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Distress situation identification by multimodal data fusion for home healthcare telemonitoring

Hamid Medjahed

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PhD Thesis from INSTITUT NATIONAL DES TELECOMMUNICATIONS
in the frame of the doctoral program in S&I co-accreditation with
EVRY-VAL D'ESSONNE UNIVERSITY

Specialty:
Computer Sciences

by
Hamid MEDJAHED

A thesis submitted to
INSTITUT NATIONAL DES TELECOMMUNICATIONS
for the degree of Doctor of Philosophy

**DISTRESS SITUATION IDENTIFICATION BY
MULTIMODAL DATA FUSION FOR HOME HEALTHCARE
TELEMONITORING**

January 19th, 2010

Thesis Committee:

M. CROWLEY James, Doctorat d'Etat, Professor INPG, Grenoble	Chairman
M. DEMONGEOT Jacques, Doctorat d'état, Professor Joseph Fourier University, Grenoble, TIMC IMAG	Reader/Reporter
M. HEWSON David, Associate Professor, HDR Université de technologie de Troyes	Reader/Reporter
M. IANCU Eugen, Doctorat D'état, Professor Craiova University, Roumanie	Moderator
M. ISTRATE Dan, PhD, Associate Professor LRIT, ESIGETEL Fontainebleau -Avon	Moderator (Supervisor n°1)
M. BOUDY Jérôme, PhD, Studies Engineer EPH, TELECOM SUDPARIS	Moderator (Supervisor n°2)
M. DORIZZI Bernadette, HDR, Professor EPH, TELECOM SUDPARIS	Thesis Director
M. BAER Michel, MD, Physician anesthesiologist, Director SAMU92 - Hôpital R. Poincaré Garches	Moderator

Thesis n°:2010TELE0002



Thèse de doctorat de l'INSTITUT NATIONAL DES TELECOMMUNICATIONS dans le cadre
de l'école doctorale S&I en
co-accréditation avec
l'UNIVERSITE D'EVRY-VAL D'ESSONNE

Spécialité:
Science de l'ingénieur

Par
Hamid MEDJAHED

Thèse présentée pour l'obtention du grade de Docteur
de l' INSTITUT NATIONAL DES TELECOMMUNICATIONS

IDENTIFICATION DE SITUATION DE DETRESSE PAR LA FUSION DE DONNEES MULTIMODLES POUR LA TELEVIGELANCE MEDICALE A DOMICILE

Soutenue le 19 janvier 2010 devant le jury composé de:

M. CROWLEY James, Doctorat d'Etat, Professeur INPG Grenoble	Président
M. DEMONGEOT Jacques, Docteur d'état, Professeur Université Joseph Fourier de Grenoble, TIMC IMAG	Rapporteur
M. HEWSON David, Enseignant chercheur, HDR Université de technologie de Troyes	Rapporteur
M. IANCU Eugen, Docteur D'état, Professeur Université de Craiova, Roumanie	Examineur
M. ISTRATE Dan, Doctorat, Maitre de Conférences LRIT, ESIGETEL Fontainebleau -Avon	Examineur (Encadrant n°1)
M. BOUDY Jérôme, Doctorat, Ingénieur d'Etudes EPH, TELECOM SUDPARIS	Examineur (Encadrant n°2)
M. DORIZZI Bernadette, HDR, Professeur EPH, TELECOM SUDPARIS	Directeur de thèse
M. BAER Michel, MD, Médecin Anesthésiste Directeur SAMU92 - Hôpital R. Poincaré Garches	Examineur

Thèse n° : 2010TELE0002

Abstract

The population age increases in all societies throughout the world. In Europe, for example, the life expectancy for men is about 71 years and for women about 79 years. For North America the life expectancy, currently is about 75 for men and 81 for women. Moreover, the elderly prefer to preserve their independence, autonomy and way of life living at home the longest time possible. The current healthcare infrastructures in these countries are widely considered to be inadequate to meet the needs of an increasingly older population. Home healthcare monitoring is a solution to deal with this problem and to ensure that elderly people can live safely and independently in their own homes for as long as possible. Automatic in-home healthcare monitoring is a technological approach which helps people age in place by continuously telemonitoring.

In this thesis, we explore automatic in-home healthcare monitoring by conducting a study of professionals who currently perform in-home healthcare monitoring, by combining and synchronizing various telemonitoring modalities, under a data synchronization and multimodal data fusion platform, FL-EMUTEM (Fuzzy Logic Multimodal Environment for Medical Remote Monitoring). This platform incorporates algorithms that process each modality and providing a technique of multimodal data fusion which can ensure a pervasive in-home health monitoring for elderly people based on fuzzy logic.

The originality of this thesis which is the combination of various modalities in the home, about its inhabitant and their surroundings, will constitute an interesting benefit and impact for the elderly person suffering from loneliness. This work complements the stationary smart home environment in bringing to bear its capability for integrative continuous observation and detection of critical situations.

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Chapter 1

Introduction

As people grow older, they depend more heavily upon outside support for health assessment and medical care. Currently many developing countries are facing various problems in delivering health care and medical services to their population, and their current healthcare infrastructures are widely considered to be inadequate to meet the needs of an increasingly older population. In this context, Telemedicine represents a potential solution towards preventing a collapse in the hospital system and to providing better health care to the population. Telemedicine, a method of health care which is carried out in many context and applications to delivery health care services such as diagnosis, treatment advice and continuous tele-monitoring, etc, aims to keep the elderly population happy and socially connected, while reducing the strain on healthcare infrastructure.

In this thesis, we contribute to the field of in-home healthcare monitoring by conducting a study of professionals who currently perform in-home healthcare monitoring, by combining and synchronizing various tele-monitoring modalities, devising algorithms that process each modality and providing a technique of multimodal data fusion which can ensures a pervasive in-home health monitoring for elderly people.

The originality of this thesis which is the combination of various modalities in the home, about its inhabitant and their surroundings, will constitute an interesting benefit and impact for the elderly person suffering from loneliness. This work complements the stationary smart home environment in bringing to bear its capability for integrative continuous observation and detection of critical situations.

1.1 Thesis Context

Many research areas are involved in the development of remote medical care systems. They include the development of communication architectures between actors of these systems, appropriate equipment devoted for monitoring and improving the quality of life, databases collected at home and tools of analysis and processing these large amounts of data. The aim is to detect and prevent the occurrence of critical situations of a person at home, involving transmission of messages and alarms to the concerned actors which are ready to intervene, if it is necessary.

The framework of this thesis is the collaboration between the EPH department of **Telecom & Management SudParis** (TMSP), LRIT laboratory of **ESIGETEL** and the medical research institution **INSERM**, U558; under **FP7 CompanionAble European Project** (Integrated Cognitive Assistive & Domotic Companion Robotic Systems for Ability & Security) which provide the synergy of Robotics and Ambient Intelligence technologies and their semantic integration to provide for a care-giver's assistive environment. This will support the cognitive stimulation and therapy management of the care-recipient. This is mediated by a robotic companion (mobile facilitation) working collaboratively with a smart home environment (stationary facilitation). These research activities deal also with **the French National Project QuoVADis** (Monitoring the Daily Life of the elderly people suffering from cognitive disorders), which meets the need to compensate the difficulties of communication due to the loss in cognitive capacities which generate social insulation, depression, insecurity and discomfort in the everyday life. The system aims at restoring the affective link with the helping people by an interactive mobile system accompanying the person and at enabling her/him to locate themselves in its environment and to control it.

1.2 Telemedicine

Research activities performed during this PhD thesis concern remote home medical monitoring, which is a dimension of telemedicine. Telemedicine - although referenced frequently - is not a clearly defined term. Basically it is medical practice at a distance using Information and Communication Technologies (ICTS) to overcome the distance between the partners involved. However, before attempting to define the term more rigorously it is useful to place telemedicine within the general application of ICTs in health care as there are many overlapping areas and possible interactions.

1.2.1 Information and Communication Technologies in Medicine

According to Thrall et al. [1, 2] the recent developments and improvements in technology and telecommunications have resulted in renewed and earnest interest in telemedicine. Over the past two decades an immense proliferation of Information and Communication Technologies, commonly abbreviated ICTs, could be observed. Communication networks from plain old telephone lines to mobile phone networks and satellite communication have reached almost every corner on our planet. The Internet has become a global repository of information and almost any type content from daily news papers over share prices at the stock exchange market to specialized scientific journals are all accessible over the Internet. And finally, today's desktop computers are capable of handling complex multimedia content such as images and also movies with ease, allowing the production of digital content for basically everyone who can afford a computer. ICTs have penetrated almost all aspects of our lives.

The concept of telemedicine is reserved, in many contexts, for applications where the subject is to render health services dependent on application of telecommunication. The most common is probably the management of administrative data such as billing and general record keeping - areas in which probably most of us do not even remember the time before ICTs. Besides, the electronic management of patient information is becoming more and more important and many hospitals are working towards digital storage of all patient associated data using electronic medical records (EMR) or electronic health records (EHR). But also in medical practice itself there are many new methods that directly depend on ICTs. In modern medical imaging such as CT (Computer Tomography) or MRI (Magnetic Resonance Imaging) but also in standard radiology (e.g. plain thorax x-ray) the conventional, film based equipment is more and more replaced by digital radiology (DR), filmless solutions, in which all image data are primarily stored in electronic form and only transferred to film for reading in locations not (yet) equipped with digital X-ray viewing stations.

ICTs can contribute to a more effective utilization of resources through tying the resources of the health sectors resources together in a large number of telemedical services [3]. ICTs will never replace the doctor or other health

care staff concerned in a patient relation. Alternatively, it provides an opportunity of increasing the combination between various health care services and in this way contributes to better care directed towards the patients. So telemedicine or service can be an important medium for economical benefit of health sectors of a country.

1.2.2 Definition

Telemedicine is not a concisely defined term. Some authors use it in the stringent sense of the word derived from the syllable *tele* applying telemedicine strictly to the practice of Medicine *at a distance*, which often involves a consultation between a patient and a geographically separated doctor, using a video conference link. Many others however use the term telemedicine in a much broader sense like the European Commission's health care telematics program which defines telemedicine as *rapid access to shared and remote medical expertise by means of telecommunications and information technologies, no matter where the patient or relevant information is located* [4].

Besides the term "Telemedicine" many other similar term are frequently encountered in the literature - e.g. *Health Telematics, Tele-health, Tele-Care, On-line Health, e-Health, Medical Informatics* or simply *ICTs for health*. The terms for describing the same phenomenon are extensive and the terms are not used in any precisely defined way. There are several definitions of telemedicine. The recent one, it is introduced by the Norwegian Centre for Telemedicine (NST), which is using the following definition: *Telemedicine is the investigation, monitoring and management of patients and the education of patients and medical staff, which allow easy access to expert advice and patient information, no matter where the patient or relevant information is located*.

According to the American Telemedicine Association (ATA) [5], to facilitate the understanding of telemedicine it is useful to distinguish between the service to be delivered and the delivery mechanisms.

1.2.2.1 Services

Technology has implied standards in process of collect, archive, communicate, and search relevant medical images, video records and other medical information as well as standards of medical devices, telemedicine systems, computers and computer network devices and communication equipment. Considering means of using telemedicine, the main telemedicine services are:

- **Teleconsultations** provide remote access to either medical professionals or information stored in electronic knowledge databases.
- **Telediagnosics** to make diagnosis to a patient with no direct contact with physician using medical data (medical report, image or video record).
- **Telemonitoring** remote monitoring of patients' physiological parameters, most often of patients with chronically diseases without hospital surveillance needs.
- **Telecare** treatment of patients outside of healthcare institutions. This includes reminders to take medication, supervision, scheduling of appointments and similar applications which are not implicitly medical but which are important to improve the outcome of care.
- **Tele-education** education and practicing of medical staff outside of healthcare institutions, remote access to medical knowledge databases using Internet. On the other side, the main fields where telemedicine is applied today include.
- **Specialist Referral Services** typically involves a specialist assisting a general practitioner in rendering a diagnosis. This may involve a patient *seeing* a specialist over a live, remote consultation or the transmission of diagnostic images and/or video along with patient data to a specialist for viewing later. Routine applications of specialist referrals include all medical disciplines that are to some extent based on visual data such as radiology, pathology, dermatology, ophthalmology, cardiology, etc.

1.2.2.2 Communication Mechanisms

The major trends of Delivery Mechanisms are given below:

- **Networked Programs** link tertiary care hospitals and clinics with outlying clinics and community health centers in rural or suburban areas within an existing or newly created network of health providers. The links may use dedicated high-speed lines or the Internet for telecommunication between sites.
- **Point-to-point Connections** using private networks are used by hospitals and clinics that deliver services directly or contract out specialty services to independent medical service providers at ambulatory

care sites. Radiology, mental health, pathology and even intensive care services may be provided under contract using telemedicine to deliver the services.

- **Primary or Specialty Care to the Home Connections** involve connecting primary care providers, specialists and home health nurses with patients over single line phone-video systems for interactive clinical consultations.
- **Home to Monitoring Center** links are used for cardiac, pulmonary or fetal monitoring, home care and related services that provide care to patients in the home. Often normal phone lines are used to communicate directly between the patient and the center although some systems use the Internet.
- **Web-Based** systems are becoming increasingly popular for two main applications. (1) e-Health patient service sites provide direct consumer outreach and services over the internet. (2) Communities of specialists who share medical data over the web for second opinions consultations and for continuous medical education.
- **Messaging-Based** system is useful for sending out reminders or quick delivery of laboratory results to smaller health care facility. Messaging services such as SMS or email do often not have a guaranteed delivery and are thus not advisable for critical information, but they are easy and cheap to deploy on a large scale.

1.2.3 Legal and Ethical Issues

As telemedicine has been developing for over 35 years, and taking in the account, the merger, of ITCs with its sudden surprising growth, many ethics approaches are indispensable for the development of any telemedicine application, from the concept stage to the prototype achievements and trials stages.

For example, the World Medical Association (WMA), the global representative body for physicians, has presented some responsibilities and ethical guidelines for e-health and telemedicine practices. The followings are some legal and ethical guidelines [6] that should be considered when offering information and services to patients and the public over the Internet.

- It is essential that the physician and the patient be able to reliably identify each other when telemedicine or e-health services (for example, e-mail communication) is employed.
- Patients or publics' data and other information may be sent to a physician or other health professional, only on the request, or with the informed consent, of the patient, and to the extent approved by given patient or public. The data transmitted should be pertinent to the problem in question.
- Because of the risks of information leakage due to some types of electronic communication, the physician must have an active commitment to ensure that all established standards of security measures have been followed to protect the patient's confidentiality.
- A physician practicing telemedicine or e-health services is responsible for the quality of care the patient receives.
- Calibration procedures as well as routine controls can be used to monitor the accuracy and quality of data gathered and transmitted.
- Physicians practicing e-health services or telemedicine services must be authorized to practice medicine in the country or locality in which they are located, and should be competent in their field. When practicing telemedicine or e-health services via internet (e.g., email communication, prescription over the Internet) directly with a patient located in another country or state, the physician must be authorized to practice in that state or country, or it should be an internationally approved service.

According to the European guidelines and national legislations, Ethics approaches have as main objectives:

- To ensure full consent of users and carers, full participation with clear explanation of the goals, full understanding and agreement for participation in a proactive part in the project with the experimenters and researchers.
- To respond to the needs and wishes of patient and carers for useful support in ADL (Activities of Daily Living).
- To respect the Hippocrates oath that is a basic principle of medical care.

- To respect intimacy and private life.
- To ensure the confidentiality of personal data that could be transmitted to external services, or may be accessible by the robotic companion to unauthorised persons.
- To ensure accessibility not only by the ergonomics of interfaces allowing easy use, but also adaptation to the impairments evolution, and explore the ways and means to address the challenge of economic accessibility. To address these challenging issues implies an inclusive design opening to wider beneficiaries target such as other impaired and disabled persons, and frail old people in the new perspective of Universal access.
- To achieve security matching with hazardous and critical situations at home with a linkage with outside mobility

1.3 Home Healthcare Telemonitoring

Home healthcare telemonitoring is the main subject of this PhD thesis. This application particularly takes on account of the remote telemonitoring, tele-consultations and tele-assistance.

1.3.1 Goals and Objectives

Main goals of these systems are to support the home life and healthcare of disabled and/or old people persons and to improve their quality of life and the alleviation of risk, by maintaining them at home with safety and providing their autonomy. These systems represent a temporary or lasting alternative to hospitalization, or to the use of accommodation establishments for a long duration, houses or retirement centers. The patient is then always connected to his home, his family and his society. These systems particularly, concern the elderly, but more generally the people with risks of walking condition (falling) or cognitive (depression, dementia, etc.), or in need of care or particular attention (diabetics, asthmatics, etc.).

1.3.2 Description

A home healthcare telemonitoring system is based on a global information system containing the following components (figure1.1):

- **A set of Various Sensors** (physiology, environment, activity) installed in the home or carried out by the person, networked between

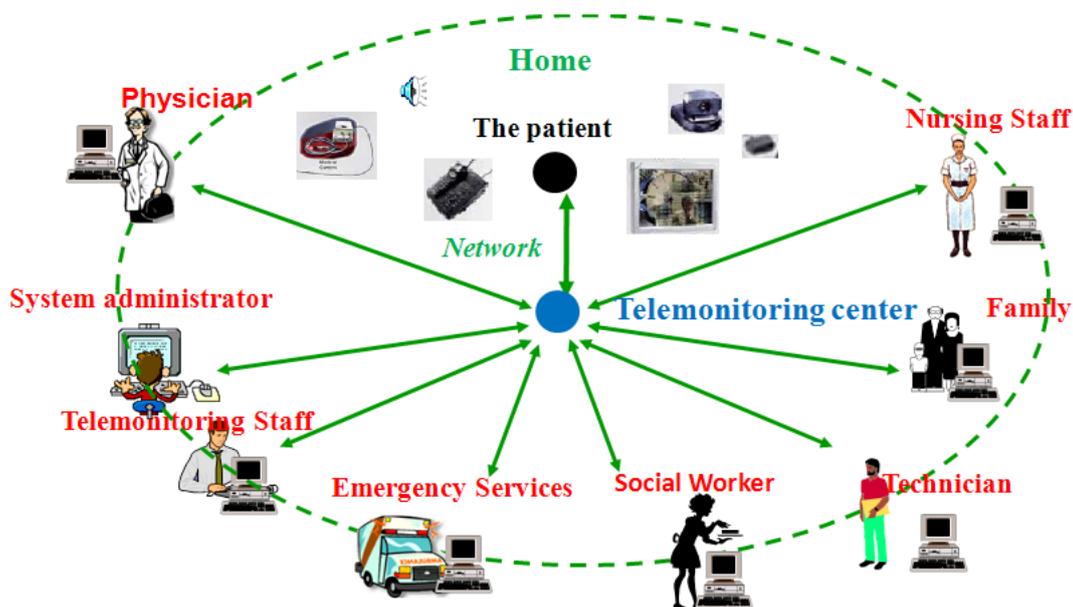


Figure 1.1: Typical remote healthcare telemonitoring system

them in order to collect data in real-time , and automatic devices (home automation) to adapt the living environment of the person to his personal motor and cognitive abilities.

- **A smart PC** for processing data generated from the different sensors, to storage these information, and for managing a knowledge database regarding the telemonitoring person, and the broadcast of messages and alarms.
- **Telemonitoring Center** for processing messages and alarms received from habitats, and decision making.
- **A Set of Stakeholders** (medical staff, telemonitoring person and his family members) can access at any time after authentication and privileges according to data system at the local unit of treatment (the smart PC).

1.3.3 Application Issues

The main features necessary for building home healthcare telemonitoring systems are the perception, the analysis, the storage and the transmission of data about the telemonitoring person. Then we have identified according to [6], five key for developing these telemonitoring systems.

- **Local Monitoring System** It is a local area network at home for telemetric recording of data about the person through physiological and environmental sensors.
- **Data Analysis System** The large amount of data collected requires intelligent assistants design for extracting information which allowed the generation of messages, alarms, diagnosis and decision.
- **Database System** Data collected and information obtained must be stored and accessible for viewing and updating.
- **Interface System** Data and information obtained from telemonitoring and analysis should be easily accessible to the various actors of the system.
- **Communication System** To enable interoperability between the four precedent subsystems, through a medical network that connects the settlements of patients, hospitals, telemonitoring centers and more generally the various actors of the telemonitoring system.

The complexity of these systems is the number of involved actors, the diversity of computer techniques used at different levels of registration, storage, analysis and transmission of data, the increasing amount of the collected data, the needness to customize their treatment in the context of each patient, the difficulty of modeling the health of a person. One of Home healthcare telemonitoring systems specificities, this is the constraint of the rapid processing of large set of data that evolves over time, in order to detect speedily distress situations at home. The difficulties of these treatments are particularly related to the heterogeneity of the collected data, to factors of influence, which sometimes act strongly on the observed parameters, and the mutual dependencies between these parameters.

1.3.4 State of the Art

Numerous projects are carried out in the world, upon the home healthcare telemonitoring topic. They aim for example to define a generic architecture for such telemonitoring systems, to conduct experiment of a remote monitoring system on a specific category of patients (insufficient cardiac heart, asthma, diabets, patients with Alzheimer's disease, etc.), or to build apartments, sensors, alarm systems adapted to the healthcare telemonitoring requirements.

1.3.4.1 Generic Architecture as a Global Information Systems

In the UK, Williams et al. [7, 8], have developed a generic architecture of a telemonitoring system (CarerNet) implemented by using prototype MIDAS [9]. Rodriguez et al. [10], in Spain, have developed a similar architecture under the EPIC Project (European Prototype for Integrated Care). In France, Thomesse et al. [6] have developed the TISSAD project, where the first objective, is the specification of a generic and modular architecture, and open for telemonitoring systems, adaptable to various diseases treated at home (tracking elderly, heart failure).

In terms of development and testing of such systems, the Shahal project [11], in Israel, is probably the most successful, with over 40 000 subscribed patients. It provides an emergency service and prevention for cardiac and pulmonary risks.

In the PERSONA project [12], the goal is to provide a scalable open technological platform upon which a broad range of services for social inclusion, independent living and a healthy lifestyle for senior citizens can be deployed. Thus the technological challenge is to provide the aging population with systems that could foster the different facets in the perception of quality of life of a person, improving the level of independence, promoting the social relationships, leveraging the immersion in the environments and elevating the psychological and physical state of the person.

Projects related to the global information systems design for home medical telemonitoring, focus in implementing these systems architectures, or in testing these systems on a specific people, with a disease or a particular risk.

1.3.4.2 Smart Home Systems

Other experiments are conducted in order to develop more specific infrastructure for smart home telemonitoring. They aim to build smart houses equipped with sensors tailored to the home healthcare systems objectives and constraints, in terms of technology and ethic, in order to ensure safety, dignity and autonomy of individuals.

Among these systems we found SmartBo[13] in Sweden, AID HOUSE [14] in the UK, Smart House in Tokushima [15]. Noury, Rialle et al. [16] have also designed and implemented a smart house for health (HIS) connected to a network to allow the users management, information about telemon-

itoring persons and alarms. In the framework of DESDHIS project [17] a medical home monitoring system which use an accelerometer based sensor, infrared sensor, an oxymeter and a blood pressure device has been developed at Grenoble.

Geoff West et al. [18] describe an approach to representing normal activities in a smart house based on the concept of anxiety. Anxiety is computed as a function of time and is kept low by interactions of an occupant with the various devices in a house. Abnormality is indicated by a lack of activity or the wrong activity which will cause anxiety to rise ultimately raising an alarm, querying the occupant and/or alerting a carer in real-time.

The concept of combining the smart house sensor technologies with an external provider in cases of emergency is shared with the EMERGE project [19]. EMERGE supports elderly people with emergency monitoring and prevention. The basic assumption is that humans are bio-psycho-social beings, whose character is to follow typical behaviour. The innovation is to observe this behaviour by a holistic approach in order to detect deviations from typical behaviour patterns and to reason on acute disorders in their health condition in case of strokes, falls or similar emergencies. NETCARITY [20] seeks to advance ambient intelligence technologies by the integration of micro and nano systems in a networked wireless/wired multi-sensing environment with plug and play capabilities and intelligent decision making for an effective detection of critical situations and support of task completion [21].

One important task at hand is the definition and development of a common open platform to simplify and speed up development and deployment of services for people with cognitive disabilities and the elderly in smart home environments. This an important goal of the MPOWER project [22] which aims to simplify and speed up the task of developing and deploying services for persons with cognitive disabilities and the elderly. The platform will in particular support the integration of smart house and sensor technology, the interoperability between profession and institution specific systems, and a secure and safe information management, including both social and medical information.

The TelePat project (French RNTS Program) [23] aims also to provide a smart home, by measuring certain physiological data and the person's activity by different sensors connected to a microcontroller based computing unit, then sent these information through radio connection to a remote central server application for exploitation and alarm decision. Now, within the TAN-

DEM project (French RNTS Program), accelerometer sensors are added to this system for the detection of falls. The aim of this French research project is to improve the quality of life and well being of patients with Alzheimer's disease at home by means of a Telecare system.

1.3.4.3 Management and Storage Database Systems

One of the difficulties related to the management and storage of data concerns the definition of models that allow easy sharing and exchange. Some projects focus on the definition of protocols for managing data and ontologies knowledge [21], or a shared electronic medical folder for patients [24].

One interesting project concerning this category of systems is CHIL [25]. It uses human-machine-interaction technologies, however not for domestic but in office and lecture environments. The objective of CHILL is to put Computers in the Human-Human Interaction Loop. Based on the understanding of the human perceptual context, CHIL computers shall be enabled to provide helpful assistance implicitly, requiring a minimum of human attention or interruptions.

1.3.4.4 Mobile Robotic Companions for Home Telemonitoring

In the field of mobile service robots in domestic environments, the research is just at the beginning of the road. Most projects are still focusing on autonomous navigation in cluttered home environments, only a few are particularly interested in advanced Human-Robot interaction technologies for assistance at home [26].

The MOVEMENT FP-6 project [27] aims at the development of a modular versatile mobility enhancement system. The core is formed by an intelligent mobile, robotic platform which can attach to a user definable selection of application modules (e.g. chair, manipulator, ICT Terminal) which are more or less inconspicuous mainstream articles but will become powerful assistive devices when the mobile platform attaches to them. Within the MOVEMENT Consortium, ARC (partner #6) is responsible for inter-module communication and integration. This way, experiences made in this project might directly inspire the specifications of CompanionAble. In the focus of the COGNIRON [28] FP-6 IP is the development of a robot whose ultimate task is to serve humans (not primary elderly or cognitively impaired persons) as a companion in their daily life. The overall objectives of COGNIRON are to study the perceptual, representational, reasoning and learning capabilities of

embodied robots in human-centred environments.

The commercially available US service robot CareBot [29] was developed with the scenario of assisting elderly people in mind. Navigating in domestic environments is carried out by using fuzzy logic, by means of a hybrid control architecture that has to utilise an external additional Personal Computer for computation via a wireless connection. The system performs simple duties such as vacuuming, patrol and errand running, while the main focus is the robust navigation in real-world home environments.

Moreover, in the mentioned projects the mobile robots are to operate as more or less autonomous systems. This is typical for most of the current projects in mobile robotics and cognitive robotics.

1.3.4.5 Intelligent Assistant Systems

The first generation of tele-alarms was consisting into *wearable buttons* linked by a wireless communication to monitoring center. The next generation of systems seeks a higher level alarms with autonomous systems.

Noury et al. [30], have studied the development of a fall sensor which integrates on a single support three accelerometers arranged orthogonally and a microcontroller which determines the inclination of the body then provides automatically fall information. Among also existing systems, RFpat system [31] developed by J.L. Baldinger et al., a wearable device fixed on the elderly person, which can measure physiological data like heart rate, activity, posture and an eventual fall done by the person.

Other systems focus on non-invasive approaches, where the patient is not equipped with any instrument. The system known as Gardien [32], for example, consists of passive infra-red sensors placed in a residence and connected to a remote computer, and data corresponding to movements are collected and processed for fall detection. Another system of multi-channel sound acquisition is presented in [33] to analyze in real time the sound environment of the home to detect abnormal noises (i.e., call for helps or screams).

This generation of system is characterized by its capacity of autonomy and its abilities of perception, reasoning and decision-making.

1.3.5 Challenges for Home Healthcare Telemonitoring

The first complexity for designing these systems is the constraints of robustness, reliability and relevance of the available information. This issue calls up the problem of the sensors selection for remote monitoring application. The objective is to find a compromise between the need to get optimal information for telemonitoring and the constraint of the respect of patients' privacy.

