the share button, whereas four participants preferred sharing their data through the public space.

5.5.9. Discussion

The statistical analysis revealed no significant differences between conditions when the data from the three sub-tasks were analysed together. This lack of difference might be attributed to averaging effect. By combining the data from different sub-tasks, the distinct effects of each condition on individual sub-tasks could be obscured. For instance, if a condition significantly influences *collab-*

subtask-1 but has little to no impact on *ind-subtask* or *collab-subtask-2*, these contrasting effects can neutralise each other in the overall analysis, leading to a lack of significant findings.

The statistical analysis showed the pairs of participants needed roughly the same amount of time to complete the three sub-tasks across different conditions. This lack of significant differences in task completion times could also be attributed to the well designed tasks and the easy-to-use IA system, and the participants' familiarity with them. However, when I consider only their performance during individual sub-tasks, the analysis showed that they were faster under *Private* view condition. This could be explained by the fact that in private views, the participants were less distracted by their partner's data and could concentrate on their own tasks.

The results also showed that the same amount of time was needed across all the conditions to position (both shared and individual) objects, probably due to averaging effect. Nonetheless, if I consider only the time needed to place shared objects, I found that under *Private* view conditions, *Non-partitioning* was better than *Partitioning*, which might be due to the fact that the participants must pay attention to the public space boundaries when placing the objects. On the other hand, in *Non-partitioning* conditions, there was no need to respect boundaries, enabling the participants to act more quickly by placing them whenever convenient. Moreover, I found that when it came to working with *Partitioning*, the public view could improve the *TAW* of shared objects. I noticed that the participants used the room's furniture (specifically tables) to place the public data, as in the [234]'s study (Fully-furnished condition). However, almost all the participants (15 participants) used the wall to place the different personal objects (data and windows). I did not observe that the use of surfaces was coupled to the type of visualisation (2D or 3D), as observed in [231]'s study in which participants used walls to organise 2D visualisations but positioned 3D visualisations in the space around them. I also found that in all the different conditions during the individual tasks, the participants maintained the social protocol by not interacting with the data that belonged to their partner, as noted in [231].

In our experiment, the participants took roughly the same amount of time to position themselves for the individual task using different conditions. This result suggests that the primary processes of orientation and task initiation were not impacted by the different factors (*WORKSPACE* or *VIEW-PRIVACY*). This result can also be explained by the size of the workspace. A larger room might have more effect on this measure, as participants would have more choices in positioning themselves for individual tasks in non-partitioned conditions, potentially leading to a longer time to decide where to work.

From the user position data, I found that the participants always maintained the same workspace configuration they learned during a *Partitioning* condition, i.e., if a participant worked in the left-hand private workspace during the previous

Partitioning condition, they would still choose to work on the left in approximately the same place during the next *Non-partitioning* condition. This behaviour underscores a natural inclination towards familiar work settings. For instance, P15 explained, "Following the partitioned space condition, I continued to use the same area where the partition had been. It felt instinctive to return and work there, despite the partition no longer being in place." This behaviour could also explain the lack of difference between conditions in terms of overall task completion time, user positioning time, and workload.

The outcomes of the quantitative data analysis do not allow us to confirm or refute **H3.2.1** and **H3.2.2**. However, the subjective data revealed that all the conditions were associated with a low workload and high usability, which support that AR can be used to visualise and analyse complex data [43, 47]. Condition C was the favourite for most of them. Three participants stated that its appeal was due to the freedom it offered; there were no constraints like boundaries, as found in the *Partitioning* condition. P4 mentioned, "I did not choose the partitioning conditions because I didn't pay much attention to the boundary on the floor." Condition B was the participants' second favourite (four participants indicated that it was their favourite). A pair of participants indicated their preference for it because the shared space facilitated data organisation and the public view space allowed them to share information about their private data without having to move their data to a public space or use a button.

Workspace partitioning with virtual boundaries using AR holds potential. Although dividing space with virtual boundaries is not commonly used in collaborative IA, using these partitions does not lead to significant differences in terms of overall task performance. Furthermore, I recommend that collaborative IA system should allow users the option to set their data as private or public during analysis tasks. It would be preferable to use buttons to change the confidentiality of objects, rather than linking confidentiality to specific spaces. Thus, even in a personal space, a user could make their objects visible to facilitate collaboration.