An additional difficulty comes from the need to design systems that allow personalized data treatment for different patients. Then the solution is to develop or to use artificial intelligence algorithms. The large amount of data to analyze can also justify the use of data fusion techniques and data mining.

Another constraint is the synchronization and the combination of different data collected from different types of sensors for providing relevant information to practitioners. This multidimensional and heterogeneous characteristics also require the use of data fusion techniques.

For developing these telemonitoring systems, it also indispensable to take into account the increasing amount of developed sensors that can be installed at home, the diversity of diseases which may require telemonitoring, and the specific behavior of each person.

The most crucial issue for all these systems is the lack of experimental data and information representing many situations and many people's profiles. In order to develop and evaluate telemonitoring systems, it is very important to have a multimodal medical database.

1.4 Thesis Objectives and Contributions

In our work we have developed a new multimodal platform for home healthcare telemonitoring, called **EMUTEM**, based on fuzzy logic data fusion approach. This multimodal platform incorporates a multimodal fusion between various sensors in order to detect a distress situation of a person at home. The platform enables us to have a full and tightly controlled universe of data sets and to evaluate the decision part of remote monitoring systems, in real time.

Currently, the distress situations detection is achieved using only one modal-

ity like: vital signal sensors, fall detection sensors, infrared or sound sensors. The main goal of this thesis is to study the multimodal fusion between various sensors in order to increase the reliability of the whole system to detect several distress situations. In the case of an ambiguous situation of fall or faintness it is essential to confirm the situation detection using several telemonitoring modalities. A multimodal fusion which can take into account the temporary sensor malfunction can increase the system reliability and the robustness in the case of environmental disturbances or material limits (battery, etc.).

1.4.1 Distress Situations Detection of Person at Home

The problem of critical situations detection of a person with data collected at home concerns specifically, the conception of intelligent systems. Devices or Projects developed and commercialized in this context, often target a particular pathology, or a limited or specific set of parameters.

Based on these effects we have decided to carry out work in this sense, given the increasing amount of developed sensors that can be installed at home, the diversity of diseases which may require a monitoring, and specific behavior of each person and his profile. To provide one answer to this problem and in order to develop a platform for several uses and to meet the needs identified above. The platform EMUTEM developed within this thesis manages a system consisting in:

- A set of microphones disposed into each room of the home of the elderly.
- A portable device that can measure ambulatory pulse heart rate, detect posture and possibly the fall of the equipped person.
- A set of infrared sensors that detect the presence of the person in a given home part and also the standing posture of the person in question.

This platform is flexible and open for adding other type of sensors. It could also be arguably less expensive than the cost of live-in helpers and caregivers, but without removing completely the human presence. The proposed platform collects and analyses the output of three distinct subsystems and makes a fusion of the three modalities in order to take the right decision about the monitored person situation. These three subsystems are detailed in the next chapter.

1.4.2 The Decision Issue of the Situation of a Person at Home

The decision issue about a situation of a person under our multimodal telemonitoring platform, concerns the wide variety of sensors, used to collect data about the patient health status and installed in a habitat or carried out by the person. They concern the activity, environment and the physiology of the person. These sensors provide different data, even complementary or even redundant, and can infer high level information about the status of the person at home. In addition to these data, we have also prior information about the person or the patient which are his clinical data.

The analysis of these large sets of heterogeneous data to make a decision at any time about the patient situation can be defined as a data fusion problem. This data fusion process, through the heterogeneous combination of information from different sources, sensors and prior knowledge, provides a synthetic representation of the patient situation. The goal of this data fusion decision, is to detect the occurrence of a critical situation, more or less on the long term, like the detection of a fall, a heart attack, etc, and also to recognize some activities of daily living (ADL) that can provide to the nursing staff information which are sometimes difficult to observe even if with a daily visiting.

Chapter 2

Data Collection for In-Home Monitoring

Practical in-home health monitoring technology suffers from a lack of experimental data and a standard medical database intended for their validation and improvement. In this chapter, we describe a novel, methodology for recording a new multimodal medical database called HOMECAD (Home remote Medical Care Database), in which physiological data, environment sounds and others different information gathered by ubiquitous sensors are used to describe the context-awareness of our application. We have developed an environment for acquiring and recording a multimodal database called EMUTEM (Environnement Multimodale pour la Télévigilance Médicale) where a user can interpret elderly activities by following a reference scenario which summarizes the everyday life of elderly persons. Taking into account the multimodality character of the data, a multidimensional indexing process is used in order to obtain a full description of data sets. Additional process of simulation is also integrated in our platform as a way to overcome the lack of experimental data and the difficulty of recording some medical data such as the cardiac frequency during distress situations. Our approach is valuable because it is practical: it provides graphical interface to manage, to process and to index these data.

2.1 Introduction

Healthcare technology for the elderly has been a popular area of research, spawning the sub-discipline of "Gerontechnology" [34]. Automatic monitoring of distress situations has been a common focus in Gerontechnology;

however, little research exists to motivate and guide such technology. For example most of monitoring systems use some form of learning method to discriminate between different types of normal and abnormal events. These algorithms require large amounts of training data that can be difficult to obtain, especially data describing abnormal events that are by definition rare occurrences. The most crucial issue for all these systems is the lack of experimental data and information representing many situations and several person's profiles.

The recording of a multimodal medical database aims to generate a large number of temporal sequences of multimodal data representing person's behavior at home, in order to develop and evaluate telemonitoring systems. The implementation of this process depends on one hand, on the context and objectives of the problem to solve, and on the other hand to produce suitable data for decision algorithms tests. The implementation and the development of any decision-making system require realistic data sets and adapted data for the studied problem. These sets of data may be formed by the experiments and / or provided and generated by databases and simulation.

In the field of in-home healthcare telemonitoring, research projects still in early stages of their development, and experiments in realistic environment have just begun. Consequently, we can't dispose of enough realistic and comprehensive data sets to constitute decision systems about the situation of a person at home. However, a comprehensive and reliable study requires taking into account several profiles of persons, facing several types of situations.

Many ubiquitous in-home telemonitoring applications depend on knowledge of how people behave in their environments. Fortunately, our pervasive multimodal platform implicitly allowed us to build the multimodal medical database HOME CAD, which gather a valuable context history as it collects and stores sensor data over time. This large amount of data is of limited use without labels that explain what was happening in some way, but fortunately this task is performed by our platform. In relation to experimentation, integrating a simulation process to our platform enables us to have a full and tightly controlled universe of data sets and to evaluate the decision part of remote monitoring systems. Performing real time experimental application in realistic environment remains essential as a second stage of remote monitoring decision systems validation, the use of database is only a first step of test. The work described in this chapter is motivated by the lack of experimental data in our research context on one hand, and the benefits to dispose of a multimodal base on the other hand. The main goals of this database

recording platform are:

- First to design and develop data fusion-based decision algorithms exploiting the measurements obtained from this platform in order to propose new processes to reinforce the secure detection of patient's distress events, in particular the fall situations: indeed one or more telemonitoring modalities might be out of order, or a particular environmental situation (ambient noise, bad wireless conditions, sensors disabilities) can hide one particular modality or more. This is a very challenging issue for hospital emergency units such as for instance SAMU in France or Telecare services providers in general.
- Secondly to allow a better description and investigation on Telecare situations for the patient at home: indeed the lack of real emergency situations data has strongly motivated our idea to develop simulation routines that would be easily adapted to the platform, for instance to simulate cardiac profiles or fall situations, or even correlated ones. This work developed for some years in GET (Groupe des Ecoles Telecom)[23] and for more time in TIMC and CLIPS [35] has for target to create a more diverse and close to real patients situations.

For these reasons building a platform for acquiring, recording, simulating and indexing a multimodal medical database seems to us of a great benefit for evaluating and improving medical remote systems.

2.2 Context Awareness

The key idea of the context-awareness for our application is to use contextual data collected by ubiquitous sensors to provide sufficient information that can be useful to make a decision about the situation of an elderly at home. Therefore, selected telemonitoring parameters should address the problem of in-home healthcare telemonitoring, in order to detect any critical evolution of the elderly. This set of parameters that we want to integrate in our in-home healthcare telemonitoring application must satisfy the following constraints:

- The parameter values must be simply obtained from the data recorded by one or several sensors installed in the home or worn by the person.
- All parameters are limited by the choice of sensors, which is constrained by ethical criteria, social and individual privacy, discretion, easiest usability, low cost.

- Parameters must be sufficiently representative of the situation of the elderly or the person susceptible to health deterioration and his daily activities, in order to be fully suitable with objectives of decision.

To provide one answer to this problem, we have developed the new multimodal platform EMUTEM for several uses and to meet the needs identified above. The platform developed within this project manages a system consisting in:

- A set of microphones disposed in all rooms of the house of the elderly.
- A portable device that can measure ambulatory pulse heart rate, detect posture, potential fall of the equipped person and his activity rate.
- A set of infrared sensors that detect the person's presence in a given home part and also the standing posture of the person in question.
- A set of change state sensors like contact sensors, temperature sensors, smoke sensors and several other domotic sensors.

The output of these heterogeneous systems are collected, processed and fused through our multimodal platform (EMUTEM). The first application of this platform is to record a multimodal medical database.

2.3 The Proposed Platform For Database Recording/EMUTEM

Faced to the scourge of the aging society, identified as a significant burden for governments, we propose the new multimodal system EMUTEM for in-home healthcare monitoring with several uses. Advances in miniaturized sensor and wireless technologies have resulted in interest to gather many sensors under our monitoring platform.

EMUTEM is based on three main subsystems, which have been technically validated from end to end, through their hardware and software, plus a multi-sensors subsystem which gathers a set of state change sensors for home appliances like contact sensors, smoke sensors, temperature sensors, water debit sensors and some sensors to control some devices (vacuum, dish washer, van, refrigerator, TV, Stove...etc). Figure 2.1 shows a proposed set of sensor to be installed at home. The first one is Anason subsystem [33, 36] with its set of microphones that allow sound remote monitoring of the acoustical environment of the elderly. The second subsystem is RFpat [31], a wearable device

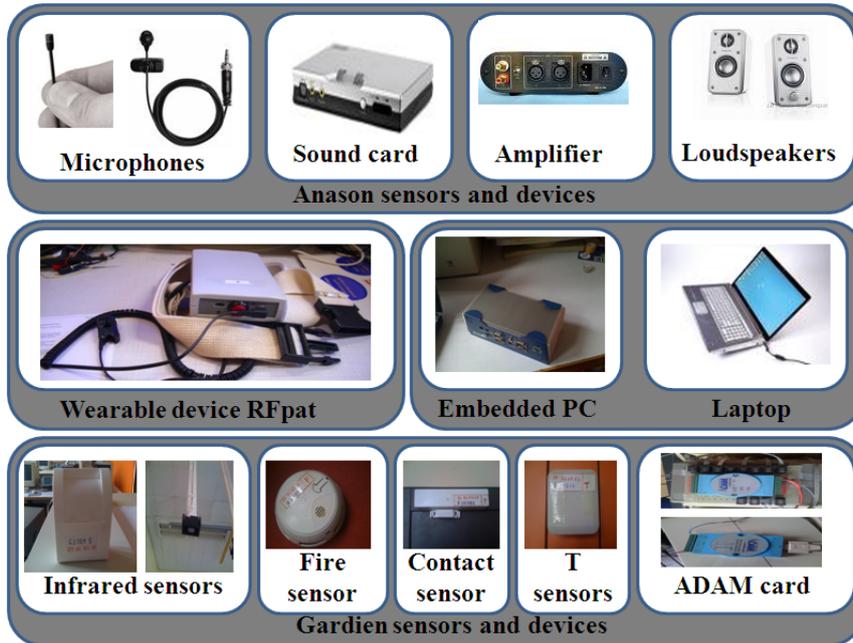


Figure 2.1: EMUTEM sensors and devices.

fixed on the elderly person, which can measure physiological data like heart rate, activity, posture and an eventual fall of the person. The last subsystem is a set of infrared sensors called Gardien [37], that detect the presence of the person in a given part and also the person's standing posture. In the following each one of these systems will be described.

2.3.1 EMUTEM Architecture

We define an intelligent environment as one that is able to acquire and apply knowledge about its inhabitants and their surroundings in order to adapt itself to the inhabitant and to improve its comfort and efficiency. To record the multimodal medical database our first aim is focused on providing such an environment. We consider our system as an intelligent agent, which perceives the state of the environment using sensors and acts consequently using device controllers.

2.3.1.1 Hardware Architecture

The hardware framework is reported in Figure 2.2. Our platform is a surface of 20 m² in our laboratory which is arranged in two rooms with a technical area in order to evaluate and to supervise the experiments. It integrates

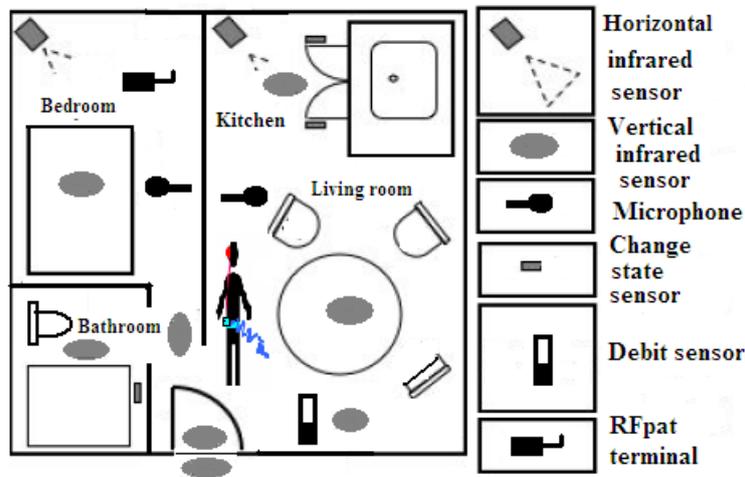


Figure 2.2: In-home sensor disposal.

smart sensors (infra-red, change state sensors, audio, physiological,) linked to a smart PC.

Microphones for audio monitoring are linked to the PC through an external sound card (in order to allow good signal to noise ratio independently from the PC), and can be interpreted as a single smart audio sensor achieved by ANASON software.

Infra-red sensors are fixed on specific places of the house in walls and ceiling. They are in permanent communication via radio frequency communication, with one receiver, which is connected to the USB port of the smart PC. Change state sensors transmit also information to this receiver through radio frequency communication. These sensors could also use powerline to provide data to the receiver. The platform includes another type of infra-red sensors which are linked to an acquisition card (ADAM) [37], which is linked to the serial port of the smart PC. The card output is RS485 which is converted in RS232.

The RFpat subsystem is composed of two main components: (1) a wearable terminal carried by the patient, continuously monitoring his physiological data and urgency call, (2) an in-door reception base station linked to the smart PC via RS232 serial link providing the information usually every 30 seconds.

2.3.1.2 Software Architecture

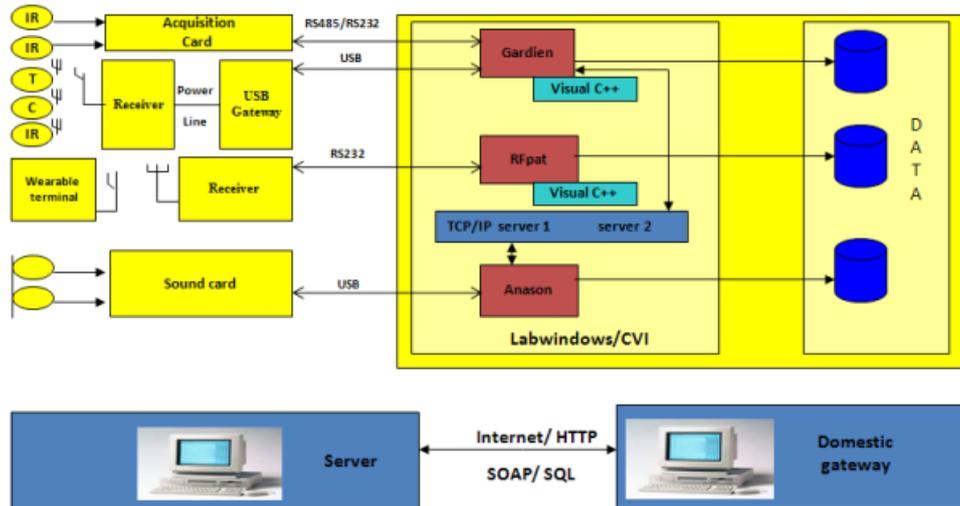


Figure 2.3: EMUTEM software architecture.

Figure 2.3 shows the software architecture of our multimodal platform EMUTEM. It provides a general user interface which encapsulates the Anason subsystem and the multi-sensors subsystem. It is implemented under LabWindows/CVI software and communicates with RFpat and Gardien subsystems by client-server model using TCP/IP and appropriate application protocols. Gardien is implemented under C++ and recovers data every 500 ms. RFpat is also implemented under C++ and receives data from receiver every 30 s. The use of the inter-module communication through TCP/IP socket allows each module (subsystem) to be run on a different computer, and to synchronize each telemonitoring modality channel.

The user can interact with the system via internet navigator and supervises the different applications. For instance, we use this web server to communicate with the person, who interprets a patient's activity by displaying a reference scenario on the monitoring screen. This feedback provides a significant help to the system manipulation and the system flexibility obtained through TCP/IP socket communication allows adding other potential sensors such as a heart monitoring sensors (ECG).

Data acquired from the patient and his environment are stored in the local computer as follow: directly as text files assigned to each modality. Data also could be exchanged using http or ftp protocol via web services technolo-

gies like SOAP, and saved in a dedicated server for recording our database.

2.3.2 EMUTEM Components

This specific platform is multimodal since it enables measurement and recording of certain vital signs, everyday life sounds and some knowledge about the patient environment, on a daily basis. These telemonitoring modalities are described below.

2.3.2.1 The Smart Sound Sensor (Anason)

In-home healthcare devices face a real problem of acceptance by end users and also caregivers. Sound sensors are easily accepted by care receivers and their family, they are considered as less intrusive than cameras, smart T-shirts, etc. In order to preserve the care-receiver privacy while ensuring his protection and safety, we propose to equip his house with some microphones. In this context, the environmental sound is not continuously recorded. This microphone array allows sound remote monitoring of the acoustical environment of the monitored person. The main advantage of this system is its real time carrying. Hence, we continuously 'listen' to the sound environment in order to detect distress situations and distress calls. This smart sound sensor described in [36] is made up of four modules as depicted in Figure 2.4.

a) **M1 Module: Sound Event Detection and Extraction**

The first module M1 continuously listens the sound environment in order to detect and extract useful sounds or speech. The signal extracted by the M1 module is processed by M2 module.

The sound flow is analyzed through a wavelet based algorithm aiming at sound event detection. This algorithm must be robust to noise like neighborhood environmental noise, water flow noise, ventilator or electric shaver. Therefore an algorithm based on energy of wavelet coefficients was proposed and evaluated. This algorithm detects precisely the signal beginning and its end, using properties of wavelet transform.

b) **M2 Module: Sound/Speech Classification Module**

The second module M2 is a low-stage classification one. It processes the sound received from module M1 in order to separate the speech signals from the sound ones.

The method used by this module is based on Gaussian Mixture Model

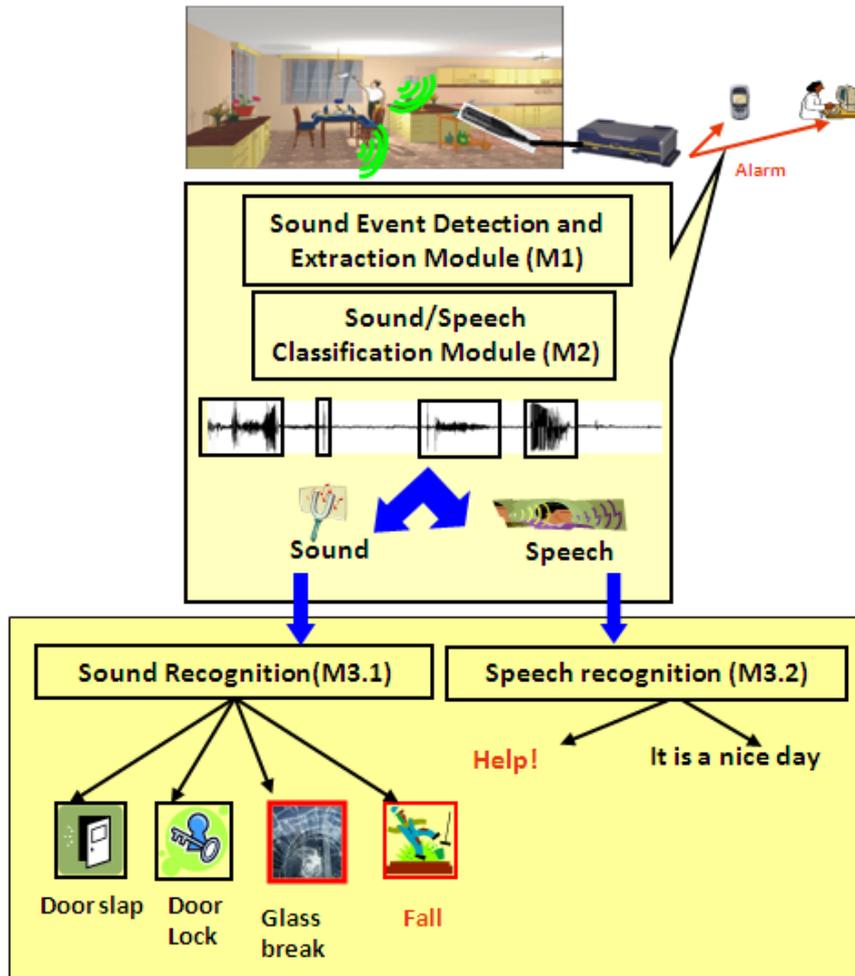


Figure 2.4: ANASON smart sensor.

(GMM) [38] (Kmeans followed by Expectation Maximisation in 20 steps). There are other possibilities for signal classification: Hidden Markov Model (HMM), Bayesian method, etc. Even if similar results have been obtained with other methods, their high complexity and high time consumption prevent from real-time implementation. A preliminary step before signal classification is the extraction of acoustic parameters: LFCC (Linear Frequency Cepstral Coefficients)-24 filters. The choice of this type of parameters relies on their properties: bank of filters with constant bandwidth, which leads to equal resolution at high frequencies often encountered in life sounds.

The BIC (Bayesian Information Criterion) is used in order to find the

optimal number of Gaussians [39]. The best performances have been obtained with 24 Gaussians.

c) **M3 Module: High-stage Classification**

This module operates within each class determined by the M2 module. It consists in two sub-modules. In the case of sound label attributed to the signal by module M2, the sound recognition sub-module M3.1 classifies the signal between eight predefined sound classes. In case of speech label, the extracted signal is analyzed by a speech recognition engine in order to detect distress sentences (M3.2 module).

- **Sound Recognition Module (M3.1):**

This module is based, also, on a GMM algorithm. The LFCC acoustical parameters have been used for the same reasons than for sound/speech module and with the same composition: 24 filters. The method BIC has been used in order to determine the optimum number of Gaussians (12 in the case of sounds). A loglikelihood is computed for the unknown signal according to each predefined sound classes; the sound class with the biggest log likelihood is the output of this module.

- **Speech Recognition Module (M3.2):**

For Speech Recognition, the autonomous system RAPHAEL is used [40]. The language model of this system is a medium vocabulary statistical model (around 11,000 words). This model is obtained by using textual information extracted from the Internet as described in [41] and from "Le Monde" corpora. It is then optimized for the distress sentences of our corpus. In order to insure a good speaker independence, the training of the acoustic models of RAPHAEL has been made with large corpora recorded with near 300 French speakers [42]: BREF80, BREF120 and BRAF100 corpora.

2.3.2.2 The Wearable Device (RFpat)

The wearable device named RFpat consists in two fundamental elements (Figure 2.5):

- **A Mobile Terminal:** This is a waist wearable device that the patient or the elderly clips, for instance, to his belt all the time he is at home. It measures the person's vital data and transmits to a reception home station.

- **A Fixed Reception Base Station:** This is a receiver connected to a personal computer (PC). It receives vital signals from the patient's mobile terminal.

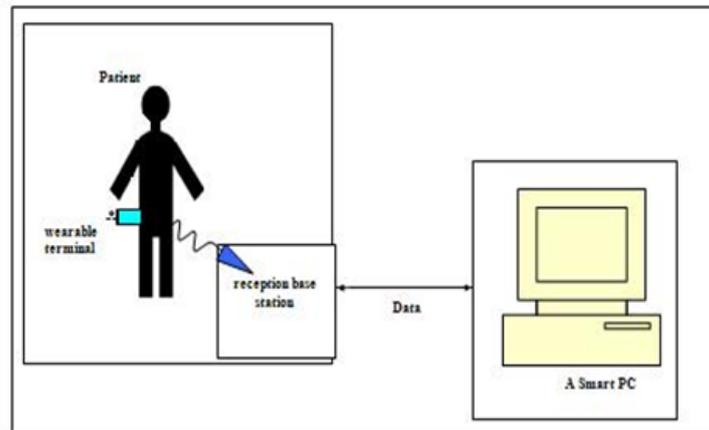


Figure 2.5: RFpat subsystem architecture.

All the data gathered from the different RFpat sensors are processed within the wireless wearable device. To ensure an optimal autonomy for the latter, we designed it using low consumption electronic components. Namely, the circuit architecture is based on different micro-controllers devoted to acquisition, signal processing and emission. Hence, the mobile wearable terminal encapsulates several signal acquisition and processing modules:

- It records various physiological and actimetric signals.
- It pre-processes the signals in order to reduce the impact of environmental noise or user-motion noise.

For the RFpat system, we made the choice to come up with the noise problem in the acquisition stage. Then, some digital noise reduction filters and algorithms were implemented within the portable device. These filters and algorithms were applied respectively to all acquired signals: movement data, posture data and namely the pulse signal (heart rate). Movement and posture data describes the actimetry status of the monitored person. It gives us information like: *he is laying, he is immobile, he is sitting/standing up*, etc.

Movement data consists also in the percentage of movement, it computes the total duration of the movements of the monitored person for each time slot of 30 seconds (0 to 100% during 30 seconds).

The posture data is information about the person posture: standing up / laying down. The posture data is a quite interesting measurement which gives us useful information about the person's activity. Thanks to an acti-metric system embedded in the portable device, we can detect the situations where the person is approaching the ground very quickly. This information is interpreted as a 'fall' when the acceleration goes through a certain threshold in a given situation. A fall-impact detector sensor is added to this system for retrofitting the fall detection.

The pulse signal is delivered by a specific sensor connected to the wearable device. After signal pre-conditioning and denoising it gives us information about the heart rate every 30 seconds. In the ambulatory mode, the challenging process consists in noise reduction. We have achieved to reduce the variations of pulse measurement lower than 5% for one minute averaging, which remains in conformity with the recommendations of medical professionals. Data gathered from the different sensors are transmitted, via an electronic signal conditioner, to a low power microcontroller based computing unit, embedded in the mobile terminal.

2.3.2.3 Gardien Subsystem

The in-home healthcare monitoring systems have to solve an important issue of privacy. When developing our multi-modal platform, we chose the monitoring modules such that they have the less intrusive incidence on the monitored elderly person. We equipped our test apartment with infrared sensors connected to a remote computer. All the sensors are connected through cables to an input/output parallel card (ADAM 4053) which is connected to a master PC. The computer automatically receives and saves data obtained from the different sensors, with the help of Gardien software. Data corresponding to movements are collected twice per second, and stored with the event time in a specific file.

The sensors are activated by the person's passage underneath, and remained activated as long as there is movement under that sensor and for an additional time period of 1/2 seconds after the movement end. The results from the automatic processing of this data are displayed in the form of list with all movements noted together with the time and each movement's duration. Gardien is also able to display the data either in the form of graph (activity duration versus days) or as three-dimensional histograms (each sensor activation versus time).

A set of wireless ambient sensors is added to this subsystem, they are designated for telemonitoring the environment of the patient and his surroundings. It includes infrared sensors for person localization, state change sensors for active devices detection, contact sensors which are responsible for door and windows opening /closing detection, temperature sensors, fire sensors, flood sensors and light sensors. An acquisition software was designed under LabwindowCVI to operate with these sensors by using radio frequency communication through an intermediate reception base station.