This partitioning design can be generalised to various tasks by first evaluating the key characteristics of the tasks, considering collaboration needs, privacy requirements, available workspace, and interaction dynamics. Once the task characteristics are clearly understood, the next step is to align these specific AR design implications with the identified characteristics. This process involves implementing spatial partitioning and managing view privacy effectively using the proposed approach. The proposed algorithm for AR-based space partitioning and view privacy can be adapted to different room configurations due to its inherent flexibility and scalability. The algorithm scans the physical environment dynamically, allowing it to gather all room object data so that different environmental settings, such as room size, shape, and furniture, do not affect its effectiveness. Furthermore, if the algorithm utilises real-time data input, it can continuously update and recalibrate the virtual partitions and privacy settings as the room configuration changes. This

is particularly useful during events where furniture is moved.

5.6. Conclusion

This chapter proposed and studied the partitioning of physical workspace and view privacy policies and various representations of the partitioned workspace boundaries for co-located immersive analytics using augmented reality.

An initial experiment was carried out to study the impact of partitioning the physical workspace using three distinct boundary visualisation techniques (*Line*, *Opaque*, and *Semi-transparent*). Six pairs of participants were engaged in a collaborative task requiring access to different sets of information for apartment decoration. The task completion time, cognitive workload, and system usability score were measured. Contrary to preliminary expectations, this experiment revealed no significant differences amongst the visualisation techniques regarding these metrics, indicating that the choice of boundary visualisation might not substantially affect overall task efficiency. Although there were no notable differences in cognitive workload and system usability scores across the techniques, the usability score for the *Line* technique was above the average, denoting favourable usability. Furthermore, the *Line* visualisation emerged as the preferred technique and was subsequently selected for the Experiment 2.

The second study aimed to evaluate the advantages of physical workspace partitioning in assisting users during co-located AR-based collaboration for data analytics tasks. This investigation explored the combination of partitioning techniques (*Partitioning* and *Non-partitioning*) and view privacy policies (*Public* and *Private*) in the context of both collaborative and individual tasks involving meteorological data analysis.

The findings indicated that the duration required to complete the tasks was consistent across various conditions. However, a detailed analysis of performance across the three sub-tasks (collaborative, individual, then collaborative task in the sequence) within the *Private* view condition showed that participants completed individual sub-tasks more efficiently. Notably, the *Non-partitioning* condition enabled faster placement of shared objects compared to the *Partitioning* condition. In contrast, the *Public* view condition within a *Partitioning* resulted in improved *Time to Arrange Workspace (TAW)* for shared objects. This suggests that partitioning with a separation of public and private view for each user has no significant impact on the workflow in collaborative work, answering **RQ3.2**.

Despite the findings, our user studies present several limitations. The partitioning of the physical workspace was limited to the floor area, omitting potential obstacles such as tables and walls that could influence spatial navigation and interaction. Moreover, the relatively modest number of participants and the specific choice of meteorological datasets for the second study, which involved lay participants, may limit the generalisability of our findings.

6 - Conclusion

Co-located COLLABORATIVE IMMERSIVE ANALYTICS (IA) using Augmented Reality (AR) primarily enables users to interact with data for sense-making, chosen as a response to the big data problem. However, interacting with small objects like data points in IA can be challenging. The first study proposed an expandable data representation model to enhance selection techniques in IA. The experiment demonstrated that using expanded points significantly improved selection speed and accuracy, and voice confirmation was preferred by users, indicating a promising approach for future IA environments.

Despite the observed benefits, the first study had limitations, such as focusing exclusively on 2D tiled data points. To address these challenges, a generalisation of the technique for 3D data points was proposed, along with a novel decoupling method for head movement and hand gestures, aiming to improve accuracy in complex data visualisation scenarios.

Displaying data without filtering or re-sampling can be overwhelming due to the field of view limitations of AR Head-Mounted Displays (HMDs) like the HoloLens and their limited computational power. The second study in the chapter 4 addressed this issue by proposing a semantic-knowledge representation approach using ontology. The user study has been conducted to evaluate this approach. In the experiment, the participants performed three different data analysis tasks under two conditions: *computer-assisted* based on ontology and linked data vs. *non-computer-assisted* using a NoSQL database (MongoDB). Excluding the query time response from the final task completion time, the *computer-assisted* approach allows the participants to solve tasks of exploring and manipulating the data faster than *non-computer-assisted* one, and all the participants rated *computer-assisted* as the best approach.

Efficient workspace management is crucial for multi-dimensional in co-located collaborative environments. In the chapter 5 I proposed a partition space technique. However, there are many ways to show the boundaries of the workspace, each with its own advantages and disadvantages. So, I first conducted an experiment to evaluate the partitioning of physical workspace with three different boundary visualisation techniques (*Line*, *Opaque*, and *Semi-transparent*). This experiment found no significant difference among the three visualisation techniques on these metrics. However, the *Line* visualisation mode was also rated as the best technique and was selected for the next user study. The second and main study investigated the combination of the partitioning technique (*Partitioning* and *Non-partitioning*) and the view privacy policy (*Public* and *Private*) during collaborative and individual analysis tasks on meteorological data. The experiment revealed that, when analysed the performance of three sub-tasks (collaborative, individual, then collaborative task in the sequence) independently, within *Private* view condition,

the participants performed individual sub-tasks more quickly.

6.1. Contributions

This thesis focuses on data visualisation in IA, particularly for multi-dimensional data such as meteorology. Three main aspects of data visualisation issues in AR are addressed: integration, interaction, and collaboration among multiple users. My research work is then organised around these aspects.

The first main contribution was to improve data point selection in IA. In that exploration, I proposed to study the expandable data representation model. The contributions of this chapter 3 are as follows:

I proposed and studied the effect of this technique on user performance. To improve the expanded selection method, I proposed different approaches to enhance the data point selection technique. More specifically, I designed and implemented a novel technique decoupling head movement for pointing and hand gestures to refine the pointing to improve its accuracy. This technique is mainly designed for the ray-casting pointing technique, which is commonly used in AR head-mounted displays. I also extended the application of the expanded data technique in two different contexts: with non-overlapped and overlapped data points. A part of this contribution was published at ACM Symposium on Virtual Reality Software and Technology (VRST) in November 2022

The second main contribution of this thesis is the design and development of an AR user interface using a semantic approach in chapter 4 that aims to enable the user to display appropriate data during the interaction and to enhance their performance in the data analytics process. The contributions of this part are as follows:

To bring forth the advantages of ontology and linked data in AR applications, I examined different ontologies in meteorology and climatology and proposed an ontology based on the existing ones by taking into account the AR limitations. Indeed, the meteorological and climatological ontologies in the literature are often large or complex in terms of concepts and dependencies on other ontologies, which reduces the query performance in AR-based systems. Moreover, they lack specific rules and concepts to allow the user to accurately formulate queries to some parts of our complex datasets. I evaluated the potential of our AR-based IA system by conducting an experiment that aims to demonstrate the relevance of our semantic approach compared to a conventional non-ontological one. This contribution was published in *Virtual Reality* Springer in 2024.

The third main contribution is discussed in chapter 5 and deals with workspace management in co-located work. The contributions of this chapter are as follows: I introduced an algorithm for space partition that allows users to partition the workspace and implemented this technique in the IA system. Additionally, I proposed and study different boundary display shapes that can be used to show the

different workspaces to the collaborators. I designed a user study to evaluate the different proposed boundary techniques. This contribution was published at European Association for eXtended Reality (EuroXR) in November 2024. The final contribution was an experimental study to explore the effect of space partition and view privacy in co-located collaboration work. This contribution was published to the ACM Symposium on Spatial User Interaction (SUI 2024).

6.2. Future Work

In this thesis, I discuss IA: the Selection, the data management using a Semantic-based approach, and Physical Space Management in co-localized collaboration. However, the proposed solutions still have limitations, leading to several future research directions.

One of my short-term objectives for future work is to study the different factors that impact each of the proposed techniques and their combinations during the selection process and data analytics tasks. For instance, one area of future work on the expansion technique of 3D data points will be to investigate the impact of the final size of expanded points and its correlation with their initial size, similar to the method used for menu items in [242].