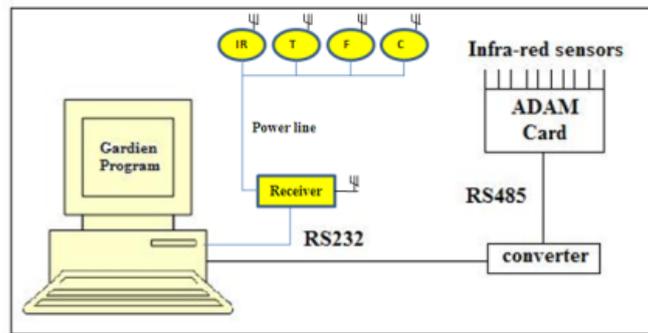


Figure 2.6: Gardien subsystem architecture.

2.3.3 EMUTEM Components Synchronization

To record the multimodal database several sensors are gathered in EMUTEM. Recording and fusing multi-sensors data enlarges the field of view and increase the certainty and precision of the estimates. A crucial part of a fusion system is the modality combination, which requires data synchronization.

As the acquired signals corresponding to the different modalities (ANASON, RFpat, Gardien and the multi-sensors subsystem) have different sample rates, we have developed a synchronization procedure in order to make the acquisition protocol synchronous. This operation is depicted on Figure 2.7. It uses the TCP/IP Protocol. The RFpat modality is launched first, because of his low acquisition rate. Then, supervisor software launches Gardien or the multi-sensor subsystem and Anason and the applications with TCP/IP commands.

This synchronization approach is probably the most favorite, as it imposes the least constraint on sensors and all measurements keep their sample rates.

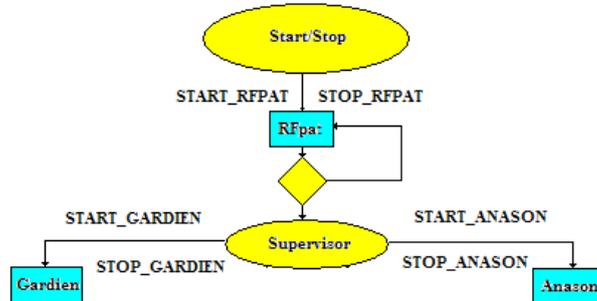


Figure 2.7: Schematic of the synchronization between the three subsystems of EMUTEM.

2.4 Multimodal Database Recording Strategy

When designing the recording strategies a special care was paid to gather data describing the everyday life of elderly people at home and therefore obtain more realistic conditions for experiments. With specially planned scenarios including many situations and many people’s profiles, an adaptive intelligence recording of the multimodal medical database HOMECAD is performed. Additional process of simulation is integrated in our platform as a way to overcome the lack of experimental data and the difficulty of recording some medical data such as the cardiac frequency during distress situations. Taking into account the multimodal data character of the data, a multidimensional-indexing process is used in order to obtain a full description of data sets. So far this database will enable us to evaluate and improve our home medical telemonitoring systems by elaborating and assessing the data fusion-based decision methods. The low level data recorded by our system will be useful for the development of each modality processing algorithms and their combination strategies.

2.4.1 Recording Conditions and Inventory

Recordings were performed in a simulated flat in our laboratory and also in some smart houses within the framework of CompanionAble European project. Those flats and houses were outfitted with all subsystems of the EMUTEM platform which have been technically validated from end to end,

through their hardware and software. Microphones have been calibrated using a standard level sinusoidal signal with a frequency of 1 KHz. Infrared sensors are also calibrated and for each one a specific monitoring zone is delimited. Contact sensors were fixed on specific doors and windows. Some devices were also equipped with change state sensors and some temperature sensors were also used. To investigate the platform usefulness a predefined standard scenario is recorded before each recording session.

Each participant or actor was asked to interpret elder activities by following a reference scenario which summarizes some activities, inspired from the everyday life of elderly persons. Monitoring screens were settled in specific places in the apartment to display these reference scenarios. Loudspeakers were also used for producing some specific environment of sounds.

2.4.2 Reference Scenarios

```

<?xml version="1.0" ?>
<Scenario>
  <Characteristic>
    <Title>Scenario 12</Title>
    <Class>Critical</Class>
    <Statut>Fall</Statut>
  </Characteristic>
  <Description>
    <Activite1>
      <Room>Living room</Room>
      <Anason>Noise</Anason>
      <RFpat>Sitting down</RFpat>
      <Gardien>C6 C4</Gardien>
      <Time>120</Time>
      <Summary>The actor is sitting on a chair in the living room (office), he reads a newspaper</Summary>
    </Activite1>
    .....
    <Activite5>
      <Room>Living room</Room>
      <Anason>Fall</Anason>
      <RFpat>lying down, Fall</RFpat>
      <Gardien>C6</Gardien>
      <Time>120</Time>
      <Summary>He gets up, he stumbles and he falls and he stays lying down</Summary>
    </Activite5>
  </Description>
</Scenario>

```

Figure 2.8: XML file for scenario

In order to support the person who is interpreting a type of an elderly person and a given situation, recordings performed by using predefined scenarios leading him during the recording process. To this purpose EMUTEM provides a software system which allows to write or to modify different scenarios via a graphical interface, and save them in an XML annotation file (Figure 2.8).

Figure 2.9 shows this graphical interface which is composed of two parts: the first one concerned with personal information relative to the person or the actor, the second one is dedicated to the scenario edition using a table composed of columns corresponding to each sensor to be activated and a summary of the actions to be carried out.

The scenario is described by the expected output from each modality like

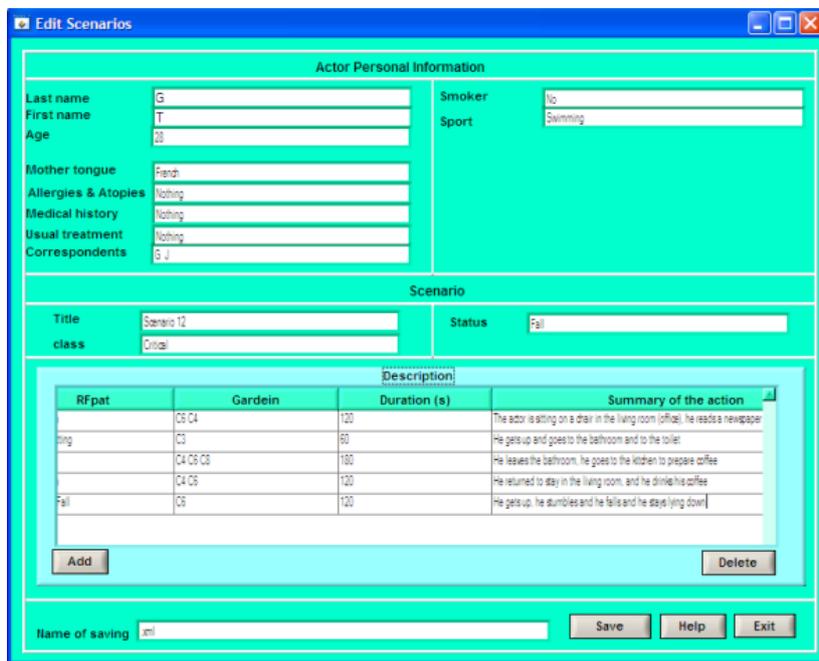


Figure 2.9: EMUTEM graphical interface for writing scenario

the room for infrared sensors or the recorded sound for sound modality.

These reference scenarios are based on real situations and they aim to reflect the everyday life of elderly people. The duration of each scenario is 10 minutes.

To define these scenarios a study is performed and they were instigated from CompanionAble project studies, where some elderly living alone were followed up by a co-worker team, in order to summarize and to describe their daily routine. By these studies scenarios were obtained, one of them is described below.

Scenario

Marisa is a 70 years old woman who lives alone since her husband died 7 years ago. She has a son who lives in the same city, he visits her 3 or 4 times a week, and he visits also on Sunday afternoons. Both of them are worried and mention that Marisa needs some overview of her activities of daily living due to her memory lost.

She usually gets up in the morning at 7:00 and dresses a wearing gown. She goes to the bathroom, uses the toilet and makes the morning hygiene.

After that she goes to the kitchen and prepares breakfast. Meanwhile, she takes the medication and at 7:15 she goes to the sitting room and turn on the TV. She sits on the sofa and watches television while she has breakfast until the 8:00 o'clock. Then she goes to the bathroom and has a shower, finishes at 8:30 and goes to her bedroom to get dressed, then returns to the bathroom to get ready. Today she has an appointment with the doctor and plans to go shopping.

She returns from health center, and after doing some shopping she arrives at home at 11:45. She goes to the kitchen and leaves the shopping bag on the table. Then she organizes the shopping.

At 12:00 she has finished and she goes to the sitting room to have some biscuit. She turns on the TV and eats the biscuits. At 12:30 she left the TV on to make some company and begins to cook the meal.

Once she has finished cooking, at 13:00 she takes the lunch to the living room and seat on the table. At 13:30 she takes the medicine and eats while she is watching TV, then she goes to the kitchen and washes the dishes. At 14:00 she returns to the living room and lies down on the sofa to nap until 15:00.

She gets up and goes to the kitchen to have a coffee. Then goes back to the living room and watches her favorite program on TV. At 17:00 she gets up and goes shopping and goes to the hairdresser.

She comes back at 19:00 and she goes to her bedroom to change her clothes for comfortable ones. She knits the wool that she has bought this afternoon and waits for her son's visit.

At 20:00 sounds the doorbell, she gets up and open the door in order her

son enter. They talk for a little time, and then she prepares dinner. They sit at the table in the living room, chatting while they are having dinner.

Between 21:00 and 23:00 the son leaves home and goes to his own flat. She stays in the living room watching TV and sometimes also knitting until she gets tired and goes to bed.

At 23:00 she goes to the bathroom and brushes her teeth, goes to the toilet, and then she goes to her bedroom where she dresses in her pyjamas and goes to the bed. Between 23:00 and 23:30 Marisa switches off the light and falls asleep.

Based on those type of scenarios, summarized reference scenarios of 10 minutes were extracted and they were used for recording the multimodal database HOMECAD. These scenarios are divided into two categories: either a critical scenario with one or more distress events, or a normal one without any distress situation. These scenarios are a set of activities and for each activity a duration is assigned. An example from each category is shown below.

A critical scenario

The actor is sitting on a chair in the living room (office), he reads a newspaper (120")

He gets up and goes to the bathroom and to the toilet (60")

He leaves the bathroom, he goes to the kitchen to prepare coffee (180")

He returned to stay in the living room, and he drinks his coffee (120")

He gets up, he stumbles and he falls and he stays lying down (120")

A normal scenario

The actor goes back to home, he opens the door, he enters and he closes the door, he puts down the keys on the table (60")

He enters in the bathroom to wash his hands (60")

He goes to the living room and he turns on the TV to watch news (240")

He lies down on the sofa to sleep the siesta (240")

These reference scenarios are automatically displayed on the monitoring screen during the recording step as show in Figure 2.10.

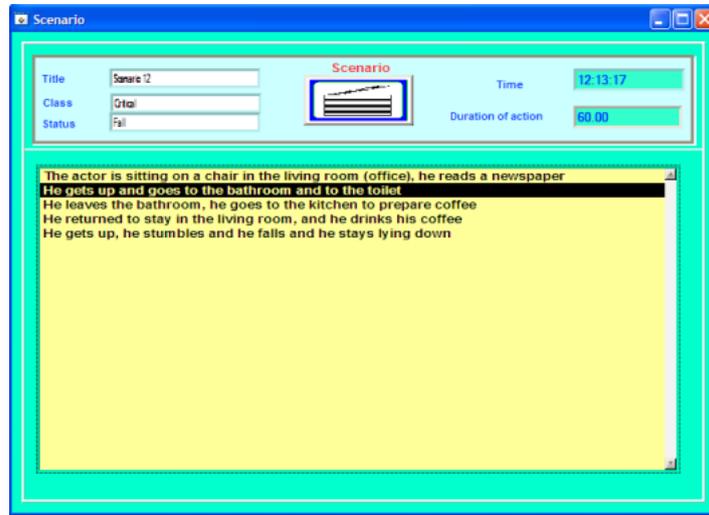


Figure 2.10: EMUTEM graphical interface for displaying scenario.

2.4.3 Simulation Process

In relation to experimentation, setting up a simulation process enables researchers to have a full and tightly controlled universe of data sets. The advantages are at least five fold [43]: (1) producing large sets of data to experiment with decision-making algorithms, (2) generating data representative of several situations and several people profiles, (3) building a process that is trustful and easily understandable by any actor of the system, in contrast with an analytic modeling approach, (4) providing a better a posteriori knowledge of the parameters observed at home and the trends of their joint variations, and (5) testing the efficiency and the robustness of detection algorithms by varying the simulation parameters.

The aim of this stage is to create pathological or critical situations for the patient at home. Indeed most of actual signals recorded on domotic platform are generally and hopefully in normal conditions. The simulator is based on the existing RFpat sensors device. The first main goal was to simulate cardiac pathological profiles such as in particular bradycardias: the design was done with the helpful collaboration of SAMU-92 (French emergencies service). In its implementation, are also foreseen functional stages for the actimetry simulation: patient's tilt (horizontal or vertical position), his body movement and in a larger extent patient's fall situations. The simulator software architecture is summarized in the Figure 2.11. For the cardiac frequency generation, three cases were proposed:

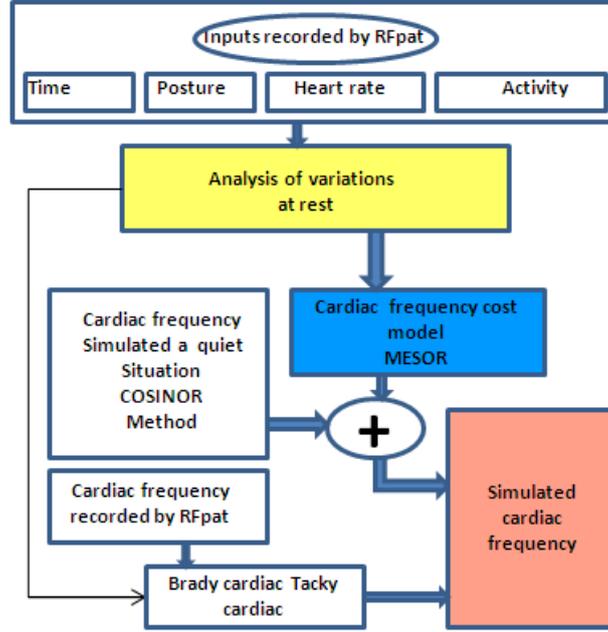


Figure 2.11: Cardiac frequency simulation process.

- A first normal cardiac category, based on the COSINOR method [44], providing a global pulse variations trend within one day; this formula gives the cardiac frequency or pulse F_c in quiet situation under the following form:

$$F_{crest}(t) = F_{moy} + A \sin\left(\frac{2\pi}{24}t + \phi\right) \quad (2.1)$$

where F_{moy} (around 70 bpm), A are respectively the average pulse or MESOR (Midline Estimating Statistic Of Rythm)[44] value and its maximal amplitude variation (about 6 bpm) along one circadian cycle; the acrophase or maximal amplitude is statistically located around 16 hour.

- A second normal situation, called "Cost model", providing a pulse variation model, still denoted ΔF_c , depending on the patient's activity; the formula is based on the pulse in a quiet situation (F_{crest}) and the delta-variation due to patient efforts, namely representing the cardiac cost:

$$F_c(t) = F_{crest}(t) + \Delta F_c(t). \quad (2.2)$$

- The bradycardia model corresponds to a situation met with elderly persons, by assuming no specific medication having a cardiac impact:

the model is either artificially inserted inside an existing pulse signal sequence by taking into account the actual pulse variance, or is completely substituting the actual pulse sequence.

This tool is still open to other simulation process, namely for the actimetry where presently are performed investigations on the potential correlations between the Cardiac Cost Model and the body movement. This simulation stage has been designed and interfaced to the multimodal platform.

2.4.4 Indexing Process

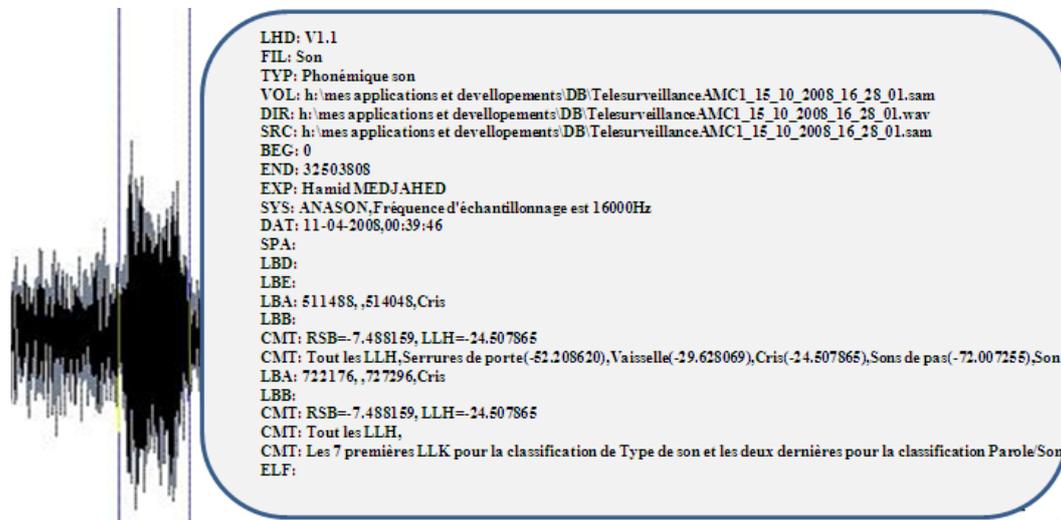


Figure 2.12: Sound file (*.wav) and its corresponding SAM file.

In order to index our multimodal database, we have retained the SAM standard indexing file [45] generally used for Speech Databases descriptions. The SAM labeling of a sound file is shown in Figure 2.12, it indicates information about the file and describes it by delimiting the useful part for further analyzing and processing.

For each modality of the database a corresponding indexing file is created, we have adapted this type of files to the specificities of each modality, and we have added another indexing file for the entire database. This indexation is done by using the graphical interface shown in figure 2.13.

This conceptual indexation model is guided by a priori knowledge, the reference scenarios and a manual indexation done by two persons during the



Figure 2.13: EMUTEM graphical interface for indexing process.

recording. They describe and report on real time activities performed by the actor, who interprets the reference scenario, in a text file.

This aims to obtain the reference information (ground truth) for our multimodal database, and therefore to generate a novel type of database to validate different modality signal processing techniques and approaches of multimodal data fusion algorithms.

2.5 Multimodal Database Description

Data acquired from the patient are stored in a server PC, in a folder named with a code number corresponding to the patient or the actor, plus the date an hour of the recording. Each recording folder is composed from eleven files corresponding to the different subsystems.

The first one, named *personnel.xml*, contains the patient's identifier and some personal information like age, native language, usual drugs treatment, etc. The second, named *scenario.xml*, describes the reference scenario. All these

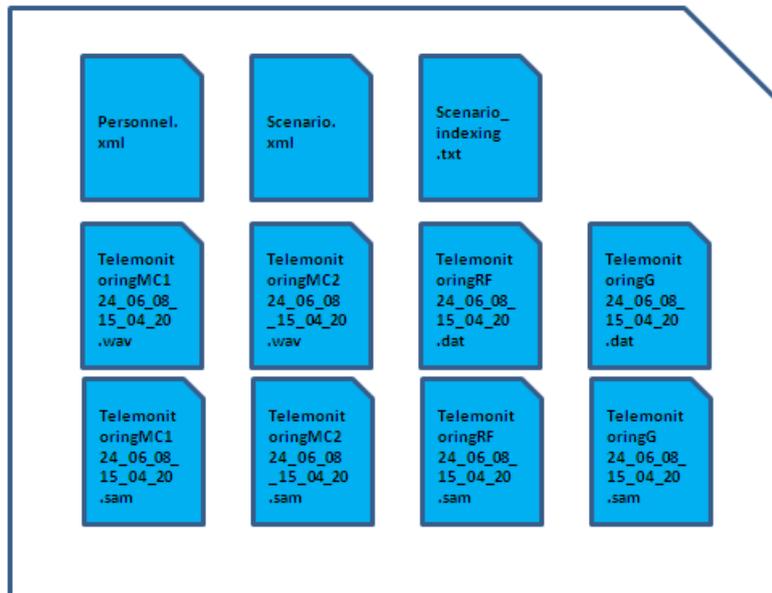


Figure 2.14: HOMECADE folder description

data relative to the actor are protected for his privacy and let to his agreement.

The sound data is saved in real time, in a wav file with 16 bit of resolution and a sampling rate equal to 44,1 KHz. Two wav file are recorded in each folder because in EMUTEM platform we use only two microphones.

The clinical data acquired from RFpat are saved in a separate text file which contains information about patient's attitude (laying down or upright/seated), his agitation (between 0% and 100%), his cardiac frequency, fall events and urgency call, plus the corresponding date and time. The acquisition sample rate is 0.03 Hz.

The data acquired every 500 ms by Gardien subsystem are also saved in a separate text adapted file format. Each line of this file contains the infrared sensors which are excited and indication about the other sensors (state change sensors, contact sensors, smoke sensors, temperature sensors, water debit sensors and some devices sensors, they are labeled by hexadecimal numbers) plus the corresponding date and time.

For each modality of the database a corresponding indexing file is created, thus four SAM file are added to each folder of the database.

It is possible also to find in each folder of this database a description file corresponding to the progress of the recording. This file is the indexation of the scenario interpretation by the actor.

2.6 Conclusion

We have developed a new multi sensors environment for recording a multimodal medical database including patients clinical data, usual environment sounds and patient localization. The originality of this system is the synchronized combination of three different telemonitoring modalities for recording a multimodal database and generating its indexation in a semiautomatic way. In relation to experimentation, integrating a simulation process to our platform enables us to have a full and tightly controlled universe of data sets and to evaluate the decision part of remote monitoring systems.

Telemedicine systems can significantly benefit from this multimodal database, since large sets of data representative of several situations and several people's profiles can easily be generated. A better a posteriori knowledge of parameters observed at home and the trends of their joint variations will be provided by the simulation process. This database fully responds to the crucial need for an objective and systematic evaluation of promising multimodal data fusion methods that are currently investigated and developed.

Chapter 3

Background and Multimodal Data Fusion

After the presentation of the multimodal platform EMUTEM and the HOMECAD database, in order to process these large sets of heterogeneous data to make a decision at any time about the elderly person status, a multisensor or multimodal data fusion is carried out in this chapter. This study tried to cover an overview of the definitions of multisensor data fusion, the model that can be implemented and the techniques that can be applied to solve the problem of the decision issue on the person's situation at home.

Detecting and gathering data about the elderly person and his environment is the first step and one of the most fundamental tasks in building intelligent telemonitoring systems. With the intelligence expectation increasing, using multiple sensors is the only way to obtain the required breadth of information, and fusing the outputs from multiple sensors or subsystems is often the only way to obtain the required depth of information when a single sensing modality is inadequate [46]. However, in our telemonitoring context different sensors use different physical principles, cover different information space, generate data in different formats at different sampling rates, and the obtained data have different resolution, accuracy, and reliability properties.

Based on those effects, the key to produce the required detection is to use the right method that properly fuses the provided data from various sources. This is what multimodal data fusion stands for. Therefore, typical multisensor data fusion methods are analyzed in this chapter, in seeking for a most generalizable and adaptable method.

3.1 Context Information and Classification

In order to maximize correct classification performance between normal and distress situations about elderly people at home, we have to provide an intelligent system that is able to acquire and apply knowledge about them and their surroundings by integrating more context information. This classification context faces some major problem:

- There is not much research published on classification of general context information about the elderly people at home.
- This research domain is at the beginning development stage.
- The difficulty of the modeling of abnormal situations and the lack of experimental data and information representing several situations and many people’s profiles.
- Legal and ethical issues to respect for the development of any telemedicine application.

Sensor	Context information
Anason Microphone	Sound detection and classification Speech recognition Localization
RFpat physiological sensors Fall detection sensor	Heart rate, Posture (lying,sitting/standing up) Activity (Movement/ Immobile), Fall Call
Gardien Infra-red sensors State change sensors Contact sensors	Localization, Posture temperature Opening/ closing Devices state on/off

Table 3.1: Context information achievable with commonly used sensors

To address these problems the first attempt is inspired from the generalizable context classification introduced by Schmidt et al. in [47]. The context information taken into account to provide a reliable classification is to use a set of sensors: physiological sensors (cardiac frequency, activity or agitation, posture and fall detection sensor), microphones, multisensory measurements (infrared sensors, debit sensors and state-change sensors integrated into three subsystems under EMUTEM platform. This platform groups the context information into three categories) (1) the physical environment around the

elderly person; (2) the elderly person’s own activity; and (3) the elderly person’s physiological states. The relationship of this three context categories and the localization of each EMUTEM’s subsystem under this relationship are illustrated in Figure 3.1. Some context elements are listed in Table 3.1.

With the context information being defined and with each of its possible modality or sensor being specified, plus the context classification that is required to discriminate between normal and abnormal situation of elderly people at home, the problematic is clearly defined. This problematic leads to study multimodal data fusion domain.

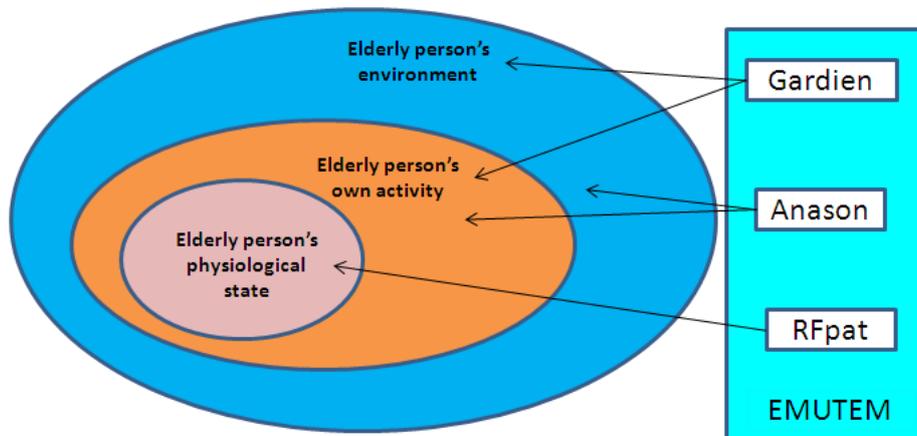


Figure 3.1: The elderly person-centered scheme to group context information under EMUTEM platform

3.2 Data Fusion

Several research teams develop techniques to combine multimodal inputs at various levels with different methods in order to improve decision and classification. First research works on classification and discriminant analysis began in 1920 and were inspired from studies on the recognition of human races with cranial measurements [48]. We call a classifier an algorithm that is able to attribute to any individual of a database a class (even if this class may be the rejected class). This classifier can then determine the class of new individuals for which information is lost, inaccessible, accessible to human but not to the machine or non-existent.

3.2.1 Generalities

Multimodal data fusion technology was originally developed in the domain of military applications research and robotics ([49], [50]). Since it is an interdisciplinary technology independently growing out of various applications research, its terminology has not yet reached a universal agreement. Generally speaking, the terms *sensor fusion*, *multimodal data fusion*, *multi-sensor data fusion*, *data fusion*, and *information fusion* have been used in various publications without much discrimination ([51], [52]). It seems that popular usage has shifted from *sensor fusion* to *data fusion* and it is now moving towards *information fusion*.

The term, multimodal data fusion, refers to the use of data from multiple sensors in an intelligent process dealing with the association, correlation, and combination of data and information from these single and multiple sources to achieve refined decision and classification and to improve results.

The main objective of employing fusion is to produce a fused result that provides the most possible detailed and reliable information. Fusing multiple information sources together also produces a more efficient representation of the data. According to [53] we can also argue the interest of using multimodal data fusion by illustrating the limitations of using single modality in the following points:

- Using a single modality can provide only partial information about the operating conditions and environment.
- Using the single modality systems, cause the resulted systems observations uncertain and occasionally it could be incorrect.
- Using multiple sensors or modalities allows the incorporation of various type of information, where multiple tasks can be achieved by the same system.
- Using single modality systems, the system will completely fail with possible sensor operational faults, which can lead to critical situations or consequences on that system.

3.2.2 Levels and Types of Fusion

Data fusion can be classified from different perspectives, for instance according to the relationship between sensors that are integrated in the process of fusion, information level of fusion and algorithms being used ...etc.

3.2.2.1 Types of Fusion

In ([54], [55]) data fusion is classified into *competitive*, *complementary*, and *cooperative* types according to the nature of information input output relationships. They are explained in the following paragraphs.

- **Competitive type of data fusion**

This combines sensor data that represent the same measurement to reduce uncertainty and solve conflicts. This is the basic data fusion type. It is often regarded as the *traditional* or *classical* sensor fusion technique.

- **Complementary type of data fusion**

This combines incomplete sensor data or modality that do not depend on each other directly to create a more complete model in order to take good decisions and classifications. For example combining measurements of pressure and airflow to estimate the propulsive force of a jet nozzle.

- **Cooperative type of data fusion**

This combines sensor observations that depend upon each other to deduce higher-level decision. In stereovision, for example, image components (pixels, featured spots) depend on each other in pairs to estimate object distances.

Roughly speaking, competitive sensor fusion enhances measurement reliability or confidence, whereas complementary and cooperative data fusion lead to higher-level measurements so reliable decision. The three data fusion types are not exclusive though, as many sensor fusion processes can belong to more than one type. Moreover, of this three data fusion types, the complementary and the cooperative types are the most used and specific which means that their methods are often valid only under specific conditions where specific based-knowledge and artificial intelligent inference techniques can be applied.

3.2.2.2 Levels of Fusion

According to the level of representation assigned to the data during the fusion process, data fusion can be roughly categorized into three categories as shown in Figure 3.2.

- **Direct level fusion**

The low-level sensory data can be directly combined in order to take

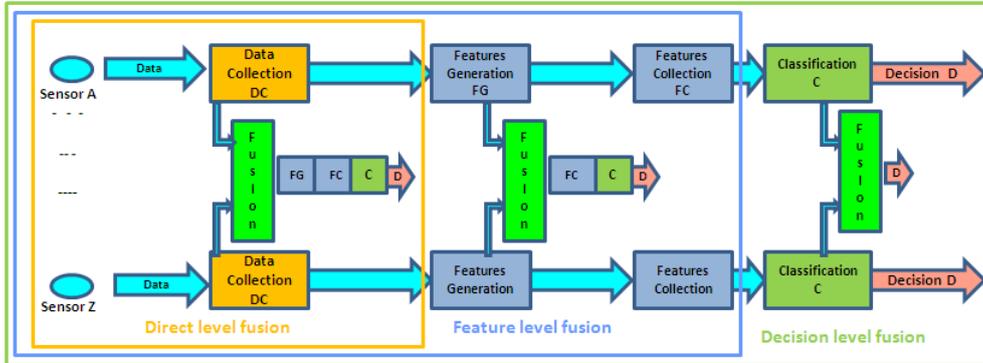


Figure 3.2: Data fusion levels

a decision. Otherwise, the information can be fused only at feature or decision level.

- **Feature level fusion**

In feature fusion, features are extracted from multiple sensor observations and combined. These representative features from sensors provide signature elements for the recognition and the decision module.

- **Decision level fusion**

In decision level fusion, each sensor makes a preliminary determination of targeted modality identity and other attributes, and the fusion algorithm combines these to generate more accurate results or higher confidence.

3.2.2.3 Discussion

As discussed earlier, among the three data fusion types, complementary and cooperative data fusion types are usually highly domain and task specific. They are typically implemented as feature-level data processing in a complex physical model [56]. On the other hand the decision level fusion is most suitable for systems that have physically distributed components and require these components to work more independently. The lower-level information is kept longer and potentially better used in the sensor data-level fusion case, and the feature level fusion model allow complex model, to fully use information.

Roughly speaking, so to form general data fusion architecture for EMUTEM fusion Module we based on the complementary and cooperative data fusion types plus the three levels of fusion as it is shown in figure 3.3.

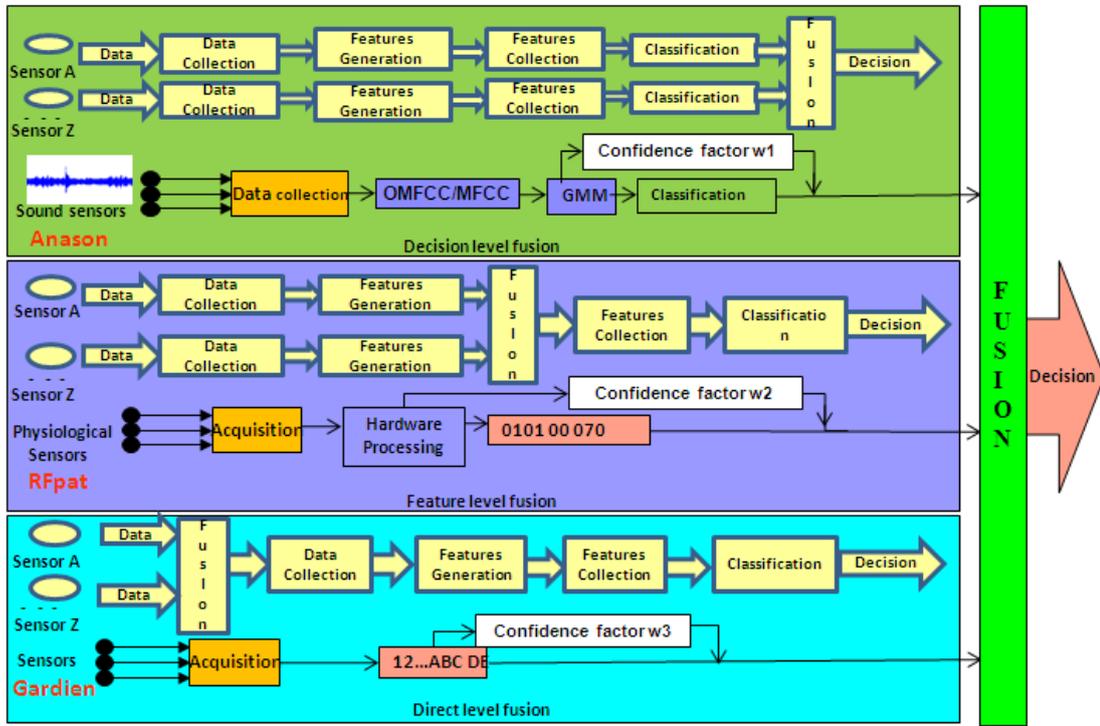


Figure 3.3: EMUTEM fusion module architecture

3.2.3 Adapted Approaches for Data Fusion

Many well-developed approaches for data fusion exist, and many applications in different domains, but there is no precise formalism to describe a data fusion process.

This section examines the commonly used data fusion methods in order to choose one as a module for building a generalizable data fusion for EMUTEM fusion module.

3.2.3.1 Classical Approaches

A) Bayesian Inference Method

The classical inference method and Bayesian inference network method are often referred as the *classical* or *canonical* data fusion methods because not only they are the most widely used, but also they are the bases, or the starting points for many new methods.

In this approach, sources are considered as a set of entities that can provide a decision at any time. Thus each source is seen as a Bayesian estimator. So, probability distributions associated with each sensor are combined into a single distribution function of joint posteriori probability using Bayes rule (3.1) where a hypothesis H_i will be realized if an event E is true or observed.

$$P(H_i/E) = \frac{P(E/H_i).P(H_i)}{P(E)} \quad (3.1)$$

To maximize this function many decision rules can be used [57], for example likelihood comparison rule suggests accepting the hypothesis H_i if the probability relationship satisfies equation 3.2, otherwise, the system should believe that the contextual fact or event is not true or has not happened.

$$P(E/H_i).P(H_i) > P(E/\bar{H}_i).P(\bar{H}_i) \quad (3.2)$$

Bayesian inference overcomes some classical limitations like the complexities that arise when multivariate data are encountered, by updating the likelihood of a hypothesis given a previous likelihood estimate and additional new observations. It is applicable when two or more hypotheses are to be assessed as in equation 3.3.

$$P(H_i/E) = \frac{P(E/H_i).P(H_i)}{\sum_j P(E/H_j).P(H_j)} \quad (3.3)$$

Where, $P(H_i)$ is the a priori probability that the contextual fact or event H_i has occurred; $P(E/H_i)$ is the likelihood that the phenomenon or evidence E can be observed given the contextual fact or event H_i has occurred. Thus the Bayesian inference method provides the following advantages: (1) given new observations, it incrementally estimates the probability of the hypothesis being true, (2) the inference process can incorporate the a priori knowledge about the likelihood of a hypothesis being true, and (3) when empirical data are not available, it permits the use of subjective probability estimated for priori hypotheses.

Despite these advantages, and the simplicity of this method, it cannot overcome the complexity when there are multiple potential hypotheses and multiple conditionally dependent events, and it is powerless to account for general uncertainty. But this approach provides a basis for other methods such as HMM (Hidden Markov Models), and more recent one such as Bayesian networks.

B) Kalman Filter

The Kalman filter is one of the methods used in dynamic environment [58] when it is necessary to fuse redundant low-level data over time. Many extensions of this filter have been proposed such as $\alpha\beta$ and $\alpha\beta\gamma$ filters. These filters are just a simplification of the Kalman filter in order to simplify processings. These multi-models filters combine several evolution models to select the best one at every moment. They can also fuse results from each model over time. According to [59] this approach contains five steps:

- **State representation:** a dynamic model of the environment is a list of primitive describing a part of the environment at an instant t . Each primitive represents estimation about the local state of the environment as a conjunction of estimated properties $X(t) \equiv \{\hat{x}_1(t), \hat{x}_2(t), \dots, \hat{x}_n(t)\}$.

The current state of the environment is estimated by an observation process which projects the environment on a vector of observations $Y(t)$ by taking into account the noise that can disturb the observation process. $X(t)$ and $Y(t)$ must be accompanied by an estimation of their uncertainty. Thus successive observations will vary the factor of trust over time.

- **Prediction:** This step allows to project the estimated vector $x(t)$ on a predicted vector $X^*(t + \delta t)$ and also to project the estimated uncertainty at $t + \delta t$.
- **Correspondence between observation and prediction:** This step assumes temporal continuity and calculates a Mahalanobis distance between predicted and observed properties. A rejection threshold separate good occurrences from false alarms.
- **Updating:** In the update step, we modify the prediction estimate to include the observation. Kalman filter proceeds to an estimation of all properties and their derivatives by associating all predicted properties to the observed properties. The interesting point in data fusion is that the Kalman filter also provides an estimation of the precision assigned with these elements of these sets.

- **Refinement:** it concerns the elimination of uncertain primitives and adding new primitives to the model. this step uses the confidence factors previously derived.

In [59], a full discussion is given on the use of symbolic properties. Murphy et al. in [60] show a reformulation of the Kalman filters in a Bayesian networks form.

C) Dempster-Shafer Theory of Evidence Method

This theory [61, 62] is a generalization of the Bayesian theory by allowing for distributing support not only to single hypothesis but also to the union of hypotheses. In a first step, this approach allows reasoning about sets of hypothesis, and gradually restricts to plausible hypothesis, as and when new evidence appears. This data fusion approach is adapted to multiple sensors fusion applications.

In this probabilistic theory, through its functions of lower probability and upper probability to which Shafer assigns respectively belief function and plausibility function, by taking into account the extension of the theory of subjective probabilities. Based on a distribution of evidence mass m clearly defined on the set of propositions Ω (space of all possible universes), it combines degrees of belief and plausibility to parts of a set A (group of propositions or information) of Ω .

The belief function is a function which attributes a degree of belief or plausibility between 0 and 1, for information or proposition obtained from an analysis or a process.

Let Ω be a set of hypothesis (H_1, H_2, \dots, H_n) mutually exclusive, called frame of discernment. The set of parts H from Ω is denoted 2Ω .

If we defined the function $m : 2\Omega \rightarrow [0, 1]$ a distribution of evidence on parties H identified on Ω (or partitions of Ω), then $H \rightarrow m(H)$ represents the distribution of evidence on the part A .

- $m(A)$ is a strict confidence and trust in A , without it can be scattered on the assumptions that compose it.
- A is a focal element if $m(A) \neq 0$.

In the case where for $m : 2\Omega \rightarrow [0, 1]$ the following two conditions are verified: $m(\emptyset) = 0$ and $\sum_{A_i \subset \Omega} m(A_i) = 1$ it is called a mass function on Ω .

For any given set of hypothesis H from Ω , the system's belief in H is the sum of all the evidence E_i objects that support H and the sub-hypotheses nested in H :

$$belief_i(H) = \sum_{E_i \subset H} m(E_i) \quad (3.4)$$

On the other hand, the evidence objects that support H 's exclusive hypotheses (i.e., the hypotheses that do not include any sub-hypotheses nested in H) are then actually the evidences that are against to H . Therefore, the *plausibility* of hypothesis H should include all the observed evidence objects that do not argue against H :

$$plausibility_i(H) = \sum_{E_k \cap H \neq \emptyset} E_k = 1 - belief_i(\bar{H}) = 1 - \sum_{E_k \cap H = \emptyset} m_i(E_k) \quad (3.5)$$

Thus in the Dempster-Shafer reasoning system, according to a sensor S'_i 's observation, the belief regarding a hypothesis is measured by a *confidence interval* bounded by its basic belief and plausibility values [$belief_i(H), plausibility_i(H)$].

Of course, there can be more than one sensor in a system. When there are multiple sensors in a system and the sensor's observations are assumed independent of each other, the Dempster-Shafer Evidence combination rule provides a means to combine these observations. For each hypothesis in Ω (e.g., a proposition, such as a detected event is A , the rule combines sensor S'_i 's observation m_i and sensor S'_j 's observation m_j) as follows:

$$belief(A) = m_i \oplus m_j(A) = \frac{\sum_{A_k \cap A_{\hat{k}} = A} m_i(k) \cdot m_j(\hat{k})}{1 - \sum_{A_l \cap A_{\hat{l}} = \emptyset} m_i(l) \cdot m_j(\hat{l})} \quad (3.6)$$

In equation 3.6, the combined proposition A stands for the intersection of the sensor S_i observed hypothesis A_k and sensor S_j observed hypothesis $A_{\hat{k}}$, whose associated probability mass functions are represented as $m_i(A_k)$ and $m_j(A_{\hat{k}})$ respectively.

Notice that this evidence combination rule is both associative and commutative [63]. This means that the probability mass functions $m_i(A_k)$ in equation 3.6 can be the results of previously combined evidence, so

the process of combining evidence from multiple sources can be chained, and the order in which the sources are combined does not affect the final results.

Dempster-Shafer method is among the most commonly used formalisms in MSDF (Multi-Sensor Data Fusion), especially in the military applications domain. The main reason that these two formalisms in particular have received so much attention is that both are associative and commutative, so the results are independent of the order in which the data are received and incorporated [64].

3.2.3.2 Statistical Modeling Approaches

★ Hidden Markov Model

Hidden markov models (HMM), are statistical models of sequential data. They have been widely used in many applications such as speech recognition [65], pattern recognition, or biological sequences modeling. Their success is mainly due to the learning algorithm of Baum-Welch, who is a special case of the EM (expectation maximization) algorithm for estimating the maximum of likelihood.

A Hidden Markov Model is a finite set of states, which is associated with a probability distribution. Transitions among the states are governed by a set of probabilities called transition probabilities. In a particular state an outcome or observation can be generated, according to the associated symbol observation probability distribution. It is only the outcome, not the state that is visible to an external observer and therefore states are *hidden* to the outside; hence the appellation hidden markov model.

In order to define an HMM completely, the following elements are needed.

- The number of states of the model, N .
- The number of observation symbols in the alphabet, M . If the observations are continuous then M is infinite.
- A set of state transition probabilities.

Formally, a hidden Markov model is a bivariate discrete time process:

$$\{X_k, Y_k\}_{k \geq 0} \tag{3.7}$$

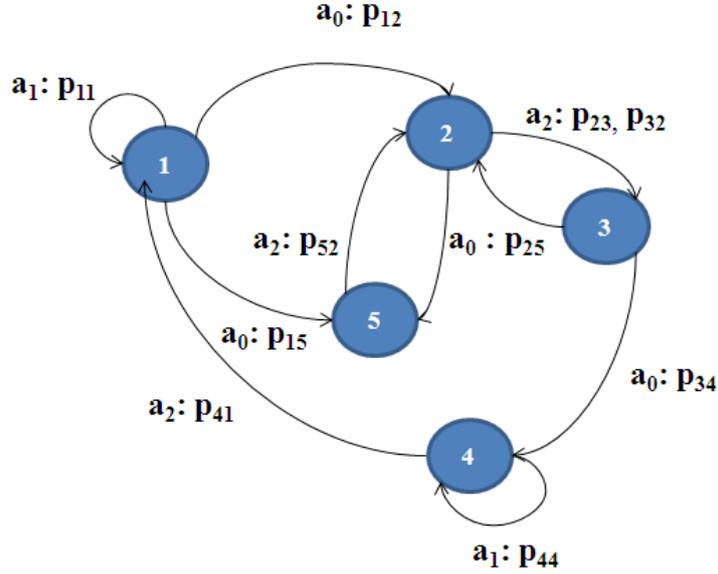


Figure 3.4: The state diagram of a Markov Decision Process

where X_k is a Markov chain and, conditional on X_k , Y_k is a sequence of independent random variables such that the conditional distribution of Y_k only depends on X_k .

An example of the state diagram of an HMM has been shown in Figure 3.4. Where a_k is the k^{th} possible action in each state. The transition of the environment from one state to the other is probabilistic in nature, and p_{ij} is the transition probability from state i to state j . The label $a_k : p_{ij}$ on the edges means a transition resulting by taking action a_k with the probability of p_{ij} , or simply showing by $p_{ij}(a_k)$. Note that there is also a scalar value as the reinforcement signal associated to each state transition in RL (real life) context.

Due to probability theory, the transition probabilities, $p_{ij}(a_k)$, must satisfy two conditions in equation 3.8:

$$\begin{aligned}
 p_{ij}(a_k) &\in [0, 1] && \forall i, j, k \\
 \sum_j p_{ij}(a_k) &= 1 && \forall i, j, k
 \end{aligned} \tag{3.8}$$

Needless to say, an HMM can be generally non-deterministic or deterministic. In figure 3.4, for instance, the result of applying action a_0 in

state 1 is non-deterministic: ends up either in state 2 with the probability $p_{12}(a_0)$, or in state 5 with the probability $p_{15}(a_0)$. In a deterministic HMM the transition probabilities are either 0 or 1.

This way of representing the problem automatically implies that each state contains sufficient information so that the probability of moving to any next state, j , and receiving any reward, r , is the same given the current state and action as when given the entire state-action-reward history of the environment. This important feature is called Markov property which shows that the transition probability from state i to state j , p_{ij} , depends entirely on the current state i and the corresponding action a_k . It is critical since it means that the current state of the environment provides the necessary information for the agent to decide what action to take.

In a formal way and with respect to time, if random variable S_t denotes the state of the environment at time step t , A_t the action taken at this time (equal to one of available possible actions), and s' and r as the resulting state and reward respectively, then by means of Markov property we have:

$$\begin{aligned}
 p_{S_t S_{t+1}}(A_t) &= Pr(S_{t+1} = s', r_{t+1} = r | S_t, A_t) = \\
 Pr(S_{t+1} = s', r_{t+1} = r | S_t, A_t, r_t, S_{t-1}, A_{t-1}, r_{t-1}, \dots, r_1, S_0, A_0) \\
 \forall S_t, s', r, A_t \text{ and past state - action - reward triples.} & \quad (3.9)
 \end{aligned}$$

In equation 3.9 r_t means the reinforcement signal received previously by transiting to the state S_t . Recall that S represents the state set, and A the action set then in mathematical notation:

$$\begin{aligned}
 \text{Reward function } R : S \times A &\rightarrow \mathfrak{R} \\
 \text{Transition probability function } p : S \times A \times S &\rightarrow [0, 1]
 \end{aligned}$$

Many algorithms have been developed for HMM. There are particular algorithm Viterbi [66] that allows, from a sequence of observations to infer the state sequence which is the most likely match for a given HMM. This algorithm is widely applied in speech recognition problems [65] or Molecular biology [67] (for example) where each state corresponds to a label classification and each state sequence form a sequence of labels.

3.2.3.3 Graphical probabilistic approaches

Graphical models are a marriage between probability theory and graph theory. They provide a natural tool for dealing with two problems that occur throughout applied mathematics and engineering. In this section we will briefly discuss about Bayesian networks which is the well-known among graphical probabilistic approaches.

★ Bayesian networks

Bayesian networks (BNs), also known as *belief networks* (or Bayes nets for short), belong to the family of probabilistic graphical models (GMs). These graphical structures are used to represent knowledge about an uncertain domain. In particular, each node in the graph represents a random variable, while the edges between the nodes represent probabilistic dependencies among the corresponding random variables. These conditional dependencies in the graph are often estimated by using known statistical and computational methods. Hence, BNs combine principles from graph theory, probability theory, computer science, and statistics.

A Bayesian network is a data structure used to give a compact graphical representation of the full joint probability distribution of a set of random variables. It is a directed graph where [68] a node represents a random variable, either discrete or continuous; a set of directed arrows connects pairs of nodes. If there is an arrow from node X to node Y , the X node is called *the parent* of Y . Each node X_i has a conditional probability distribution $P(x_i/Parent(X_i))$ that quantifies the effect of its parents on it. For discrete variable, this is represented as a conditional probability of table, where each row contains the conditional probability of each node value for a possible combination of values of its parent nodes. The graph is directed and acyclic.

These graphs play a key role in the decomposition of large probability distribution functions because they provide a visual representation of the sets of random variables that are relevant to each other in any given state of knowledge. Bayesian networks allow conditional independence statements that apply to subsets of variables, as opposed to all variables.

The topology of the Bayesian network specifies the conditional independence relationships that hold within that universe. Combined with

a conditional probability distribution for each child node given its parents and prior probability distributions for source variables (nodes with no parents), the topology of the Bayesian network is sufficient to specify the full joint probability distribution for all of its components variables [68]. Given a distribution P defined on n discrete variables X_1, X_2, \dots, X_n the probability of conjunction of particular assignments to each variable $P(X_1, \dots, X_n)$ is given by:

$$P(X_1, \dots, X_n) = \prod_{i=1}^n P(X_i / \text{Parent}(X_i)) \quad (3.10)$$

Where $\text{parents } X_i$ denotes specific value of the variables in $\text{Parents}(X_i)$. This implies that each entry in the full joint probability distribution can be calculated by the product of the appropriate elements of the conditional probability tables in Bayesian network, and thus that the Bayesian network can answer any query about the given domain [68].

One of the main advantages of Bayesian networks is that they are often much more compact than the full joint distribution. If a network contains n Boolean variables and each variable can be influenced by at most k other nodes, the amount of information needed to specify each conditional probability table for each node is at most 2^k and the complete network can be specified using $n \cdot 2^k$ numbers.

However, it is often possible to reduce the number of needed nodes to specify a Bayesian network even further. Deterministic nodes (nodes whose value is exactly specified by the value of their parents) often require no conditional probability tables because their values can directly be calculated from their parents' values using a formula. Noisy-OR logical relationships can also be used to reduce the size of the conditional probability table of random variable which depends on K parents from 2^K numbers [68]. A noisy-OR represents the situation where each Boolean parent of a Boolean node has some probability of being sufficient to cause the child node to be true, and the event of a given parent P_i being true is independent from the event of each other parent P_j being true. The noisy-OR relationship is often used to represent causal relationships such as those where several different diseases can each cause a common symptom [69]. When using the noisy-OR relationship, it is often useful to introduce a leak node which can be used to represent all other unknown causes. It is used to encode the probability that a given effect/symptom can occur in the absence of any cause explicitly

represented as a random variable in the Bayesian network topology [69].

Bayesian networks allow the decomposition of complex subjective judgments into simple subjective judgments about the probabilities of component events. Components of the model are then reassembled and the Bayesian network used to infer probabilities implied by these simpler judgments in order to facilitate the making of complex subjective judgment [68]. In medicine these systems are used for aiding in diagnosis: inferring the most probable cause of an observed problem given a set of symptoms, patient history, physical signs and test results. They are especially useful in the medical domain because they allow the creation of a probabilistic network using expert knowledge of causal dependencies in a given domain but can then be used for diagnostic inference (predicting probabilities in the reverse direction from effect to cause). Bayesian networks also easily support inter-causal inference (when the increased beliefs in one possible cause of an observed effect decrease the belief in another possible cause of the same effect) [69].

3.2.3.4 Connectionist Approaches

Connectionist models are less famous than linear models for two reasons: they are much more complex to implement, and they belong to another domain beyond statistics.

However, as they overcome various problems (including statistical problems which are only a small fraction) and now machines are powerful, they become more and more useful. In this section, we will detail how neural networks deal with discrimination problems.

★ Artificial Neuronal Networks

Artificial Neural Networks (ANN) are mathematical algorithms that are able to learn mappings between input and output states through supervised learning, or to cluster incoming information in an unsupervised manner [70]. Neural networks open a new door for fusing outputs from multiple sensors.

A neural network consists of an array of input nodes to accept sensors' output data, one or a few output nodes to show sensor fusion results, and sandwiched in between the input and output nodes is a network of interconnecting data paths. The weights along these data paths decide the input-output mapping behavior, and they can be adjusted to

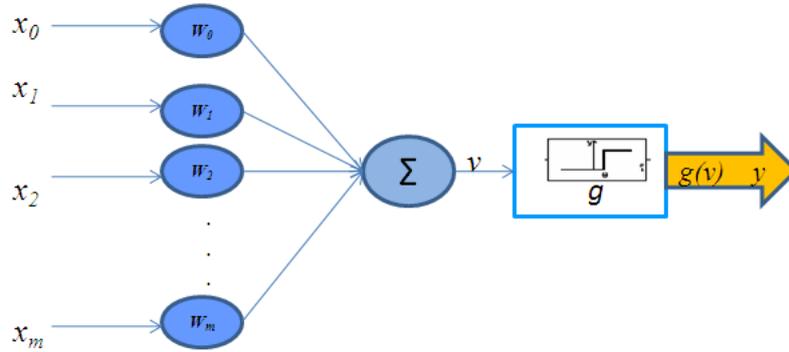


Figure 3.5: The fundamental building block in an ANN

achieve desired behavior. This weight-adjusting process is called training, which is realized by using a large number of input-output pairs as examples.

Neurons are connected with each other via synapses. Each synapse has a weight attached [71]. The output of a neuron is usually calculated with a function such as:

$$y_k = f\left(\sum_{j=0}^m w_{kj} * x_j\right) \quad (3.11)$$

Where y_k is the output of the neuron, f is an activation/transfer function, w_{kj} is the weight attached to synapse j for the neuron k , and x_j is the input signal of the neuron.

For summarizing the operating of an artificial neuronal networks, the fundamental building block in an artificial neuronal network is the mathematical model of a neuron as it is shown in figure 3.5. The three basic components of the (artificial) neuron are:

- The synapses or connecting links that provide weights, w_j , to the input values, x_j for $j = 1, \dots, m$;
- An adder that sums the weighted input values to compute the input to the activation function:

$$v = w_0 + \sum_{j=1}^m w_j x_j \quad (3.12)$$

where w_0 is called the bias (not to be confused with statistical bias in prediction or estimation) is a numerical value associated with the neuron. It is convenient to think of the bias as the weight for an input x_0 whose value is always equal to one, so that

$$v = \sum_{j=0}^m w_j x_j \quad (3.13)$$

- An activation function g (also called a squashing function) that maps v to $g(v)$ the output value of the neuron. This function is a monotone function.

The neural network training process can be simplified as follows. From the input nodes to output nodes, the data-path network provides many ways to combine inputs: those that lead to the desired output nodes are strengthened, whereas those that lead to undesired output nodes are weakened. Thus, after using the large number of input-output pair as training examples to adjust weights, the input data are more easily transferred to desired output nodes through the strengthened paths.

The neural networks can work in a high-dimensional problem space and generate high-order nonlinear mapping. Many successful applications have been reported. In [71, 72] generalities of neural networks focusing on the traditional method of implementation are illustrated.

3.2.3.5 Machine Learning Approaches

★ Support vector machines SVM

Support vector machines (SVMs) appeared in the early nineties as optimal margin classifiers in the context of Vapnik's statistical learning theory [73]. Since then SVMs have been successfully applied to real-world data analysis problems. Burges's tutorials [74] detail SVMs algorithm and in [75] some applications are exhibited.

This approach consists in determining the discriminating surfaces (boundaries between classes) rather than to model the membership probabilities of an object to a class. SVMs operate within the framework of regularization theory by minimizing an empirical risk in a well-posed and consistent way.