The approach to dealing with the problem of overlapped data points, such as "exploding" the neighbourhood area of the data, can help to decluster for an effective selection and confirmation of a data point as the target. However, this approach may change the local visualisation context of the data because adding a spatial buffer between data points can alter any existing patterns in the dataset within this zone. A study could be conducted to see if this change affects user performance when looking for different patterns in the data.

For the Head-and-Hand switching technique for pointing using Ray-casting, another study could consider the three main factors that can influence our technique's performance: user's distance to the target, target's size, and the technique subsequently used to validate the pointed target. The potential of our pointing technique could be evaluated in terms of time performance of selection, workload, accuracy, and user experience.

A common challenge with any ontological approach is the time and domain knowledge required to build an accurate ontology. Besides this, my work presents some limitations: First, regarding the user study, due to the Covid-19 pandemic, I could only recruit participants from my university who were not experts in meteorology and climatology. This necessitated simplifying the experimental tasks, which did not fully demonstrate the potential of my system in these domains. Second, the query response time of the ontological approach increases exponentially with the number of queried data points, making it unsuitable for real-time interactive systems when dealing with big data. To overcome this limitation, the short-term future work will be to improve the user interface and the process to design the

ontology. Also to enhance query execution time by implementing the graph-based indexing and query processing technique proposed by [281] within the client-server architecture of my system but also an make a user study with expert meteorological participants.

The user studies conducted to explore the different boundary representations and the partitioning space still have several limitations. First, when we performed the partitioning of the physical workspace, we only considered the floor and remove a mesh of the object like tables and walls. The limited number of participants and the use of meteorological datasets in the second study with laymen may limit the generalisability of the results. For future studies, we will improve the partitioning technique by including other available surfaces on objects such as furniture. Additionally, we could implement a warning mechanism to alert users if they are about to enter someone else's personal space. We also plan to extend our study to experts in meteorology and climatology, and to other types of IA tasks in various domains to see if our findings hold in different contexts.

One of the long-term works can be to explore how to improve all aspects of meteorological and climatological visualisation using AR. Additionally, it is important to study the impact of this immersive analytics approach over extended periods with a large number of expert participants.

Another potential long-term work could be to explore alternative approaches to expanded data points. This could involve expanding the cursor, as proposed by Vanacken et al. [9], with the 3D Bubble Cursor. Their proposed 3D Bubble Cursor dynamically resizes to select the nearest target, using a semi-transparent sphere that makes occluded targets visible by rendering them semi-transparent when they are close to the cursor. Another approach worth exploring is the predictive selection technique, as recently proposed by Wei *et al.* [80] (Fig. 2.6).

Additionally, we can explore alternative approaches such as machine learning or deep learning algorithms for data integration. Instead of building an ontology, we can store raw data in a MySQL database and design an interface that allows users to directly apply ML algorithms through drag-and-drop gestures or by using trigger buttons. Users can employ deep learning models, such as convolutional neural networks (CNNs), to extract meaningful features from complex data types like satellite imagery. They can also use anomaly detection algorithms, such as regression models or artificial neural networks (ANNs), to identify and correct outliers or erroneous data points, ensuring data quality. Furthermore, clustering algorithms can be used to group related data points and identify patterns. Given the power limits of headsets, for such an approach all the calculations of ML models must be done at the server level, and the headset will just display the graphs or results. However, I believe that in the coming decades, VR and AR technology will advance significantly, allowing for the direct use of powerful algorithms for data analysis, which will encourage many companies to use these technologies for complex data visualisation.

Another long-term project could be to improve the system that ensures interoperability between different types of interfaces, such as desktop, AR, and VR, making it usable for all kinds of collaborative work (synchronous co-located, synchronous distributed, asynchronous co-located, and asynchronous distributed). This would enable users to connect and work collaboratively across these interfaces, and also globally for climate crisis management. This is important because, to effectively manage various climatological crises such as hurricanes, droughts, and wildfires, diverse profiles must work together. For example, meteorologists provide critical weather forecasts, engineers design resilient infrastructure, and public health officials prepare for health impacts, ensuring a comprehensive and effective response.

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(2) Ouedraogo, I., Nguyen, H., & Bourdot, P. (2024). Immersive analytics with augmented reality in meteorology: an exploratory study on ontology and linked data. *Virtual Reality*, 28(3), 144.

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