The context of SVM learning focuses into recognizing optimal separating surfaces which can take any shape and constructed with several parties. Their discrimination degree depends on the margin value (more accurately slack variables) which forms the expression of the objective function (convex function with one minimum). The idea is to move from the space of inputs to another one called *feature space* in which we seek to render the discrimination linear (recoding data). This transition from a non-linear function of discrimination to a linear function is performed by the kernel trick method. This so-called *kernel trick* gives the SVM great flexibility. With a suitable choice of parameters an SVM can separate any consistent data set (that is, one where points of distinct classes are not coincident). Usually this flexibility would cause a learner to overfit the data; i.e. the learner would be able to model the noise in the data as well as the data-generating process.

Two key elements in the implementation of SVM are the techniques of mathematical programming and kernel functions.

- The parameters are found by solving a quadratic programming problem with linear equality and inequality constraints; rather than by solving a non-convex, unconstrained optimisation problem.
- The flexibility of kernel functions allows the SVM to search a wide variety of hypothesis spaces.

In order to simplify the description of SVM, we give a simple example of support vector machine. The details are referred to Burges tutorial [76]. Given that training samples:

$$\{X_i, y_i\}, \quad i = 1, \dots, N, \quad y_i \in \{-1, 1\}, \quad X_i \in \mathfrak{R}^n \quad (3.14)$$

where y_i is the class label, support vector machine first maps the data to the other Hilbert space H (also called feature space), using a mapping ϕ ,

$$\phi : \mathfrak{R}^n \rightarrow H.$$

The mapping ϕ is implemented by a kernel function K that satisfies Mercers conditions [77] such that:

$$K(X_i, X_j) = \phi(X_i) \cdot \phi(X_j). \quad (3.15)$$

Then, in the high-dimensional feature space H , we find an optimal hyperplane by maximizing the margin and bounding the number of training errors. The decision function can be given by

$$\begin{aligned}
 f(X) &= \theta(W \cdot \phi(X) - b) \\
 f(X) &= \theta\left(\sum_{i=0}^N y_i \alpha_i \phi(X_i) \cdot \phi(X) - b\right) \\
 f(X) &= \theta\left(\sum_{i=0}^N y_i \alpha_i K(X_i, X) - b\right). \tag{3.16}
 \end{aligned}$$

Where

$$\theta(\mu) = \begin{cases} 1 & \text{if } \mu > 0 \\ -1 & \text{otherwise} \end{cases}$$

If α_i is nonzero, the corresponding data x_i is called support vector. Training a SVM is to find α_i , $i = 1, \dots, N$, which can be achieved by minimizing the following quadratic cost function:

$$\begin{aligned}
 \text{maximize } L_D(\alpha) &= \sum_{i=1}^N \alpha_i - 1/2 \sum_{i=1}^N \sum_{j=1}^N \alpha_i \alpha_j y_i y_j K(X_i, X_j) \tag{3.17} \\
 \text{Subject to } & 0 \leq \alpha_i \leq C \quad i = 1, \dots, N \\
 & \sum_{i=1}^N \alpha_i y_i = 0.
 \end{aligned}$$

where C is a parameter chosen by the user, a larger C corresponds to a higher penalty allocated to the training errors.

Since kernel K is semi-positive definite and constraints define a convex set, the above optimization reduces to a convex quadratic programming. The weight W is uniquely determined, but with respect to the threshold b , there exist several solutions in the special cases (see [78] [79] [80]).

Now we focus on an other SVM's example with two-class classification, classes being P, N for $y_i = 1, -1$ respectively. This can easily be extended to k class classification by constructing k two-class classifiers [73].

The geometrical interpretation of support vector classification (SVC) is that the algorithm searches for the optimal separating surface, i.e.

the hyperplane that is, in a sense, equidistant from the two classes [74]. This optimal separating hyperplane has many nice statistical properties [73]. SVC is outlined first for the linearly separable case. Kernel functions are then introduced in order to construct non-linear decision surfaces. Finally, for noisy data, when complete separation of the two classes may not be desirable, slack variables are introduced to allow for training errors.

SVMs fall into the intersection of two research areas: kernel methods, and large margin classifiers. These methods have been applied to feature selection, time series analysis, reconstruction of a chaotic system, and non-linear principal components. Further advances in these areas are to be expected in the near future. SVMs and related methods are also being increasingly applied to real world data mining.

3.2.3.6 Fuzzy logic

The idea of fuzzy set theory was proposed by Lutfi A. Zadeh forty years ago [81] as the foundation for computing with words. The fuzzy logic method accommodates imprecise states or variables. It provides tools to deal with context information that is not easily separated into discrete segments and is difficult to model with conventional mathematical or rule-based schemes.

There are three primary elements in a fuzzy logic system, namely, fuzzy sets, membership functions, and production rules.

Fuzzy sets consist of the imprecisely labeled groups of the input and output variables that characterize the fuzzy system, like the *cold*, *warm* and *hot* status in modeling temperature for example. Each fuzzy set has an associated membership function to provide a representation of its scope and boundaries. A variable of a fuzzy set have a partially membership degree to belong to this set. This membership degree is expressed by a value between 0 and 1.

The fuzzy inference system uses fuzzy equivalents of logical *AND*, *OR* and *NOT* operations to build up fuzzy logic rules in the form of IF-THEN statements. These rules connect inputs and outputs of the fuzzy system. The basic algorithm is that the *AND* operation returns the minimum value of its arguments, and the *OR* operation returns the maximum value of its two arguments by aggregating the defined rules according to Mamdani or Takagi/Sugeno methods.

The fuzzy variables generated by the fuzzy logic rules are turned into real values again that can be used by target applications. There are many different methods to perform this defuzzification step of fuzzy inference system.

The fuzzy logic sensor fusion method provides an effective tool to handle requirements of human daily-life, where imprecision is an inherent property in nature. These approaches will be widely discussed in the chapter 4, which is devoted to fuzzy inference systems.

3.2.4 Discussion

To select a suitable method for EMUTEM's multimodal data fusion module, we have probabilistic approaches whose performance can be reconsidered in our application for many reasons.

The classical inference method quantitatively compares the probability that an observation can be attributed to a given assumed hypothesis. But it has the following major disadvantages [82](1) difficulty in obtaining the density functions that describe observations used to classify the object, (2) complexities that arise when multivariate data are encountered, (3) its capability to assess only two hypotheses at a time, and (4) its inability to take direct advantage of a priori likelihood probabilities.

Bayesian inference method also has some weaknesses that prevent it from being used in our multimodal data fusion module. The key limits ([32]) are: (1) difficulty in defining a priori probabilities, (2) complexities when there are multiple potential hypotheses and multiple conditionally dependent events, (3) mutual exclusivity required for competing hypotheses, and (4) inability to account for general uncertainty and to represent imprecision.

Even if Dempster-Shafer methods use a general level of uncertainty, they cannot be the main data fusion method for two reasons: the difficulty to estimate mass function and their restrict domain of application.

The neural networks method is not adapted to EMUTEM's Data fusion module because of the drawbacks. First, the mapping mechanism is not well understood even if the network can provide the desired behavior, only in the simplest toy-like problems does examination of the weights in the trained network give any clue as to the underlying analytical connection between the inputs and outputs, Second, the neural network method is, generally speak-

ing, not suitable to work in a dynamic sensor configuration environment, because each sensor needs a unique input node and each possible sensor-set configuration needs to be specifically trained. Third, the complex architecture of neural networks prevents expert to add their knowledge with easily way.

SVM methods, despite of their transit in the characteristics space which is disconnected from any physical reality, could fulfill the requirement of intelligibility because only support vectors are important in identifying margins between classes. However, it is necessary that boundaries between classes are rendered intelligible by a graphical way in the space of inputs. This vision must take into account an input space of any size even if greater than 3. In this case, the SVM identifies a large majority of learning examples as support examples. It means that an analyst should remember too many relevant individuals for the construction of boundaries between classes and this is impossible.

The Fuzzy logic method is the proposed way to meet these challenges of our multimodal data fusion application. According to nature of data to process in EMUTEM platform Fuzzy logic is the well adapted approach for the telemonitoring decision. It deals with inaccuracy and uncertainty. It allows great flexibility for combination between sensors.

3.3 Conclusion

In order to maximize correct classification performance between normal and distress situations, data fusion over the different sensors types is studied. The area of data fusion has generated great interest among researchers in many science and engineering disciplines. We have identified two major classes of fusion techniques: (1) Those that are based on probabilistic models (such as Bayesian reasoning and the geometric decision reasoning), but their performance is limited when the data are too complex, therefore the model is uncontrollable. (2) Those based on connectionist models (such as neuronal networks MLP and SVM) which are very powerful because they can model the strong nonlinearity of data but with complex architecture, thus lack of intelligibility.

Based on those facts and considering the complexity of the data to process (audio, physiologic and multisensory measurements) plus the difficulty of the statistical modeling of abnormal situation of elderly people, fuzzy logic has

been found useful to be the decision module of our multimodal monitoring system EMUTEM. Fuzzy logic can gather performance and intelligibility and it deals with imprecision and uncertainty. It has a history of application for clinical problems including use in automated diagnosis [33], control systems [83], image processing [84] and pattern recognition [85]. Some experts find it easier to map their knowledge onto fuzzy relationships than onto probabilistic relationships between crisply defined variables.

A general data fusion architecture for EMUTEM fusion Module based on fuzzy logic is adopted. It includes complementary and cooperative data fusion types plus the three level of fusion illustrated previously in this chapter.

Chapter 4

Fuzzy Logic: A well-Adapted Approach for Multimodal Data Fusion

In the previous chapter we have highlighted a certain number of methods for data fusion that are susceptible to meet needs expressed by our multimodal platform for home healthcare telemonitoring EMUTEM. Fuzzy logic has been selected as the best adapted approach for the EMUTEM decision module. In this chapter this approach is detailed by introducing the basic elements of this theory and the derived notions of fuzzy logic and fuzzy inference.

4.1 Introduction

The idea of fuzzy sets was originated by Zadeh [81], although not very popular at this first conception time, this fuzzy sets theory has attached much attention in the last decade. This popularity of fuzzy logic is due in large part to the successful commercial devices that brought fuzzy micro-controller inside. Despite its widespread applications in commercial products, it is still one of the main concepts in soft computing and intelligent control.

The main concept of fuzzy logic is that many problems in the real world are imprecise rather than exact. It is believed that the effectiveness of the human brain is not only from precise cognition, but also from fuzzy concepts, fuzzy judgment, and fuzzy reasoning. An advantage of fuzzy classification techniques lies in the fact that they provide a soft decision, a value that describes the degree to which a pattern fits within a class, rather than only a

hard decision, i.e., a pattern matches a class or not.

Moreover fuzzy logic is a way to link an input space to an output space. It can also model arbitrary complex nonlinear functions. The other main advantage of fuzzy logic is that it can be built on top of the human expert experience; in other words it is able to formulate expert's knowledge. Fuzzy logic is based on natural language which makes it quite attracting field in artificial intelligence. It allows the natural description of problem domains, in linguistic terms, rather than in terms of relationships between precise numerical values.

4.2 Motivations

The use of fuzzy logic in EMUTEM fusion is motivated by two main raisons from a global point of view:

- Firstly the characteristic of data to merge which are measurements obtained from different sensors, thus they could be imprecise and imperfect. These data will be classified into two class normal situation and distress one, that are fuzzy because there is no clear limit between them.
- Secondly, the history of fuzzy logic proves that it is used in many steps which are necessary for a data classification application. Fuzzy logic methods are used because they require less computational power than conventional mathematical computational methods, they require few data samples in order to extract the final result, and they can be effectively manipulated since they use human language to describe problems.

4.3 Fuzzy Set

A fuzzy set, as the foundation of fuzzy logic, is a set without a hard, clearly sharp defined boundary. A fuzzy set extends a standard set by allowing degrees of membership of an element to this set, measured by real numbers in the $[0, 1]$ interval. If X is the universe of discourse (the input space variable) and its elements are denoted by x , then a fuzzy set A on X is defined as a set of ordered pairs $(x, \mu_A(x))$ such that:

$$A = \{x, \mu_A(x) | x \in X, 0 \leq \mu_A(x) \leq 1\} \quad (4.1)$$

Where $\mu_A(x)$ in equation 4.1, is the membership function (MF) of each x in A . in contrast to classical logic where the membership function $\mu_A(x)$ of an element x belonging to a set A could take only two values: $\mu_A(x) = 0$ if $x \notin A$ or $\mu_A(x) = 1$ if $x \in A$, fuzzy logic introduces the concept of membership degree of an element x to a set A and $\mu_A(x) \in [0; 1]$, here we speak about truth value.

Zadeh's original description of a membership value was linguistic interpretation: membership is partial because it refers to a vaguely defined concept. Over the years, other interpretations have been given to a membership value. Here we list some of the most popular ones:

- **Applicability:** $\mu_A(x)$ measures the degree of applicability of the description A to the individual x [86]. This interpretation differs from Zadeh's interpretation that it takes concepts as ontologically crisp, and puts the vagueness in the decision of their applicability to individuals.
- **Possibility:** $\mu_A(x)$ measures the degree of possibility that the individual x has the property A [87]. If x denotes a state of the universe, then $\mu_A(x)$ is read as the degree of possibility that state x satisfies the fuzzy predicate A .
- **Similarity:** $\mu_A(x)$ measures the degree of similarity between the individual x and an archetypical instance of the concept A [88]
- **Utility:** $\mu_A(x)$ measures the utility of x having the property A . If x denotes a state of the universe, then $\mu_A(x)$ is read as the utility of being in state x from the point of view of the criteria A [89].

4.3.1 Fuzzy Variable

A linguistic variable or fuzzy variable, X_f , is a variable whose values are words and linguistic terms or labels, rather than numbers; in order to show qualitative values not quantitative ones. X_f is the fuzzy representation of X . There may be defined n linguistic terms (L_i) over a given fuzzy variable, where there is a fuzzy set associated to each linguistic label:

$$X_f = L_i | 1 \leq i \leq n. \quad (4.2)$$

$$L_i = \{x, \mu_{L_i}(x) | 0 \leq \mu_{L_i}(x) \leq 1\} | 1 \leq i \leq n. \quad (4.3)$$

Linguistic labels can be any inaccurate human's expressions to interpret different variables. For instance to describe the temperature it can be: low,

medium, high and so on. On the universe of discourse of a fuzzy variable any number of linguistic labels can be defined; this will actually partition the whole universe of discourse of the fuzzy variable; and it is called fuzzy partitioning. There are two kinds of fuzzy partitioning:

- Ordinary or weak partition: In this way there is no restriction on how the membership functions (labels) should be formed over the universe of discourse of the variable.
- Strong partition: In this case the defined MFs for different linguistic terms on the given variable X_f should satisfy the following equation 4.4:

$$\sum_{i=1}^n \mu_{L_i}(x) = 1, \quad \forall x \in X. \quad (4.4)$$

The equation 4.4 eventually results in the fact that for all possible x at least one fuzzy set will have a non-zero membership degree; however under this condition at most two fuzzy sets would have non-zero membership degrees for all x . Using strong partitioning besides giving a guarantee to cover the whole input space of desired variable, simplifies some further assumptions about fuzzy reasoning. Thus it is of more interest in intelligent control.

4.3.2 Fuzzy Operators

Like ordinary logic it is needed to redefine logical operators such as *NOT*, *AND*, *OR* in this domain. But as its doctrine itself, fuzzy logic in contrast with conventional logic allows several possibilities to implement these operators in a fuzzy way. Generally the following operators will be defined:

- *NOT* (Fuzzy Complement): mostly the following has been used, equation 4.5:

$$\begin{aligned} \text{If } A &= \{x, \mu_A(x) | x \in X, 0 \leq \mu_A(x) \leq 1\} \text{ Then} \\ \text{NOT } A &= A' = \{x, \mu_{A'}(x) | x \in X, \mu_{A'}(x) = 1 - \mu_A(x)\} \end{aligned} \quad (4.5)$$

- *AND* (Fuzzy Conjunction \cap): T-norm operators.
- *OR* (Fuzzy Disjunction \cup): T-conform or S-norm operators .

The general well-known operators T-norm and T-conform should comply with specific conditions which also verify them for the traditional crisp logic

as a special case. For instance for two fuzzy sets A and B the notation to indicate conjunction and disjunction is:

$$\begin{aligned} A \text{ AND } B &= A \cap B = T_{norm}(\mu_A(x), \mu_B(x)). \\ A \text{ OR } B &= A \cup B = T_{conform}(\mu_A(x), \mu_B(x)). \end{aligned} \quad (4.6)$$

T-norm is any binary relation, $T_{norm}(\cdot, \cdot)$ that satisfies the following conditions:

- Boundary: $T_{norm}(0, 0) = 0$, $T_{norm}(\mu, 1) = T_{norm}(1, \mu) = 1$.
- Monotonicity: if $\mu_A \leq \mu_C$ and $\mu_B \leq \mu_D$ then $T_{norm}(\mu_A, \mu_B) \leq T_{norm}(\mu_C, \mu_D)$.
- Commutativity: $T_{norm}(\mu_A, \mu_B) = T_{norm}(\mu_B, \mu_A)$.
- Associativity: $T_{norm}(T_{norm}(\mu_A, \mu_B), \mu_C) = T_{norm}(\mu_A, T_{norm}(\mu_B, \mu_C))$.

It is almost the same for T-conform as the dual of T-norm, any binary relation, $T_{conform}(\cdot, \cdot)$ that satisfies the following conditions:

- Boundary: $T_{conform}(1, 1) = 1$, $T_{conform}(\mu, 0) = T_{conform}(0, \mu) = \mu$.
- Monotonicity: if $\mu_A \leq \mu_C$ and $\mu_B \leq \mu_D$ then $T_{conform}(\mu_A, \mu_B) \leq T_{conform}(\mu_C, \mu_D)$.
- Commutativity: $T_{conform}(\mu_A, \mu_B) = T_{conform}(\mu_B, \mu_A)$.
- Associativity: $T_{conform}(T_{conform}(\mu_A, \mu_B), \mu_C) = T_{conform}(\mu_A, T_{conform}(\mu_B, \mu_C))$.

As it would be clear, the first condition in both cases is to provide support for crisp logic as a special case of fuzzy logic.

Thus there can be defined plenty of operators as T-norm and T-conform, the most famous ones are shown in table [4.1]. The detailed description of

T-norm	T-conform
Minimum	Maximum
Algebraic product	Sum
Bounded product	Probabilistic OR

Table 4.1: The most famous T-norm and T-conform operators

above operators can be found in [90]. Among these algebraic product and maximum are common operators for T-norm and T-conform respectively. While minimum operator is the simplest and with less computational cost,

the problem is that the resulting surfaces are not continuous; meanwhile the algebraic product gives smooth surfaces and also it is greedier in giving the MF values than minimum, which comes up with less probable mistake in deduction. The bounded product is the most complex one, and also the effect is very close to that of algebraic product. Table [4.2] summarizes the most used operators in a fuzzy inference system.

Fuzzy AND $\mu_{A \cap B}(x)$	Conjunction (T-norm)	Fuzzy Disjunction OR (T-conform) $\mu_{A \cup B}(x)$	Complement $\mu_{A'}(x)$	NOT
Zadah's operators Min/Max				
$\min(\mu_A(x), \mu_B(x))$		$\max(\mu_A(x), \mu_B(x))$		$1 - \mu_A(x)$
Probabilistic PROD/PROBOR				
$\mu_A(x) * \mu_B(x)$		$\mu_A(x) + \mu_B(x) - \mu_A(x) * \mu_B(x)$		$1 - \mu_A(x)$

Table 4.2: The most used operators in fuzzy inference systems

4.3.3 Membership Degree and Probability

Both the membership degree and the probability, quantify the imprecision by a real number between 0 and 1, where the confusion is often expressed between the two concepts. But these two concepts are completely different nature as it is emphasized by Bouchon Meunier [91]. She invites the reader to debrief about the contents of a bottle according to what is written on its label. Let U be the set of all liquids and L the subset of potable liquids. On the first bottle (A) it is denoted $\ll membership\ degree\ of\ A\ to\ L = 0.9 \gg$. On the second bottle (B), it is indicated $\ll probability\ that\ B\ belongs\ to\ L = 0.9 \gg$.

The membership degree of A to L = 0.9 means that the liquid in the bottle A is close to a pure liquid (e.g., a bottle of water have been opened since three days). The probability that B belongs to L = 0.9 means that after many experiments, we find that 90% of the bottles contain a potable liquid and in the remaining cases a dangerous or deadly liquid. Thus, we take a risk of 10% to be died by drinking the contents of B while the contents of A risks just to make us ill.

Thus, membership degrees are a special characteristic of the considered object (a sort of qualification). In contrast, a probability is associated with the notion of occurrence of an event repeatable; we are in waiting to see

the realization of this event. Chances to obtain the realization of this event depend on the value assigned to the probability (the probability of obtaining the number 4 with a singular dice is 1/6, but nothing warranties that we see the number 4 during a launch).

4.4 Fuzzy Logic System Components

Fuzzy logic reflects human reasoning based on inaccurate or incomplete data. As it is said in the previous section, it uses the concept of partial membership, each element, partially or gradually belongs to fuzzy sets that have been already defined. A typical fuzzy logic inference system has four components: a fuzzification, a fuzzy rule base, an inference engine, and a defuzzification as it is shown in figure 4.1.

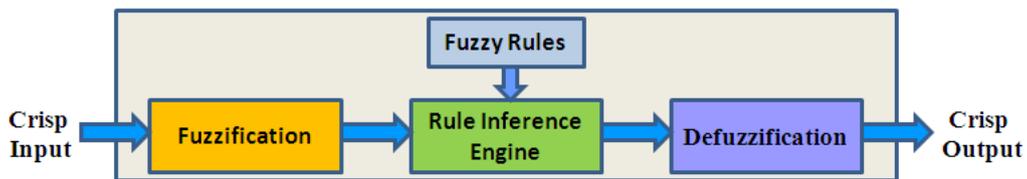


Figure 4.1: A block diagram of a fuzzy inference system.

4.4.1 Fuzzification

First step in fuzzy logic is to convert the measured input data and output into a set of fuzzy variables. It is done by giving value (these will be our variables) to each of a set membership functions.

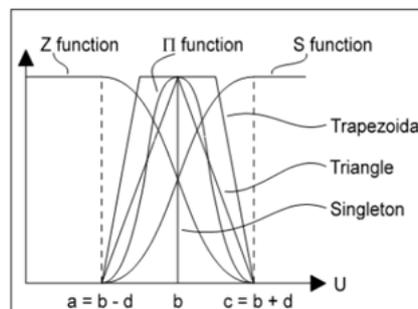


Figure 4.2: Membership functions.

A membership function is a curve that defines how each point in the input space is mapped to a membership value (or degree of membership) between 0 and 1. The input space is sometimes referred to as the universe of discourse. The simplest membership functions are formed using straight lines as it is shown in figure 4.2. Of these, the simplest is the triangular membership function. It is nothing more than a collection of three points forming a triangle. A Triangular membership function with straight lines can formally be defined as follows:

$$\Lambda(x, a, b, c) = \begin{cases} 0, & x \leq a \\ (x - a)/(b - a), & a \leq x \leq b \\ (c - x)/(c - b), & b \leq x \leq c \\ 0, & x \geq c \end{cases} \quad (4.7)$$

The Trapezoidal membership function has a flat top and really is just a truncated triangle curve. Trapezoidal Function Furnished in the equation 4.8.

$$f(x, a, b, c) = \begin{cases} 0, & x \leq a \\ (x - a)/(b - a), & a \leq x \leq b \\ 1, & b \leq x \leq c \\ (d - x)/(d - c), & c \leq x \leq d \\ 0, & x \geq d \end{cases} \quad (4.8)$$

These straight line membership functions have the advantage of simplicity. Gaussian and Bell membership functions are popular methods for specifying fuzzy sets because of their smoothness and concise notation. Both of Gaussian and bell curves have the advantage of being smooth and nonzero at all points. A Gaussian membership function with the parameters m and σ to control the center and width of the membership function is defined by:

$$G(x, m, \sigma) = e^{-\frac{(x-m)^2}{2\sigma^2}} \quad (4.9)$$

The generalized Bell function depends on three parameters a , b , and c is given by:

$$f(x, a, b, c) = \frac{1}{1 + \|(x - c)/a\|^{2b}} \quad (4.10)$$

There is also other membership functions like sigmoid shaped function, single function, etc. The choice of function shape is determinate iteratively, according to type of data and taking into account the experimental results.

4.4.2 Fuzzy Rules

Fuzzy rules are used to connect fuzzified inputs and outputs, but before introducing the fuzzy rules concept we have to illustrate the human reasoning

and its fuzzy modeling.

4.4.2.1 Fuzzy Modeling of Human Reasoning

The modeling of human perception and human reasoning collides with various difficulties. Indeed, the human perceives fundamentally imperfect information which may be classified into three types:

- Imprecise: Because of the imprecision of measurement systems which provide data, or because that the data are issued from subjective judgments.
- Uncertain: If the data are issued from a measurement system including damaged components, then the lack of reliability
- Incomplete: due to failure transmission for example.

However, despite of these imperfections, the human being continues to reason and provides specific information or conclusions. By reasoning, we mean the general process of using knowledge into a system in order to build additional knowledge about this system [92]. The fuzzy theory will allow, via the generalized modus ponens (see Appendix A) and fuzzy inference systems, to model as much as possible the human reasoning. The human reasoning remains poorly understood, but it appears that conclusions are made without explicating deduction rules, without that problems previously solved or similar cases already encountered are involved in the formulation of certain conclusions. Fuzzy logic has so many forms of reasoning where the main is the fuzzy deductive reasoning, which accommodates imperfect statements through the generalized modus ponens (see Appendix A) presented by Zadeh.

The idea is to manage these difficulties by modeling uncertainty and imprecision by fuzzy sets, then to model the human reasoning by using generalized modus ponens and finally building fuzzy inference systems (FIS) based on simple deduction rules that take account of uncertainties and inaccuracies.

4.4.2.2 Fuzzy Rules

Fuzzy sets and fuzzy operators are the subjects and verbs of fuzzy logic. Usually the knowledge involved in fuzzy reasoning is expressed as rules in the form:

If x is A Then y is B.

Where x and y are fuzzy variables and A and B are fuzzy values defined by fuzzy sets. The if-part of the rule $\ll x \text{ is } A \gg$ is called the antecedent or premise, while the then-part of the rule $\ll y \text{ is } B \gg$ is called the consequent or conclusion. Statements in the antecedent (or consequent) parts of the rules may well involve fuzzy logical connectives such as *AND* and *OR*. In the if-then rule, the word *is* gets used in two entirely different ways depending on whether it appears in the antecedent or the consequent part.

Fuzzy If-Then rule or, fuzzy rule, is the main aspect of fuzzy reasoning process. Traditional reasoning versus fuzzy reasoning can be explained in what follows. Remember the simple rule of inference in traditional logic, modus ponens, from which the truth of a proposition B from the truth of the if-then rule $A \rightarrow B$ along with the truth of A , can be deduced. But in fuzzy fashion we usually deduce the grade up to which proposition the consequent B is correct by knowing how much the antecedent A is correct. There are several types of fuzzy rules, we cite only the two most used [93]:

- Mamdani

$$\begin{array}{l} \textit{if} \quad x_1 \quad \textit{is} \quad A_1 \quad \textit{and...and} \quad x_p \quad \textit{is} \quad A_p \\ \textit{Then} \quad y_1 \quad \textit{is} \quad B_1 \quad \textit{and...and} \quad y_p \quad \textit{is} \quad B_p. \end{array} \quad (4.11)$$

Where A_i and B_i are fuzzy sets that define the partition space. The conclusion of a Mamdani rule is a fuzzy set. It uses the algebraic product and the maximum as T-norm and S-norm respectively, but there are many variations by using other operators.

- Takagi/Sugeno

$$\begin{array}{l} \textit{if} \quad x_1 \quad \textit{is} \quad A_1 \quad \textit{and...and} \quad x_p \quad \textit{is} \quad A_p \\ \textit{Then} \quad y = b_0 + b_1.x_1 + \dots + b_p.x_p. \end{array} \quad (4.12)$$

Where each b_i is weight assigned to each membership function. In the Sugeno model the conclusion is numerical. The rules aggregation is in fact the weighted sum of rules outputs.

In order to calculate the fuzzy implication rule a fuzzy implicative function $\Phi : [0, 1] \times [0, 1] \rightarrow [0, 1]$ is used.

$$\forall x \in X, \forall y \in Y, f_I(x, y) = \Phi(\mu_A(x), \mu_B(y)). \quad (4.13)$$

This is an equivalent to the classical implication when the proposals are classic. There are different functions of fuzzy implications (Lukasiewicz, Goguen

...etc). We add to the list of fuzzy implication functions two special relationship due to Mamdani ($\min(\mu_A(x), \mu_B(y))$) and Larsen ($\mu_A(x) * \mu_B(y)$) which are not really implications but which are commonly used [94].

After all the process of interpreting fuzzy If-Then rule can be summarized as three steps:

- Fuzzification which means resolving all the crisp input variables in the antecedent to their degree of membership.
- Applying the fuzzy operators in the antecedent part to resolve all fuzzified values in one value called truth rule value (rule degree of support), by applying T-norm and T-conform operators.
- Performing implication by applying T-norm over the truth rule value and the consequent.

4.4.3 Rules Inference Engine

Fuzzy inference engine is the process of formulating the mapping from a given input to an output using fuzzy logic. The process of fuzzy inference involves membership functions, fuzzy logic operators and if-then rules. The most popular models of fuzzy inference systems are the Mamdani models [95] and the Takagi-Sugeno (TS) models [96]. The main difference between them is the consequent part of fuzzy rules. The Mamdani models describe the consequent part using linguistic variables, while the Takagi-Sugeno models use the linear combination of the input variables. Both models use linguistic variables to describe the antecedent part of fuzzy rules.

4.4.3.1 Mamdani Model

Mamdani fuzzy-rule based systems [95] consist of a linguistic description in both the antecedent parts and the consequent parts. The original idea was to use the algebraic product and the maximum like T-norm and T-conform respectively but there are many variants when other operators are used. Each rule is a description of a condition-action statement that may be clearly interpreted by the users. To describe a mapping from input $U_1 \times U_2 \times \dots \times U_n$ (where \times is the Cartesian product) to output W , the linguistic rule structure of Mamdani models is as follows:

$$R_i: \text{ If } x_1 \text{ is } A_{i1} \text{ and } \dots \text{ and } x_n \text{ is } A_{in} \text{ Then } y \text{ is } C_i, i = 1, \dots, L$$

Where L is the number of fuzzy rules, $x_j \in U_j, j = 1, 2, \dots, n$, are the input variables, y is the output variable, and A_{ij} and C_i are linguistic variables or fuzzy sets for x_j and y respectively. A_{ij} and C_i are characterized by membership functions $\mu_{A_{ij}}(x_j)$ and $\mu_{C_i}(y)$, respectively. Inputs are of the form:

$$x_1 \text{ is } A'_1, x_2 \text{ is } A'_2, \dots, x_r \text{ is } A'_n$$

Where A'_1, A'_2, \dots, A'_n are fuzzy subsets of U_1, U_2, \dots, U_n , which are the universe of discourse (or the domain of interest) of inputs.

Figure 4.3 illustrates a fuzzy inference engine Mamdani type involving two rules with two fuzzy propositions each. The chosen operator for the implication is the minimal and maximum for the aggregation.

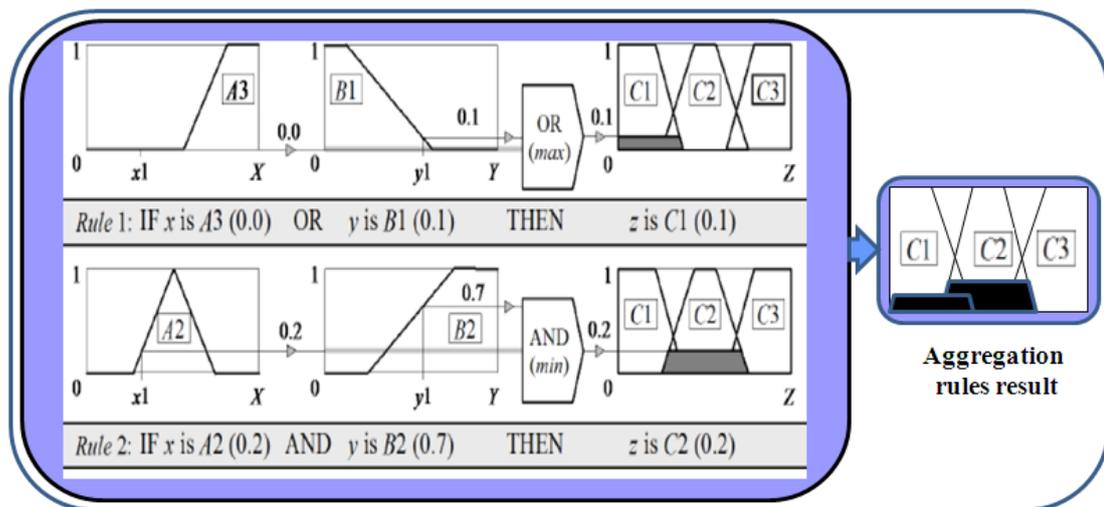


Figure 4.3: Example of Mamdani fuzzy inference model

4.4.3.2 Takagi-Sugeno Model

Instead of working with linguistic rules as in Mamdani models, Takagi, Sugeno, proposed a new model based on rules where the antecedent was composed of linguistic variables and the consequent was represented by a function of the input variables. This model uses the fuzzy rules of Takagi-Sugeno. In fact the output of each rule is a function of inputs $f(x_1, x_2, \dots, x_p)$. In general, f is a polynomial and the order of the polynomial gives the order of the Sugeno fuzzy inference model. The most usual form of these kinds of rules is the one shown in the following, in which the consequent comprises

a linear combination of the variables involved in the antecedent. The main difference between Mamdani and Sugeno is that the Sugeno output membership functions are either linear or constant. A typical rule in a Sugeno fuzzy model has the form:

If $Input_1 = x$ **and** $Input_2 = y$, *Then theOutput is* $z = a.x + b.y + c$

Where $Input_1$ and $Input_2$ are the system input variables, z is the output variable, a, b, c are the numerical constant parameters, and x and y are linguistic labels associated in the form of fuzzy sets.

The output level z_i of each rule is weighted by the firing strength W_i of the rule. For example, for an *AND* rule with $Input_1 = x$ and $Input_2 = y$, the firing strength is:

$$W_i = AndMethod(F_1(x), F_2(y)) \quad (4.14)$$

Where F_1, F_2 are the membership functions for $Input_1$ and $Input_2$ respectively. The final output of the system is the weighted average of all rule outputs, computed as:

$$FinalOutput = A = \frac{\sum_{i=1}^N W_i z_i}{\sum_{i=1}^N W_i} \quad (4.15)$$

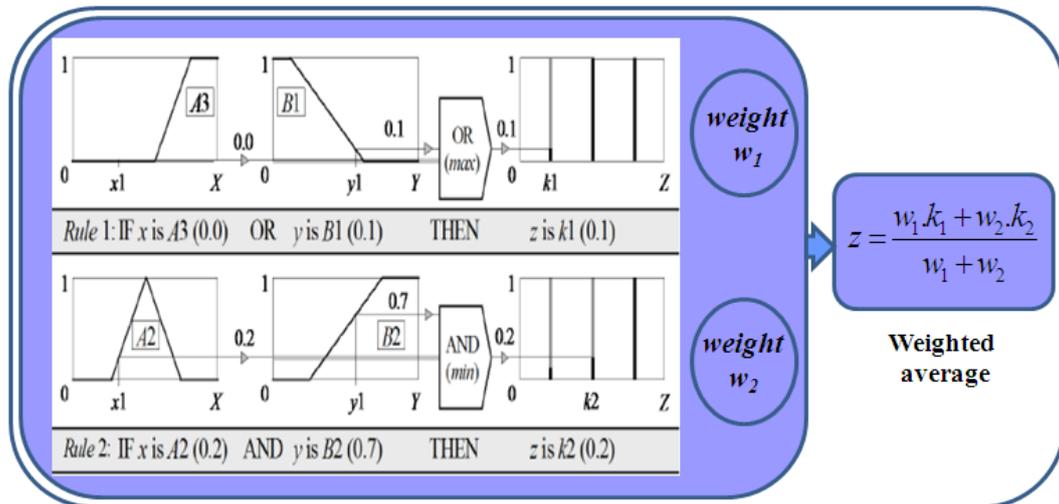


Figure 4.4: Example of Takagi/Sugeno fuzzy inference model

The inference performed by the TS model is an interpolation of the entire relevant linear model. The degree of relevance of a linear model is determined

by the degree the input data belong to the fuzzy subspace associated with the linear model. These degrees of belongingness become the weight in the interpolation process. Figure 4.4 illustrates a TS fuzzy inference engine model with two rules.

4.4.4 Defuzzification

The defuzzification is the last step in building a fuzzy logic system, it consists in turning the fuzzy variables generated by the fuzzy logic rules into real value again which can then be used to perform some action. There are different defuzzification methods, the most adapted for a Mamdani fuzzy inference engine are *Centroid of area (COA)*, *Bisector of area (BOA)*, *Mean of Maximum (MOM)*, *Smallest of Maximum (SOM)* and *Largest of Maximum (LOM)*. Equations 4.16, 4.17, 4.18, 4.19 and 4.20 illustrate them.

$$Z_{COA} = \frac{\sum_{i=1}^n \mu_A(x_i)x_i}{\sum_{i=1}^n \mu_A(x_i)} \quad (4.16)$$

$$Z_{BOA} = x_M; \sum_{i=1}^M \mu_A(x_i) = \sum_{j=M+1}^n \mu_A(x_j) \quad (4.17)$$

$$Z_{MOM} = \frac{\sum_{i=1}^N x_i^*}{N} \quad (4.18)$$

$$Z_{SOM} = \min(x_i^*) \quad (4.19)$$

$$Z_{LOM} = \max(x_i^*) \quad (4.20)$$

Where x_i^* ($i = 1, 2, \dots, N$) reach the maximal values of $\mu_A(x)$.

Weighted average method is used to defuzzify TS fuzzy inference engine.

$$Z(x) = \frac{\sum_{k=1}^{NbRules} w_k \mu_k(x) z_k}{\sum_{k=1}^{NbRules} w_k \mu_k(x)} \quad (4.21)$$

Where w_k weigh of the rule, $\mu_k(x)$ membership degee, z_k output of the each rule.

4.5 Fuzzy Inference System Process (FIS)

Figure 4.5 summarize the process of a fuzzy inference system. This system contains five inputs fuzzified with Gaussian membership functions and one outputs. This process is the process of formulating the mapping from a given input to an output using fuzzy logic. The mapping then provides a basis from which decisions can be made. It uses one of the mainly two types of fuzzy inference systems that are defined in the previous section: Mamdani-type (M-FIS) and Takagi-Sugeno-type (TS-FIS).

FIS actually consists of a rule-base including a collection of fuzzy If-Then

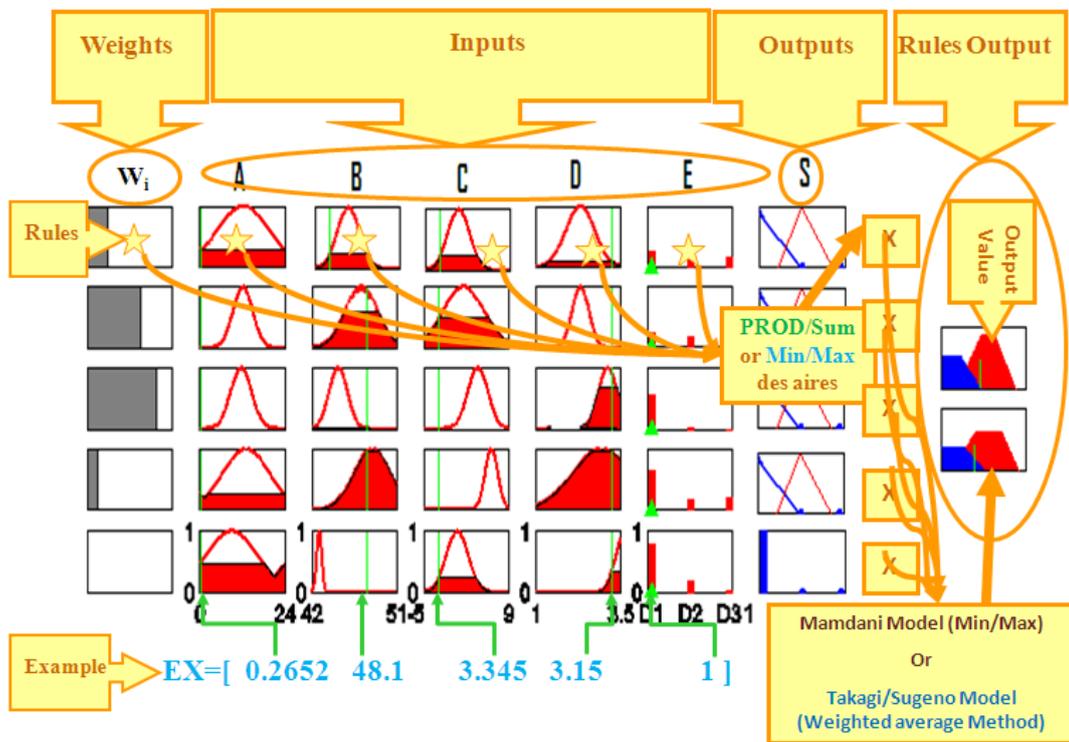


Figure 4.5: The process of a fuzzy inference system

rules to mimic the way of the human expert decision making process. In general the rule-base in a FIS consists of arbitrary number of different form of rules constructed out of AND and/or OR operators; but it is clear that a rule base consisting of all possible combination of different linguistic terms of all variables with just AND operator can cover all situations and conditions, since any rule as a combination of OR with other operators can be interpreted into a group of possible rules constructed just with AND operator.

The functionality of a FIS can be summarized in five steps:

- Fuzzification of the input and output variables i.e. taking the crisp of inputs and outputs and determine the degree to which these inputs and outputs belong at each of the appropriate fuzzy sets.
- Application of the fuzzy operators (AND and OR) in the antecedent part of all rules, using T-norm and T-conform operators respectively.
- Implication from the antecedent to the consequent, using T-norm operator in order to perform the rule evaluation step.
- Aggregation of the consequents across the rules by using Mamdani model or TS model: It is the unification process of the all rules outputs.
- finally the process of defuzzification is done by extracting out one crisp value as the output, out of the aggregated output as a representative. In TS-FIS it is simply the weighted average of all output singletons as having the rules truth values as weights. In M-FIS one of defuzzification functions described in the defuzzification section is used.

4.6 Fuzzy Logic and Classification Methods

Since that L.A. Zadeh introduced the concept of fuzzy logic, this concept has been more studied, and several applications were developed, essentially in Japan. The use of fuzzy sets can be done mainly at three levels:

- **Attributes representation:** It may happen that data are incomplete or noisy, unreliable, or some attributes are difficult to measure accurately or difficult to quantify numerically. At that time, it is natural to use fuzzy sets to describe the value of these parameters. The attributes are linguistic variables, whose values are built with adjectives and adverbs of language: large, small, medium etc...and as an illustrating example, we found the recognition system proposed by Mandal et al [97]. Some methods are based on a desecrating of the attributes space which is a language. Thus a numerical scale of length will be replaced by a set of fuzzy labels, for example (very small, small, medium, large, extra large), and any measure of length, even numerical is converted on this scale. The underlying idea is to work with the maximum granularity, i.e. the minimum accuracy.

- **Class representation:** Classes don't create a clear partition of the data space, but a fuzzy partition where recovery is allowed will be better adapted. A significant number of fuzzy patterns recognition methods, are just an extension of traditional methods based on the idea of fuzzy partition for example the fuzzy c-means algorithm [98]. Historically, the idea of fuzzy partition was first proposed by Ruspini [99] in 1969.

Rather than creating new methods of fusion and classification based on entirely different approaches, fuzzy logic fit naturally in the expression of the problem of classification, and tend to make a generalization of the classification methods that already exist. Taking onto account the four steps of a recognition system proposed by Bezdek et Pal [100], fuzzy logic is very useful for these steps.

- **Data description:** Fuzzy logic is used to describe syntactic data [101], numerical data and Contextual, conceptual data or data based on rules [102] which is the most significant contribution for the data description.
- **Analysis of discriminate parameters:** In image processing, there are many techniques based on fuzzy logic for segmentation, detection, contrast enhancement [103]. There are also techniques based on fuzzy logic for extraction [104].
- **Clustering algorithms:** The aim of these algorithms is to label a set of data into C class, so that obtained groups contain the most possible similar individuals. Fuzzy c-mean algorithm and fuzzy ISODATA [105] algorithm are the famous in this category.
- **Design of the discriminator:** The discriminator is designed to produce a fuzzy partition or a clear one, describing the data. This partition corresponds to classes. Indeed the fuzzy ISODATA algorithm will be adapted for this step.

4.7 Conclusion

After the presentation of the fuzzy logic concept in this chapter, we realized that the notion of class used in pattern recognition or in classification found its natural expression framework under this concept. Indeed, we can define a class as a group of individuals with several similarities. These similarities may be more or less severe between the individuals of the same class, and secondly, the same individual may have similarities with individual from other classes, so that the membership of an individual is not localized into a

particular class, but it is distributed among several classes. Thus, the concept of fuzzy set fits with this problem, because in this formalism, an element may belong more or less strongly to several fuzzy sets.

Taking into account that, the goal of this thesis is to produce a new system that is able to discriminate between normal and distress situation of an elderly person at home, a fuzzy logic approach is well adapted to fuse EMUTEM's modalities and to take a good decision. Now, with the adoption of this approach our platform is called FL-EMUTEM (Fuzzy Logic EMUTEM). Fuzzy logic has attracted the attention of several researchers in health care. Fuzzy logic provides a methodology that simulates human thinking by explicitly modeling and managing the imprecision and uncertainty inherent in EMUTEM's subsystems. Fuzzy logic will allows high flexibility to EMUTEM platform especially in combining between modalities or adding other sensors.

Chapter 5

Fuzzy Logic Multimodal Data Fusion Approach: Implementation and Clarification

To adapt fuzzy logic to the fusion context and to realize the the fuzzy logic multimodal data fusion approach, there are some major concerns that need to be addressed carefully. One is the methodology to use in order to make the system architecture efficient in collecting information about the elderly person and to take the best decision about his situation. The other is how to combine all the modalities under this multimodal data fusion approach. It is also important to address the question regarding how Fuzzy logic concept can be applied in practice to the multimodal data fusion.

5.1 Methodology

5.1.1 Design Criteria

Based on the foundation of fuzzy logic discussed thoroughly in previous chapters 4, now it is the time to go through Fuzzy adaptation and implementation methodology. Fuzzy set theory offers us a wide variety of aggregation operators to combine the outputs of the three subsystems of FL-EMUTEM (RFpat, Anason, Gardien).

However, because there is no standard for interpreting fuzzy inference systems, we have to investigate the way to build a special fuzzy inference system

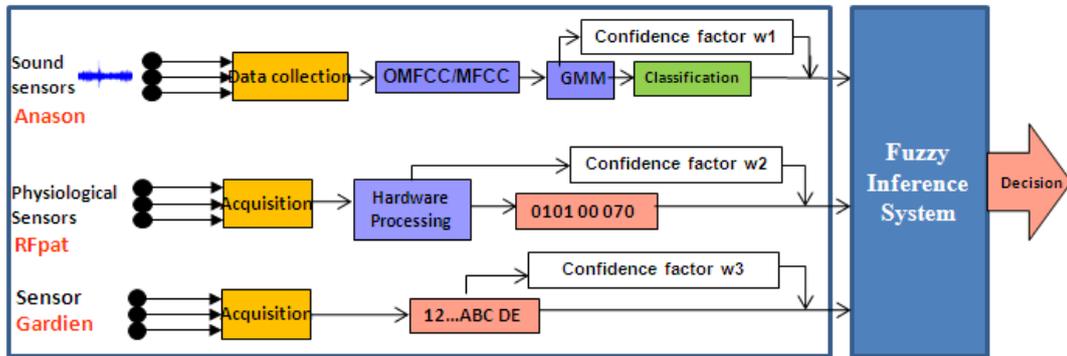


Figure 5.1: FL-EMUTEM data fusion architecture.

for FL-EMUTEM decision module.

The overall architecture of the system is shown in figure 5.1. Each subsystem provides a certain number of outputs and a value as a confidence assigned to each one of these outputs. The decision in Anason is based on likelihood value which is calculated for each classification, this value represent the confidence factor w_1 . The confidence value w_2 assigned to RFpat is calculated during denoising step and it represents the cleanness degree of the data. The confidence factor w_3 of Gardein subsystem depends on the number of activated infrared sensors on a data stream, and also their position in the telemonitoring area. For example the best value of w_3 which is 1 is reached when we have a data frame with only two activated infrared sensors, one horizontal and one vertical. These provided outputs from each subsystem or madality are the crisp input for the inference fuzzy system and they need to be correctly partitioned into the fuzzification step.

As fuzzy set theory offers a convenient way to do all possible combinations with these inputs, it is indispensable to build rules that reflect the maximal of combination between inputs in order to take into account all the possible situations of an elderly person at home recognized by those sensors or modalities.

5.1.2 The Choice of Membership Functions

Based on a review of the data and discussions with the expert medical members of our team, for the fuzzification, we needed membership functions with different characteristics according to each inputs from each subsystem, satisfying our requirements. For example we will use membership functions with

characteristics of smoothness, asymmetry or with a quick rise suitable for each inputs and according to the decision module.

Membership function must be defined by parameters which are easy to handle in order to facilitate the choice of these parameters experimentally or by experience.

5.1.3 Fuzzy Rules Construction

Fuzzy rules for FL-EMUTEM decision module should be decided by a priori knowledge about each modality, expert intervention, and intuition or through experimentation. These rules must be easy to retrofit or to change during experiments in order to enhance results.

In order to build an effective fuzzy logic inference system, it is very important to avoid conflicting or contradictory rules. Rules involved in FL-EMUTEM fuzzy inference system, they should be also flexible in the number of modalities involved in each rules.

5.1.4 The Choice of Fuzzy Inference Aggregation Model

The most popular model of fuzzy inference aggregation is the Mamdani model and Takagi-Sugeno model. Both models use linguistic variables to describe the antecedent part of fuzzy rules.

The main difference between Mamdani model and Takagi Sugeno is that the output membership functions are only linear or constant for Takagi-Sugeno, as mentioned. While Mamdani model the output membership functions to be fuzzy sets (the most general form).

Based on the above discussion, the choice of the fuzzy inference aggregation model will be defined according to fuzzy outputs of the system and fuzzy rules involved in the system.

5.1.5 Validation of the Approach

The main advantage of using fuzzy logic system is the capacity of the approach to deal with the complex data acquired from the three subsystems: Anason, RFpat and Gardien in FL-EMUTEM platform. Fuzzy set theory offers a convenient way to do all combinations that we want with these data.

Fuzzy set theory is used in this system to determine the most likely distress situations that might occur for elderly persons in their home. In order to prove this choice and to validate this approach a good strategy of implementation and evaluation must be selected.

This approach should be implemented in the way that takes in the account a multi-component architecture of implementing. This architecture will allow to the FL-EMUTEM platform to operate in off line by using data bases and simulation and also to work in online (in real time), thus to have a great universe of evaluation and validation of this fuzzy logic multimodal data fusion approach.

5.2 Approach Description and Implementation

5.2.1 Software Architecture

Figure 5.2 provides a synoptic block-diagram scheme of the software architecture of the FL-EMUTEM system; it is implemented under LabWindows CVI and C++ software. It is developed in a form of design component.

We can distinguish three main components, the acquisition module, the synchronization module and the fuzzy inference component. It can run on off-line by reading data from a data base or online by processing in real time data acquired via the acquisition module.

To avoid the loss of data, a real time module with two multithreading tasks is integrated in the synchronization component. The EMUTEM system is now synchronized on Gardien subsystem because of his smallest sampling rate (2 Hz) and periodicity. The data from others modalities are memorized and used several time in order to have the same sampling rate (a RFPAT data is used 60 times). These technique allow a maximum delay for an asynchronous data (sound or alarm from RFPAT) of 0.5s.

We have developed a data fusion based Fuzzy tools which allow the easy configuration of input intervals of Fuzzification, the writing of fuzzy rules and the configuration of the defuzzification method. It is also possible to add others modalities to this fuzzy inference system which make the FL-EMUTEM platform flexible. Two outputs are associated to the fuzzy inference system, *Alarm* for distress situation detection and *Localization* for

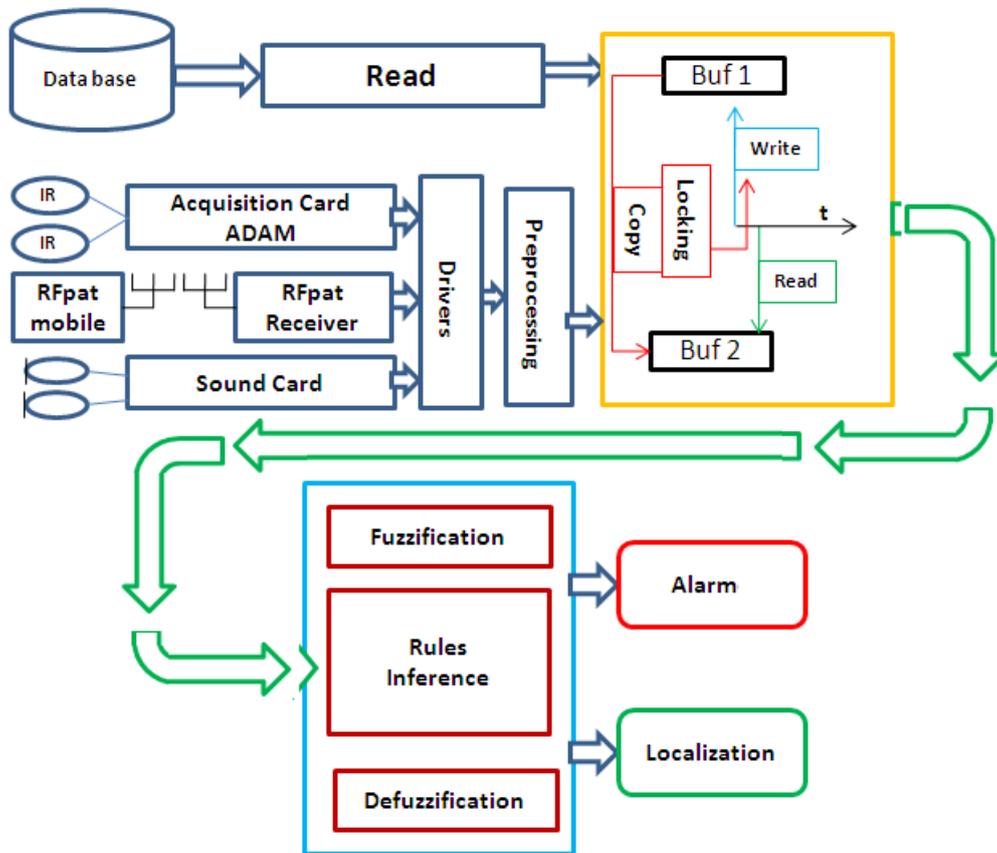


Figure 5.2: FL-EMUTEM software architecture.

elderly person position detection.

5.2.2 Fuzzy Inference System Modeling

A hierarchical of implementing the fuzzy inference system (FIS) is adopted and modeled under UML (Unified Modeling Language). UML diagrams represent two different views of a system model:

- Static (or structural) view: Emphasizes the static structure of the system using objects, attributes, operations and relationships. The structural view includes class diagrams and composite structure diagrams.
- Dynamic (or behavioral) view: Emphasizes the dynamic behavior of the system by showing collaborations among objects and changes to the internal states of objects. This view includes sequence diagrams, activity diagrams and state machine diagrams.

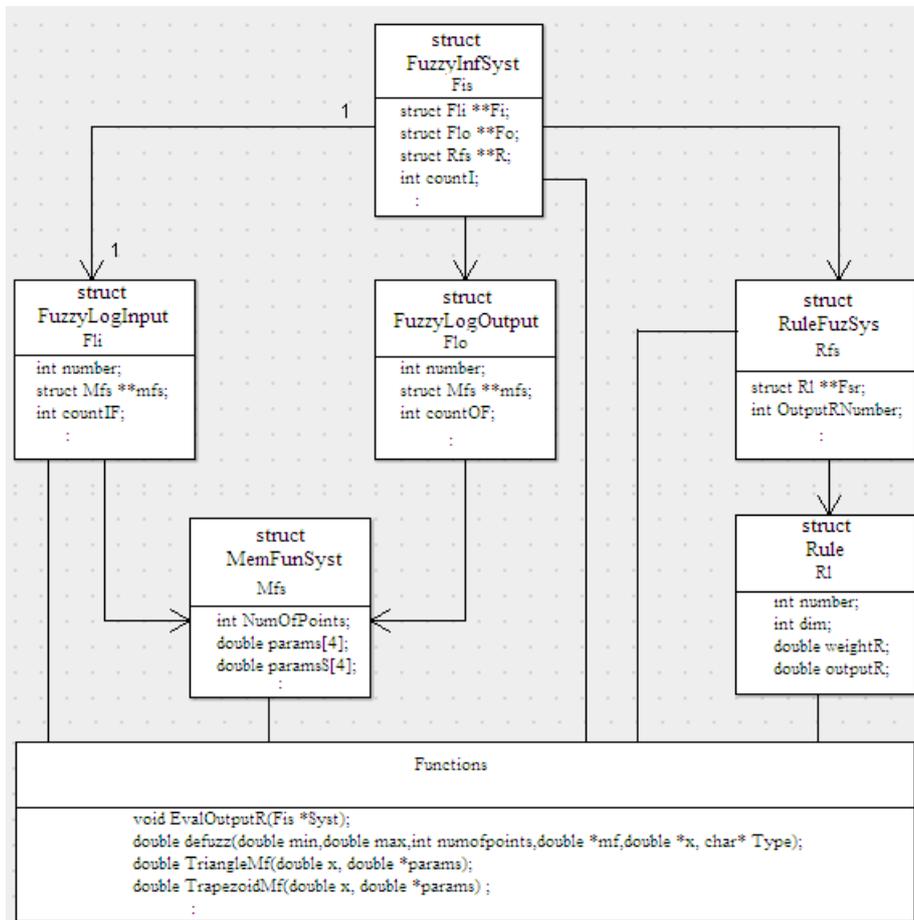


Figure 5.3: Fuzzy inference system modeling.

Figure 5.3 summarizes this hierarchical arrangement, where the *Fis* structure is the principal structure including the inputs (*Fli*), outputs (*Flo*) structures of the system plus another structure (*Rfs*) for rules. *Mfs* structure is devoted to model membership functions of the fuzzy inference system, and this structure is used by the *Fli* and *Flo* structures. The *Rfs* structure exploits the *Rl* structure to generate each rule of the system. A set of functions is used to interact and to manage all these structures.

This UML diagram offers a standard way to visualize a system's architectural blueprints, it is used to specify, visualize, modify, construct and document the artifacts of an object-oriented software intensive of the system.

5.2.3 Inputs and Outputs Fuzzification

The first step for implementing the fuzzy logic multimodal data fusion approach is the fuzzification of outputs and inputs of the fuzzy inference system (FIS) obtained from each subsystem.

5.2.3.1 Anason Fuzzification

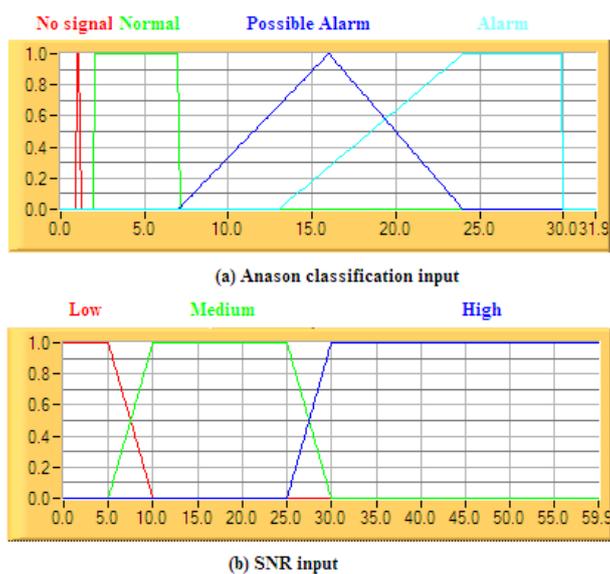


Figure 5.4: Fuzzy sets defined for input variables produced by Anason.

From Anason subsystem three inputs are built. The first one is the sound environment classification and speech recognition, where all sound classes and distress expressions detected are labeled on a numerical scale according to their alarm level. Four membership functions are set up in this numerical scale according to the following fuzzy levels: *no signal*, *normal*, *possible alarm* and *alarm* as it is shown in figure 5.4.

The no signal membership function is represented by a singleton function. A trapezoid membership function is used to characterize the *normal* and *alarm* linguistic variables. The *possible alarm* linguistic value is symbolized by a triangular function. These membership functions are determined by some parameters which are adjustable during experiments. Thus specific choices for these membership functions to model the linguistic variables were chosen experimentally.

Two other inputs are associated to each SNR (Signal-to-noise ratio) calculated on each microphone (two microphones are used in the current application), and these inputs are split into three fuzzy levels: *low*, *medium* and *high*. A triangular membership function is chosen to model these linguistic variables.

5.2.3.2 RFpat Fuzzification

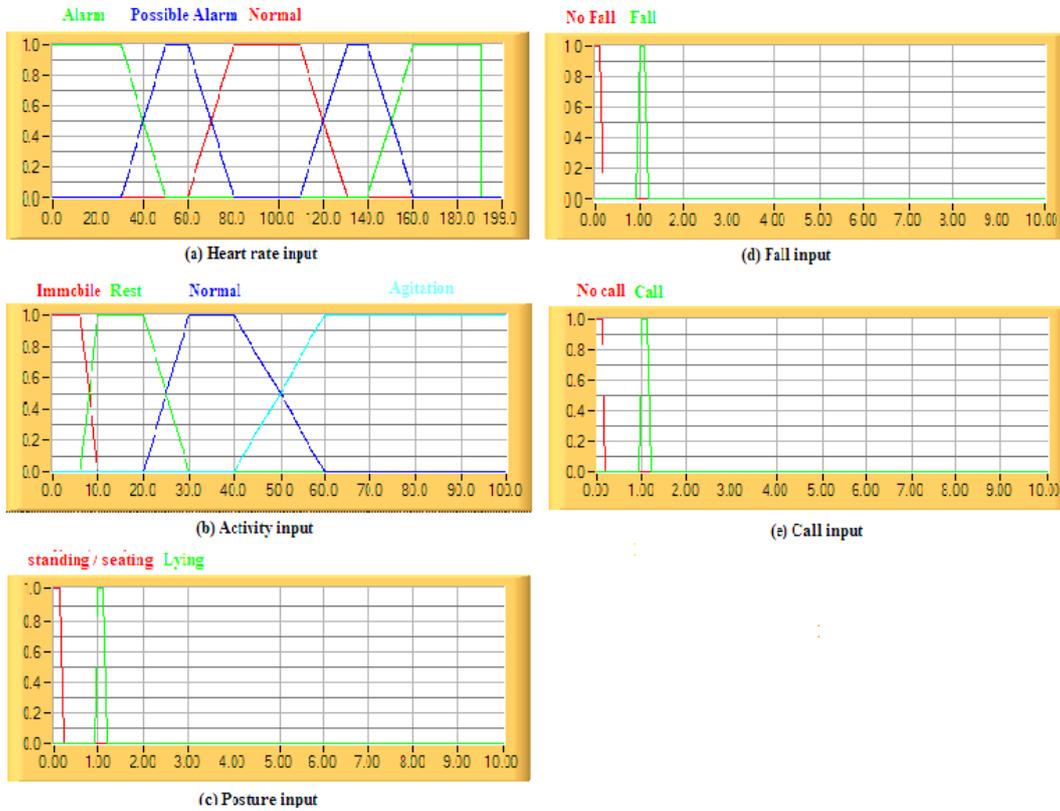


Figure 5.5: Fuzzy sets defined for input variables produced by RFpat.

RFpat provides physiological data to the FL-EMUTEM platform. As seen in figure 5.5, RFpat produce five inputs:

- Heart rate for which three fuzzy levels are specified *normal*, *possible alarm* and *alarm*;
- Activity which has four fuzzy sets: *immobile*, *rest*, *normal* and *agitation*, the trapezoid function displays all these linguistic variables;

- Posture is represented by two membership functions *standing up / sitting down* and *lying*;
- Fall and call have also two fuzzy levels: *Fall/Call* and *No Fall/Call* and a singleton function is associated to these linguistic variable.

Parameters of each membership function associated to heart rate or activity are adjustable to each monitored elderly person. An automatic procedure to adapt these intervals based on 30 minutes recording was proposed.

5.2.3.3 Gardien Fuzzification

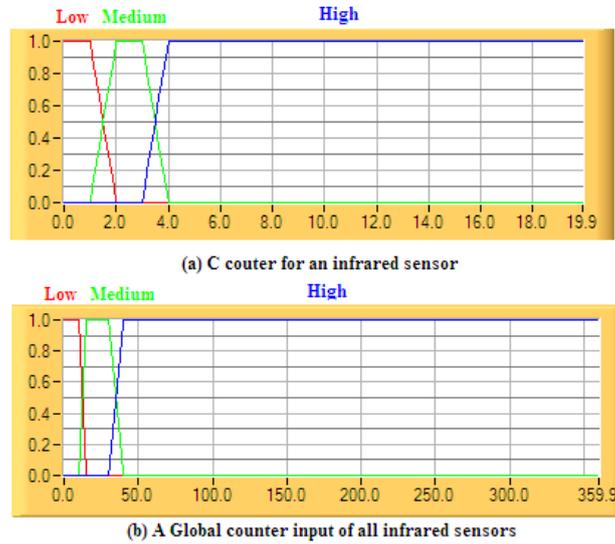


Figure 5.6: Fuzzy sets defined for input variables produced by an infrared sensor.

For each infrared sensor a counter of motion detection with three fuzzy levels (*low, medium, high*) is associated, it is reset every 5 seconds. A global counter for all infrared sensors with three fuzzy membership functions (*low, medium, high*) is also used and it is reset every 60 seconds. A trapezoid membership function is chosen to characterize these fuzzy sets.

As we use six vertical infrared sensors and two horizontal infrared sensors, Gardien subsystem delivers nine other inputs to the fuzzy inference module from infrared sensors.

A singleton membership function is assigned to each change state sensor with two linguistic variables on and off.

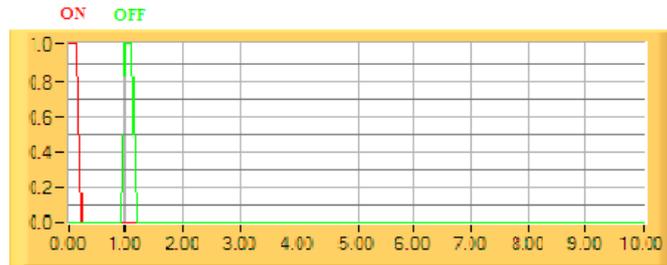


Figure 5.7: Fuzzy sets defined for input variables produced by a change state sensor.

5.2.3.4 Time Fuzzification

Figure 5.8 displays the last input which is time; it has two membership functions day and night which are also adaptable to each patient habits. Trapezoid functions are used to divide the time input.

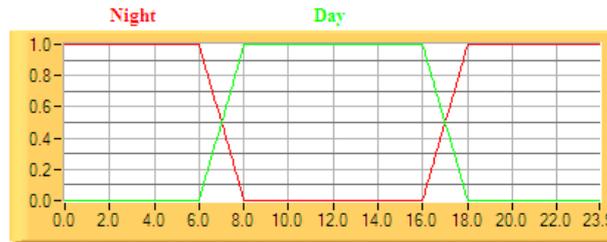


Figure 5.8: Fuzzy sets defined for the time input.

5.2.3.5 Outputs Fuzzification

In order to reach the objective of FL-EMUTEM platform which is the identification of distress situation of an elderly person at home two outputs are associated to fuzzy inference component of the FL-EMUTEM platform.

The first one is called *Alarm* with two linguistic variables *normal* and *alarm*. To refine the decision of the FL-EMUTEM platform a second output is added to its fuzzy inference system component.

This second output is *Localization* which is a very important information for the diagnostic because the identification of the position of the person during a distress situation is a helpful knowledge for medical staff diagnostic.

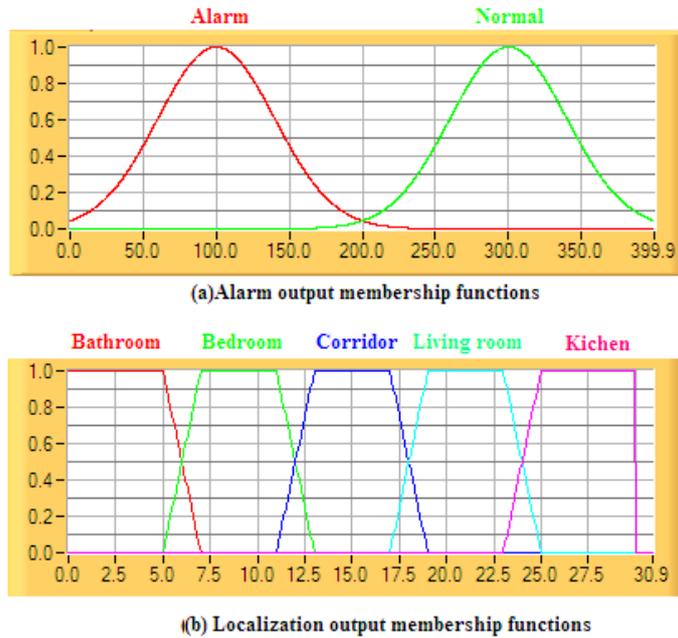


Figure 5.9: Fuzzy sets defined for output variables.

Figure 5.9 displays the membership functions of these outputs, Two membership function models are selected:

- Gaussian functions is chosen for the alarm outputs;
- Trapezoid functions for the localization output where the classical areas of a house are its fuzzy levels or linguistic variables.

We have chosen the Gaussian function for the *alarm* output in order to obtain also a confidence level of each alarm rule necessary for a better alarm decision.

Membership functions of *Localization* are ordered according to the repartition of the classical areas in the house.

Figure 5.10 shows the assigned area for each infrared sensor.

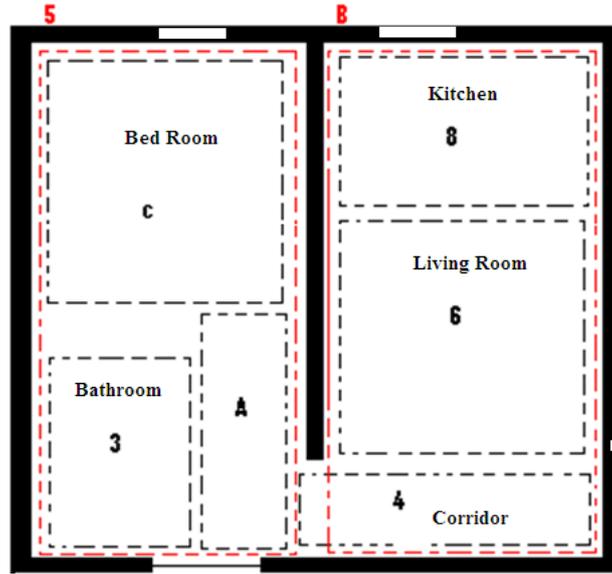


Figure 5.10: Infrared sensors area calibration.

5.2.4 Fuzzy Rules Aggregation and Defuzzification

FL-EMUTEM fuzzy inference engine is formulated by two groups of fuzzy *IF-THEN* rules.

One group controls the output variable localization according to values of the input variables issued from infrared sensors C_i and SNR of each microphone. The other group controls the output linguistic variable alarm according to all inputs.

These fuzzy rules are decided through experimentation and according to some expert knowledge.

An example fuzzy rule for alarm detection is:

If (Anason classification is no signal) and (Heart rate is possible alarm) and (Activity is immobile) and (C_c is low) and (C_8 is low) and (C_G is low) Then(Alarm is alarm).

An example fuzzy rule for localization detection is:

If (SNR1 is high) and (C_A is high) and (C_G is high) and (C_B is low) and (SNR₂ is low) Then (Localization is Bedroom).

A confidence factor is accorded for each rule and each output involved in a rule is multiplied by the confidential factor issued from each subsystem. Thus output's rules value depends on reliability of each subsystem and confidences of rules.

To aggregate these rules we have chosen the Mamdani model instead of the Takagi Sugeno one which is also available under the FL-EMUTEM fuzzy logic component. Mamdani model offer us a good way of modeling the normal and distress situations, because these two classes don't form a clean partition but a fuzzy one.

After rules aggregation the defuzzification is performed by the smallest value of maximum method for the alarm output in order to obtain also a confidence level of each alarm's decision, and the centroid of area for the output localization.

5.3 Graphical Interfaces for Intelligibility

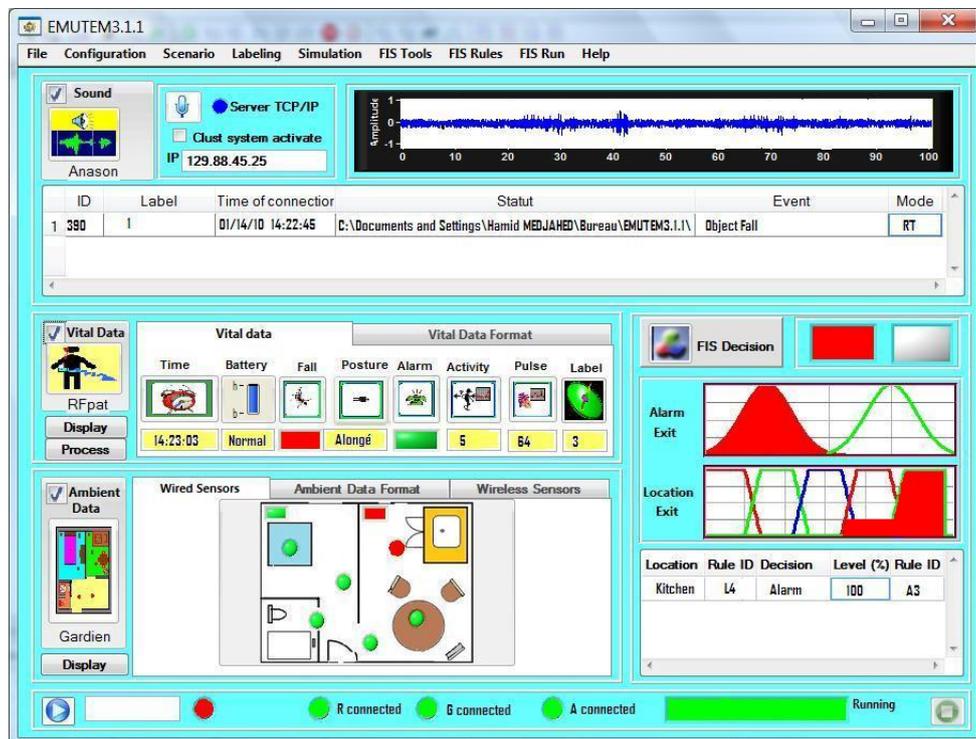


Figure 5.11: FL-EMUTEM general graphical interface.

To offer an enhanced intelligibility for FL-EMUTEM platform, the use of graphical interface is very useful for this task. We have developed a data fusion based Fuzzy tools which allow easy configuration of input intervals of fuzzification, the writing of fuzzy rules and the configuration of the defuzzification method through graphical interfaces.

The general interface of the system allows configuration of all subsystems and all the fuzzy tools. Figure 5.11 shows this general graphical interface.

It is possible to build up membership functions of inputs and outputs and displaying them under this graphical interface.

We could also write rules via the graphical interface displayed in figure 5.12. It is also possible to write rules on text file by using a specific language, that we have developed, understandable by our system.

These Graphical interfaces provide FL-EMUTEM with a useful simplic-

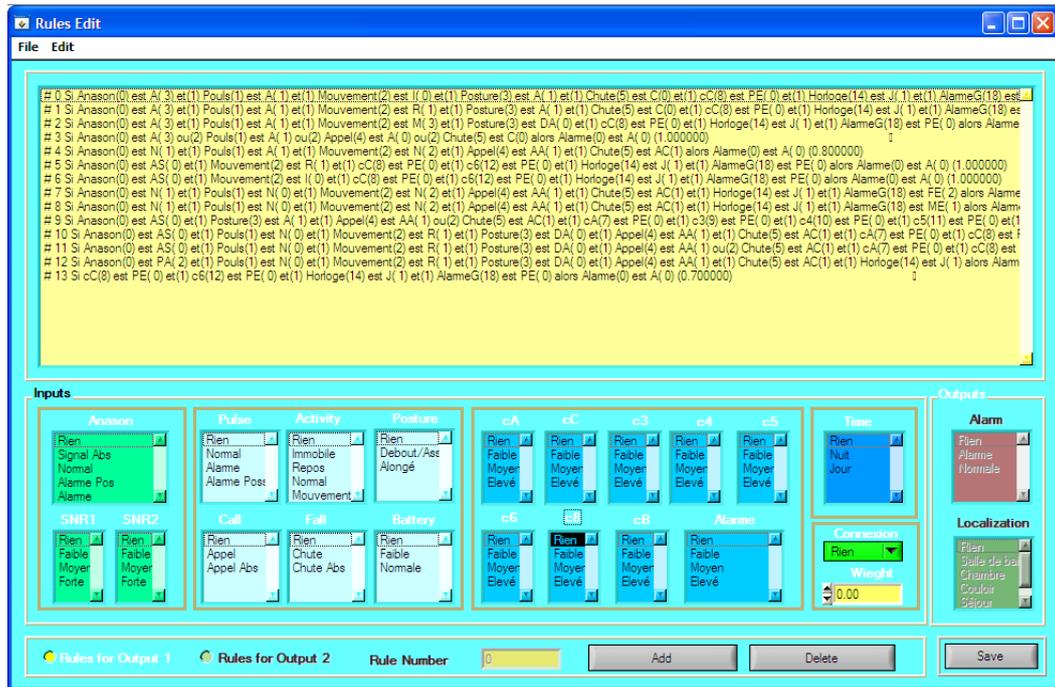


Figure 5.12: Graphical interface for rules writing.

ity for users and with a flexibility that allows adding other modalities. They allows expert to add their knowledge with a friendly user way.

5.4 Conclusion

The multimodal data fusion approach is based on fuzzy logic concept and its implementation is performed in this chapter. Fuzzy inference systems (FIS) are universal approximators [106], and they can be enhanced during experiments.

The most important feature of FIS is that it can incorporate human priori knowledge into its parameters and that these parameters have clear physical meaning [107]. A FIS is based on a rule-base, in which each rule got an antecedent part and its corresponding consequent. Usually the antecedent combination is not matter in tuning FIS, while the main argue is on the choice of the different linguistic terms for each fuzzy variable and the conclusion of each rule.

With the method developed here it is possible to tune the conclusion part of each rule in a Mamdani aggregation model and this would be done over the whole possible rules in the rule-base.

Chapter 6

Experimental Results and Validation

The proposed approach for distress situation identification about elderly person at home by multimodal data fusion is experimented under the framework of home healthcare telemonitoring. Implementation details of this approach are presented in the previous chapter.

For completing this experimental task and to validate the fuzzy logic multimodal data fusion approach, the HOMECAD database described in chapter 2 will be exploited and used. This database offers us a large number of temporal sequences of multimodal data, representing person's behavior at home, in order to develop and evaluate the multimodal data fusion approach, thus the FL-EMUTEM telemonitoring platform.

In this chapter the experimental process appropriate to the evaluation of the FL-EMUTEM platform will be explored. The obtained results from these experimentations will be also discussed.

6.1 Experimental Process

The implementation of an experimental process requires the definition of the experimental context, data needed for experimentation, the experimentation methodology and how to access the system.

6.1.1 Experimental Context

The experimentation of the proposed approach is realized under the home healthcare telemonitoring context. In this context the main objective of the FL-EMUTEM platform is the identification of distress situations that may occur to an elderly person living alone at home. This platform is employed for monitoring the elderly person and his environment by using several modalities as it is described in chapter 2.

The realization of an experimental process to evaluate the performance of a decision system in a any given context requires to define the following: a set of appropriate data to the experimental context and an experimentation method that must be used.

6.1.2 Experimental Data

Among the experimental data there is the data issued from the HOMECAD database previously described in chapter 2, in which physiological, environment sounds and others different information gathered by ubiquitous sensors are used to describe the context-aware of our application. This database fully responds to the crucial need for an objective and systematic evaluation of the fuzzy logic multimodal data fusion method that is already investigated and developed.

As we don't have sufficiently large records representing complete and representative data, experimentation is also performed by using simulated data. The advantage of considering simulated data is the ability to generate sequences representing several situations, including several behavioral of the elderly person.

6.1.3 Performance Metrics

The realization of an experimental process requires the use of appropriate metrics for evaluating the performance of the platform by comparing system's results to expected results. It is useful to describe some parameters or metrics that allows an objective evaluation of the results.

- **Sensitivity (Se):** Identify patterns of real abnormal situation as distress one.
- **Specificity (Sp):** Don't identify normal situations as distress situations.

- **Error rate (Err):** It is the ratio between the number of the misclassified samples and the total number of the samples.
- **Perfect classification(Pc):** It is the ratio between the number of the correct classified samples and the total number of the samples.

We consider the following assumptions for each event detected about the situation of the elderly person at home:

- H_1 : *The detected event is a distress situation.*
- H_2 : *The detected event is not a distress situation.*

Then we estimate the following parameters:

- *True Positive (TP):* Distress events correctly considered as belonging to the instance of distress situations.
- *True Negative (TN):* Normal events correctly considered as not belonging to the instance of distress situations.
- *False Positive (FP):* Normal events mistakenly viewed as belonging to the instance of distress situations.
- *False Negative (FN):* Distress events mistakenly viewed as not belonging to the instance of distress situations.

Indices of sensitivity (Se), specificity (Sp), error rate (Err) and perfect classification (Pc) are calculated from rates of true /false positive/negative, marked respectively with these symbols TP, FP, TN, and FN. They are estimated by the following equations:

$$Se(\%) = \frac{TP}{TP + FN} \times 100 \quad (6.1)$$

$$Sp(\%) = \frac{TN}{TN + FP} \times 100 \quad (6.2)$$

$$Err(\%) = \frac{FN + FP}{TN + FN + FP + TP} \times 100 \quad (6.3)$$

$$Pc(\%) = \frac{TN + TP}{TN + FN + FP + TP} \times 100 \quad (6.4)$$

The just exposed metrics of the statistic data are very important to estimate the classification accuracy.

		FL-EMUTEM Classification	
		Distress sequence	Normal sequence
Simulated sequences	Distress sequence	68	2
	Normal sequence	1	29

Table 6.1: Classification results for Alarm output with simulated data by using 10 rules

After that 100 sequences of simulation are used to test FL-EMUTEM, where 70 sequences represent distress situation and 30 sequences for normal situation.

In order to evaluate the classification accuracy the confusion matrix has been calculated for this simulation. The table 6.1 displays the obtained results with 10 rules.

Sensitivity Se	97%
Specificity Sp	96%
Error rate Err	3%
Perfect classification	97%

Table 6.2: Performance indices for Alarm output obtained with simulated data by using 10 rules

From the table 6.1 we can deduce some indices of performance which are displayed in table 6.2. The obtained results of FL-EMUTEM's performance are good and they demonstrate the reliability of the FL-EMUTEM platform.

Even if we have 3% of misclassified sequences, this error rate could be overcome by adding to the fuzzy inference system the right rules that take into account the misclassified situations, and also by associating to each rules the right weight.

For the localization output, also we have obtained about 98% of good localization as it is shown in the following confusion matrix.

The confusion matrix for the localization output obtained with simulated data by using 10 rules.

$$\left(\begin{array}{c} \text{Bathroom} \\ \text{Bedroom} \\ \text{Corridor} \\ \text{Livingroom} \\ \text{Kitchen} \end{array} \begin{array}{ccccc} \text{Bathroom} & \text{Bedroom} & \text{Corridor} & \text{Livingroom} & \text{Kitchen} \\ 9 & 1 & 0 & 0 & 0 \\ 0 & 30 & 0 & 0 & 0 \\ 1 & 0 & 9 & 0 & 0 \\ 0 & 0 & 0 & 30 & 0 \\ 0 & 0 & 0 & 0 & 20 \end{array} \right)$$

The 2% corresponding to the error rate can be explained by two main reasons. Firstly there are two specific infrareds sensors, the first one is shared between the bedroom and the bathroom, the second one is shared between the corridor and the bathroom. Secondary in FL-EMUTEM platform, only two microphones are used, thus the localization by using only the SNR fuzzy variable gives two global areas of localization, one contains Bedroom, bathroom and one part of the corridor, the second area matches to the kitchen, living room plus the second part of the corridor as it is described in figure 2.2 in chapter 2.

Then FL-EMUTEM platform was tested with 20 scenarios selected from HOMECAD database, 10 scenarios with distress situations and 10 normal scenarios. As we have seen in chapter 2, these reference scenarios are based on real situations and they aim to reflect the elderly person's everyday life.

As each scenario lasts 10 *minutes* and the FL-EMUTEM platform process data every 1/2 second, 1200 frames of data are processed by the FL-EMUTEM platform for each scenario. This experimentation task corresponds to analyzing 200 *minutes* of recorded data.

This first study is devoted to the evaluation of the system by taking into account rules used in this fuzzy inference system. The used strategy consisted in realizing several tests with different combination rules, and based on the obtained results one rule is added to the selected set of rules, or removed from this selected set of rules in order to get the missed detection. Based on the obtained results some weights of rules are also changed. With this strategy good results are reached for the alarm output with 10 rules and 16 rules for the localization outputs.

The confusion matrix for the alarm output is calculated in order to explain these results.

The confusion matrix for the alarm output obtained with recorded scenarios by using 10 rules.

$$\begin{pmatrix} & \text{Distress scenario} & \text{Normal scenario} \\ \text{Distress scenario} & 9 & 1 \\ \text{Normal scenario} & 0 & 10 \end{pmatrix}$$

Figure 6.2 shows the histogram of error rate for the alarm output according to the number of rules used in the FIS; it decreases when the number of rules increases. With 10 rules for alarm output and 16 rules for localization output, about 95% of good Alarm detection and 97% for good Localization are reached. The rate of misclassification for the alarm output corresponds to situation that are not detectible by the sensors used by FL-EMUTEM and also the difficulty to find the right rule to overcome these situations. For the localization output the error rate could be justified by the effect that we use an area where an apartment is simulated thus the calibration of infrared sensors is very hard.

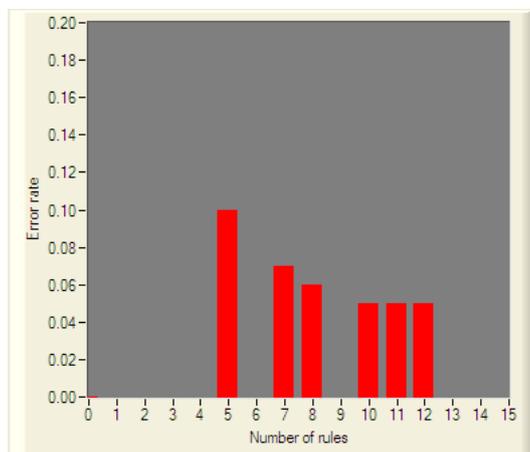


Figure 6.2: Error rate for Alarm output according to the number of rules used by FL-EMUTEM platform .

Based on these effects, these first results encourage us to perform further tests in real time in order to have an effective evaluation of the FL-EMUTEM platform.

6.3 Synthesis

According to the used strategy in this experimentation and the obtained results the fuzzy inference system that is used in the FL-EMUTEM platform presented four important properties:

- **Intelligibility**

The description of the decision model of FL-EMUTEM platform becomes relatively easy since it is mainly based on the use of linguistic rules describing the expertise, heuristic strategies, associating a set of data provided by a set of sensors, which are necessary for the distress situation detection of an elderly person at home. The previous experiments confirm these strategies.

The graphical interface of FL-EMUTEM platform and its architecture allows a good supervision for the experiments by its flexibility in adding removing rules and also in modifying the weights of each rule, membership functions and the model of rule aggregation. This rules based formalism facilitates dialogue between engineers, ergonomists, cognitive psychologists, and geriatrician doctors in the framework of a multidisciplinary exploitation. We can say that the engineer does not need to explain qualitatively what is quantitatively or statistically modeled with equations.

- **Locality**

During experiments we have seen that each rule models the decision of the FL-EMUTEM platform about a given situation, which can be described in vague, uncertain and subjective. The modification of FL-EMUTEM's decision about a given situation is then obtained by changing local rules associated to one of the two output of the platform. This local rule modification will not lead to an overall change in the platform's decision but it only produce change in the decision system about the referred situation. This property of location facilitates the supervision of the FL-EMUTEM platform.

- **Traceability**

In the previous experiments we have the ability to trace the path used by the fuzzy inference system to achieve the final decision by listing the fuzzy rules that were activated with their degrees of activation for taking this decision. This technique was used to validate each rule of FL-EMUTEM platform. This property allows an easy validation of the fuzzy inference system of the FL-EMUTEM platform.

- **Flexibility**

The FL-EMUTEM allows us to add other modalities, thus increasing the number of input for the FIS. It is also possible, locally to refine a rule whose behavior is considered rude, by replacing it with a group of more specialized rules. A localization's rule was refined with this technique during experiments.

These properties of intelligibility, locality, traceability and flexibility offer a great suppleness to FL-EMUTEM platform in supporting nonlinear models even if in the absence of systemic prior knowledge.

6.4 First Step to Activity Daily Living Recognition

In order to reinforce the previous results the fuzzy logic multimodal data fusion approach is applied to human activities of daily living recognition for monitoring elderly person at home. This application consolidates the previous results and shows the flexibility of the fusion approach.

Everyday life activities in the home split into two categories. Some activities show the motion of the human body and its structure. Examples are walking, running, standing up, setting down, laying and exercising. These activities may be mostly recognized by using sensors that are placed on the body [108]. A second class of activities is recognized by identifying or looking for patterns in how people move things. In this work we focus on some activities identification belong to these both categories.

6.4.1 Activity Detection Approach

Automatic health monitoring is predominantly composed of location and activity information. Abnormality also could be indicated by the lack of an activity or a abnormal activity detection which will cause or rise the home anxiety. In order to monitor and to recognize the activities of people within the environment in order to timely provide support for safety, comfort, and convenience. First step to perform this application is to introduce some changes in Anason fuzzification and we keep the previous fuzzification of RFpat and Gardien subsystems. The sound environment classification is fuzzified, all detected sound class and expressions are labeled on a numerical scale according to their source. Nine membership functions are set up in this numerical scale according to sound sources as it is in table 6.4.1.

membership function	Composition
Human sound	snoring, yawn, sneezing, cough, cry, scream, laught
Speech	key words and expressions
Multimedia sound	TV, radio, computer, music
Door sound	door claping, door knob key ring
Water sound	water flushing, water in washbasin coffee filter
Ringtone	telephone ring, bell door, alarm, alarm clock
Object sound	chair, table, tear-turn paper, step foot
Machine sound	coffee machine, dishwasher, electrical shaver,microwave, vaccum cleaner, washing machine air conditioner
dishwasher	glass vs glass, glass wood, plastic vs plastic, plastic vs wood, spoon vs table...etc

Table 6.3: Fuzzy sets defined for Anason classification input in the activity daily living recognition application.

The second change concerns the output, now the output deals with ADL recognition, it contains some activities which are selected from the table I. They are *Sleeping (S)*, *Getting up (GU)*, *Toileting (T)*, *Bathing (B)*, *Washing hands (WH)*, *Washing dish (WD)*, *Doing laundry (DL)*, *Cleaning (CL)*, *Going out of home (GO)*, *Enter home (EH)*, *Walking (W)*, *Standing up (SU)*, *Setting down (SD)*, *Laying (L)*, *Resting (R)*, *Watching TV (WT)* and *Talking on telephone (TT)*. These membership functions are ordered, firstly according to the area where they may be occurred and secondly according to the degree of similarity between them.

The next step of this application is the fuzzy inference engine which is formulated by a set of fuzzy IF-THEN rules. To aggregate these rules Mamdani model is used. After rules aggregation the defuzzification is performed by the centroid of area for the ADL output.

6.4.2 Activity Detection Experiments and Results

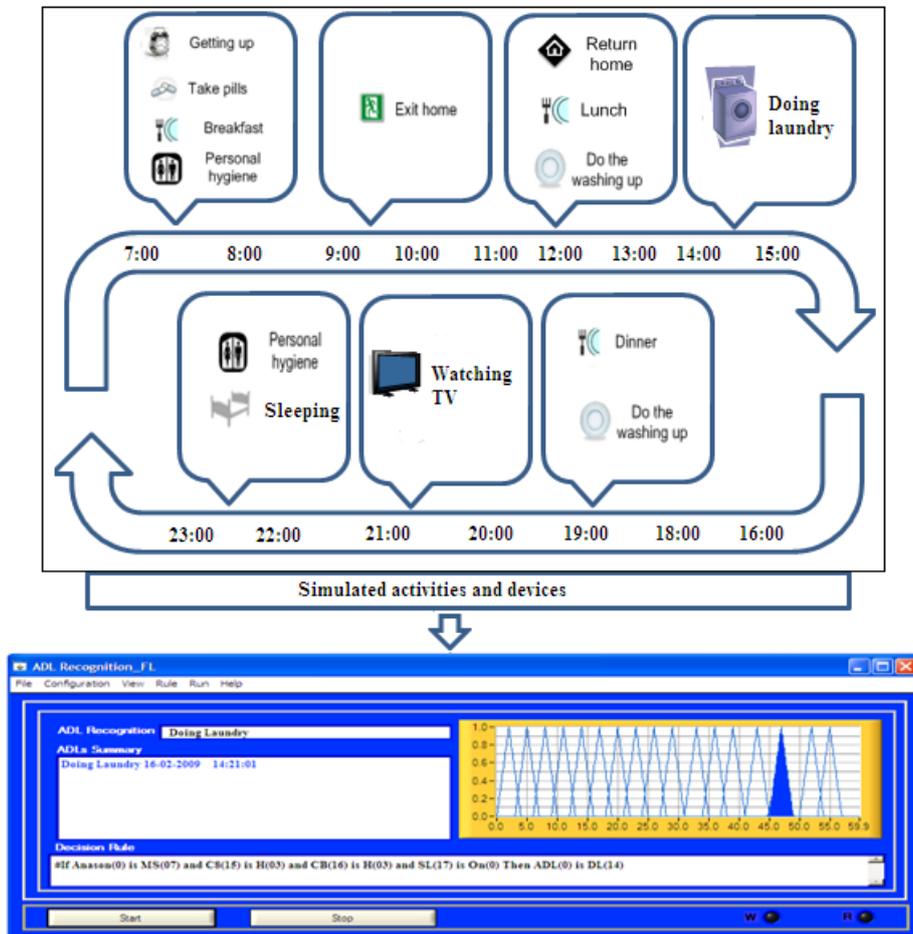


Figure 6.3: ADL recognition experiment for a simulated data stream.

The proposed application was experimentally achieved on a simulated data in order to demonstrate its effectiveness. This simulation gave very promising results for the ADL recognition. Figure 6.3 shows results for a stream of a simulated data. This first study was devoted to the evaluation of the system by taking into account rules used in this fuzzy inference system and good results are obtained.

The simulation described here is preliminary but demonstrates that ubiquitous, simple sensor devices can be used to recognize activities of daily living from real homes. The system can be easily retrofitted in existing home environments with no major modifications or damage. This application re-

inforces the obtained results in the previous section and the effectiveness of our fusion approach.

6.5 Conclusion

The new fusion architecture based on fuzzy logic for in-home elderly remote monitoring is very reliable and it gave very promising results. The FL-EMUTEM platform which encloses this architecture is implemented and validated by simulation and real data. Experimental results were accurate and robust. The activity daily living recognition application reinforced the effectiveness of this fusion approach.

The fuzzy logic decision module reinforces the secure detection of older person's distress events and his localization. This approach allows easiest combination between data and adding other sensors. This constitutes a great asset of FL-EMUTEM system to offer the possibility in a next future to implement very intelligent remote monitoring system in care receiver houses.

Chapter 7

Conclusions and Perspectives

In this thesis, we focused on the area of automatic home healthcare telemonitoring, in which health information is automatically collected with the help of sensors and processed by special algorithms and fused in order to take a good decision about elderly persons living alone at home. The work in this thesis contributes to the present and future of automatic home healthcare telemonitoring in the following ways:

- In-depth knowledge of current practices in in-home healthcare telemonitoring could inform the development of future technologies, ultimately helping an increased portion of the growing elderly population to live safely and independently in their own homes.
- Algorithms using sensors frequent to security systems could relatively instantaneously initiate ubiquitous computing services to thousands of business and residential buildings, possibly changing the way of our society lives and works.

The proposed study includes the definition of the context and objectives the problematic of the thesis. Then data and appropriate sensors which deal with this context are selected. After these investigations are performed in order to propose a good solution to fuse data collected by the different sensors in the dynamic and uncertain environment of the elderly person. Once the good multimodal data fusion approach is selected an experimental process is established in order to evaluate this approach.

In this thesis work, to respond to the thesis context, firstly we have developed a new multi sensors environment platform for acquiring different data provided by different sensors. Among these modalities we find physiological data, usual environment sounds and patient localization plus some sensors for

environment controll. The originality of this system is the synchronized combination of three different telemonitoring modalities. A simulation process is added to our platform and enables us to have a full and tightly controlled universe of data sets and to evaluate the decision part of remote monitoring systems. This acquisition platform is valuable because it allows to record a new multimodal medical database called HOMECAD (Home remote Medical Care Database) and to provide a substantial assistance in order to generate the indexation of this database.

After that, to process these large sets of heterogeneous data acquired with the different modalities or sensors, in order to make a decision at any time about the elderly person status, multisensor or multimodal data fusion is carried out. However, in our thesis context different sensors use different physical principles, cover different information space, generate data in different formats at different sampling rates, and the obtained data have different resolution, accuracy, and reliability properties. Based on those effects, the key to produce the required detection is to use the right method that properly fuses the provided data from various sources. This is what our multimodal data fusion study stands for. From this study we have identified two major classes of fusion techniques; those that are based on probabilistic models (such as Bayesian reasoning and the geometric decision reasoning), but their performance is limited when the data are too complex, therefore the model is uncontrollable; and those based on connectionist models (such as neuronal networks MLP and SVM) which are very powerful because they can model the strong nonlinearity of data but with complex architecture, thus lack of intelligibility. Taking into account this above discussion considering the complexity of the data to process (audio, physiologic and multisensory measurements) plus the difficulty of the statistical modeling of abnormal situation of elderly people, fuzzy logic has been found useful to be the decision module of our multimodal home healthcare telemonitoring platform FL-EMUTEM. Fuzzy logic approach is well adapted to fuse FL-EMUTEM's modalities and to take a good decision. Fuzzy logic has attracted the attention of several researchers in health care because it provides a methodology that simulates human thinking by explicitly modeling and managing the inaccuracy and uncertainty inherent in EMUTEM's subsystems. Fuzzy logic will allow high flexibility to EMUTEM platform especially in combining between modalities or adding other sensors.

Thus a logic multimodal data fusion approach was adopted to be the decision module of FL-EMUTEM platform and it was implemented. This approach was validation and evaluated with experiments and results were accurate and

robust. The effectiveness of this fusion approach was reinforced with an activity daily living recognition application which gave very promising results.

In this thesis work, we conducted research in a new domain and very promising for the future because many professionals who currently perform in-home healthcare assessment and identified promising areas for technological innovation. We posed a new multimodal platform for in-home healthcare telemonitoring which was validated with good results obtained from experimentation. We further extended this fuzzy logic data fusion approach to be compatible with high-level temporal logic constraints by introducing decision tree approach in this method. After that an embedded implementation on a real time system in order to obtain a functional system will be very useful.

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Appendix A

Fuzzy Logic: Theoretical Background

A.1 Set Theory

A classical set is a collection of objects of any kind. A set is fully specified by the elements it contains. In fuzzy set theory, normal sets are called crisp sets, in order to distinguish them from fuzzy sets. Let C be a crisp set defined on the universe X . Then for any element x of X , either $x \in C$ or $x \notin C$. In fuzzy set theory this property is generalized. Therefore in a *fuzzy set* F , it is not necessary that either $x \in F$ or $x \notin F$ but it can be the member of that set with a certain degree of membership that is assigned to every $x \in X$ a value from the unit interval $[0, 1]$ instead of the two-element set $1, 2$. The set that is defined based on such an extended membership function is called a *fuzzy set*.

Definition A.1.1 *Fuzzy set:* A fuzzy set F in a universe of discourse X is defined by a membership function μ_F which takes values in the interval $[0, 1]$. Specifically this may be represented by the mapping, $\mu_F : X \rightarrow [0, 1]$. When the universe of discourse X is continuous, a fuzzy set F is written concisely as,

$$F = \int_{x \in X} \mu_F(x)/x \quad (\text{A.1})$$

When U is discrete, a fuzzy set F is represented as,

$$F = \sum_{i=1}^n \mu_F(x_i)/x_i \quad (\text{A.2})$$

Definition A.1.2 *Support set:* The support set of a fuzzy set F is the crisp set formed by the collection of all elements $x_i \in X$ such that $\mu_F(x_i) > 0$.

Definition A.1.3 *Fuzzy Singleton:* A fuzzy set whose support set is a single point (or element) in X is referred to as a fuzzy singleton. Typically but not necessarily, the associated membership grade is unity; $\mu_F = 1.0$.

A.2 Operations on Fuzzy Sets

Definition A.2.1 *Equal:* Two fuzzy sets are equal ($A=B$) if and only if

$$\forall x \in X : \mu_A(x) = \mu_B(x). \quad (\text{A.3})$$

Definition A.2.2 *Subset:* A is a subset of B ($A \subseteq B$) if and only if

$$\forall x \in X : \mu_A(x) \leq \mu_B(x). \quad (\text{A.4})$$

Definition A.2.3 *Complement:* A' is the complement of the fuzzy set A if and only if

$$\forall x \in X : \mu_{A'}(x) = 1 - \mu_A(x). \quad (\text{A.5})$$

Definition A.2.4 *Union (OR) $A \cup B$:* Consider two fuzzy sets A and B in the same universe X . Their union is a fuzzy set $A \cup B$. The membership function is given by:

$$\mu_{A \cup B}(x) = \max[\mu_A(x), \mu_B(x)], \quad \forall x \in X. \quad (\text{A.6})$$

Definition A.2.5 *Union (AND) $A \cap B$:* Consider two fuzzy sets A and B in the same universe X . Their intersection is a fuzzy set $A \cap B$. The membership function is given by:

$$\mu_{A \cap B}(x) = \min[\mu_A(x), \mu_B(x)], \quad \forall x \in X. \quad (\text{A.7})$$

Definition A.2.6 *A triangular norm or T-norm:* Denotes a class of binary operations that can represent the generalized intersection operation, which has the following properties:

$$T : [0, 1][0, 1] \rightarrow [0, 1] \quad (\text{A.8})$$

$$xTy = yTx \quad (\text{A.9})$$

$$(xTy)Tz = xT(yTz) \quad (\text{A.10})$$

$$x < y \quad w < z \quad \text{implies} \quad xTw < yTz \quad (\text{A.11})$$

$$xT1 = x \quad \text{and} \quad xT0 = 0 \quad (\text{A.12})$$

Definition A.2.7 A Triangular Co-norm or S-norm: denotes a class of binary operations that can represent the generalized union operation which has the following properties: the first three criteria of the T-norm are the same as S-norm but $xS0 = x$.

Definition A.2.8 Cartesian Product of Two Fuzzy Sets: Let A be a fuzzy subset of universe of discourse U , and let B be a fuzzy subset of a possibly different universe of discourse V . The cartesian product of A and B as denoted by $A \times B$ is the set of all possible ordered pairs constructed by combining elements of A with elements of B such that the first element in each pair is a member of A and the second element is a member of B . Its membership function is defined by:

$$\mu_{A \times B}(\mu, \nu) = \min[\mu_A(u), \mu_B(\nu)] \quad \forall u \in U, \forall \nu \in V \quad (\text{A.13})$$

A.3 Classical Relation

A relation can be considered as a set of tuples, where a tuple is an ordered pair. A binary tuple is denoted as (x, y) ; a ternary tuple is (x, y, z) ; and an n-ary tuple is (x_1, x_2, \dots, x_n) .

A.4 Fuzzy Relation

The former section stated that a relation can be considered as a set of tuples. Extending this, a fuzzy relation is a fuzzy set of tuples, where each tuple has a membership degree between 0 and 1. Fuzzy Relation are fuzzy sets defined on universal sets which are cartesian products.

Definition A.4.1 : Let U and V be continuous universe, and $\mu_R : U \times V \rightarrow [0, 1]$. Then

$$R = \int_{U \times V} \mu_R(u, \nu)/(u, \nu) \quad (\text{A.14})$$

is a binary relation on $U \times V$.

If U and V are countable (discrete) universes, then $R = \sum_{U \times V} \mu_R(u, \nu)/(u, \nu)$.

A.4.1 Example

Let $U = V = \{1, 2, 3\}$. Then approximately equal is the binary fuzzy relation R .

$1/(1, 1) + 1/(2, 2) + 1/(3, 3) + 0.8/(1, 2) + 0.8/(2, 3) + 0.8(2, 1) + 0.8(3, 2) + 0.3(1, 3) + 0.3/(3, 1)$

The membership function μ_R of this relation can be described by

$$\mu_R(x, y) = \begin{cases} 1 & \text{when } x = y \\ 0.8 & \text{when } |x - y| = 1 \\ 0.3 & \text{when } |x - y| = 2 \end{cases}$$

A.5 Operations on Fuzzy Relations

Fuzzy relation are very important in fuzzy control because they can describe interactions among fuzzy variables. This is quite important in the case of If-Then rules.

Definition A.5.1 : Let R and S be binary relations defined on $X \times Y$. The intersection of R and S is defined by:

$$\forall (x, y) \in X \times Y : \mu_{R \cap S}(x, y) = \mu_R(x, y) T \mu_S(x, y) \quad (\text{A.15})$$

where T is the T -norm operation. Since minimum operation is the most common operation in the category of T -norm, the intersection operation may also be defined as:

$$\mu_{R \cap S}(x, y) = \min(\mu_R(x, y), \mu_S(x, y)) \quad (\text{A.16})$$

However, any other operation that satisfies the T -norm conditions, can be used as well.

Definition A.5.2 : Let R and S be binary relations defined on $X \times Y$. The union of R and S is defined by:

$$\forall (x, y) \in X \times Y : \mu_{R \cup S}(x, y) = \mu_R(x, y) S \mu_S(x, y) \quad (\text{A.17})$$

where T is the S -norm operation. Since maximum operation is the most common operation in the category of S -norm, the intersection operation may also be defined as:

$$\mu_{R \cup S}(x, y) = \max(\mu_R(x, y), \mu_S(x, y)) \quad (\text{A.18})$$

However, any other operation that satisfies the S -norm conditions, can be used as well.

Definition A.5.3 : In the binary case let R defined on $X \times Y$. The projection of R on Y can be defined as follows:

$$Proj R \text{ on } Y = \int_y \sup_x \mu_R(x, y) / y. \quad (\text{A.19})$$

Instead of the sup (supremum) operation which is necessary when X and Y are continuous, it is usual to deal with discrete domain using the maximum operation. In fact the projection operation brings a ternary relation (three dimension) back to a binary relation or a binary relation to a fuzzy set, or a fuzzy set; to a single crisp value.

Definition A.5.4 : In the binary case let F a fuzzy set defined on Y . The cylindrical extension of F on $X \times Y$ is the set of all tuples $(x, y) \in X \times Y$ with membership degree equal to $\mu_F(y)$

$$ce(F) = \int_{X \times Y} \mu_F(y) / (x, y). \quad (\text{A.20})$$

In fact, cylindrical extension extends fuzzy sets to fuzzy binary relations; fuzzy binary relations to fuzzy ternary relations; ect. If we consider A as a fuzzy set defined on X , and R as a fuzzy relation defined on $X \times Y$, it is obviously not possible to take the intersection of A and R . But, when A is extended to $X \times Y$, it will make the cylindrical extension possible.

Definition A.5.5 : Let A be a fuzzy set defined on X and R be a fuzzy relation defined on $X \times Y$. Then the composition of A and R resulting in a fuzzy set B defined on Y is given by:

$$B = A \circ R = Proj(ce(A) \cap R) \text{ on } Y. \quad (\text{A.21})$$

or, if intersection is performed with the minimum operation and projection with the maximum, then

$$\mu_B(y) = \max_x \min(\mu_A(x), \mu_R(x, y)) \quad (\text{A.22})$$

This is called the max-min composition.

A.6 Implication (IF-THEN)

Consider a fuzzy set A in a universe X and a second fuzzy set B in another universe Y . The fuzzy implication $A \rightarrow B$ is a fuzzy relation in the cartesian product space $X \times Y$. Different methods for determining the implication operation have been proposed in literature. Some examples are given below:

- Mamdani's method (Logical Product), $A \rightarrow B \equiv A \wedge B$.
- Algebraic Product $A \rightarrow B \equiv A\dot{B}$.
- Bounded Product $A \rightarrow B \equiv 0 \vee (A + B - 1)$.
- Drastic Product

$$A \rightarrow B \equiv \begin{cases} A & \text{as } B = 1 \\ B & \text{as } A = 1 \\ 0 & \text{otherwise} \end{cases}$$

- Zadah's Method (Lukasiewicz's implication method), $A \rightarrow B \equiv 1 \wedge (1 - A + B)$
- Boolean Logic Implication $A \rightarrow B \equiv (1 - A) \vee B$.
- Goedel Logic Implication

$$A \rightarrow B \equiv \begin{cases} 1 & \text{as } A \leq B \\ B & \text{as } A > B \end{cases}$$

- Goguen's Implication

$$A \rightarrow B \equiv \begin{cases} 1 & \text{as } A \leq B \\ B/A & \text{as } A > B \end{cases}$$

A.7 The Compositional Rule of Inference

If R is a fuzzy relation from U to V , and A is a fuzzy subset of U , then the fuzzy subset B of V which is induced by A is given by the composition of R and A ; that is

$$B = A \circ R \tag{A.23}$$

Therefore, we should take the cylindrical extention of A , take the intersection with R and project the result onto the Y axis.

A.8 Modus Ponens (Deduction)

In classical logic, modus ponendo ponens (Latin for mode that affirms by affirming; often abbreviated to MP or modus ponens) is a valid, simple argument form sometimes referred to as affirming the antecedent or the law of detachment. It is closely related to another valid form of argument, modus tollens or denying the consequent.

The modus ponens rule may be written in sequent notation or in rule form: *If statement IF A THEN B is true and we know that A is true too, then we can infer that B is true well.*

A.8.1 Explanation

The argument form has two premises. The first premise is the "ifthen" or conditional claim, namely that P implies Q . The second premise is that P , the antecedent of the conditional claim, is true. From these two premises it can be logically concluded that Q , the consequent of the conditional claim, must be true as well. In Artificial Intelligence, modus ponens is often called forward chaining.

An example of an argument that fits the form modus ponens:

If today is Tuesday, then I will go to work.

Today is Tuesday.

Therefore, I will go to work.

This argument is valid, but this has no bearing on whether any of the statements in the argument are true; for modus ponens to be a sound argument, the premises must be true for any true instances of the conclusion. An argument can be valid but nonetheless unsound if one or more premises are false; if an argument is valid and all the premises are true, then the argument is sound. For example, I might be going to work on Wednesday. In this case, the reasoning for my going to work (because it is Tuesday) is unsound. The argument is only sound on Tuesdays (when I go to work), but valid on every day of the week. A propositional argument using modus ponens is said to be deductive.

A.9 Approximate Reasoning

The inferencing technique of fuzzy logic could be considered as a generalization of the classical rule of implication of modus ponens. A major difference from the modus ponens based on binary logic is that in the generalized modus ponens, we can use a different fuzzy set for A in premise 2 must be completely identical. In other words, in the generalized modus ponens based on fuzzy logic, fuzzy sets A and A' in premise 1 and premise 2 do not have to be precisely the same. We can still infer the conclusion that B' is true. For this reason, fuzzy reasoning is called approximate reasoning.

Appendix B

Support Vector Machines

The support vector machine (SVM) is a training algorithm for learning classification and regression rules from data, for example the SVM can be used to learn polynomial, radial basis function (RBF) and multi-layer perceptron (MLP) classifiers. SVMs were first suggested by Vapnik in the 1960s for classification and have recently become an area of intense research owing to developments in the techniques and theory coupled with extensions to regression and density estimation.

SVMs arose from statistical learning theory; the aim being to solve only the problem of interest without solving a more difficult problem as an intermediate step. SVMs are based on the structural risk minimisation principle, closely related to regularisation theory. This principle incorporates capacity control to prevent over-fitting and thus is a partial solution to the bias-variance trade-off dilemma.

Two key elements in the implementation of SVM are the techniques of mathematical programming and kernel functions. The parameters are found by solving a quadratic programming problem with linear equality and inequality constraints; rather than by solving a non-convex, unconstrained optimisation problem. The flexibility of kernel functions allows the SVM to search a wide variety of hypothesis spaces.

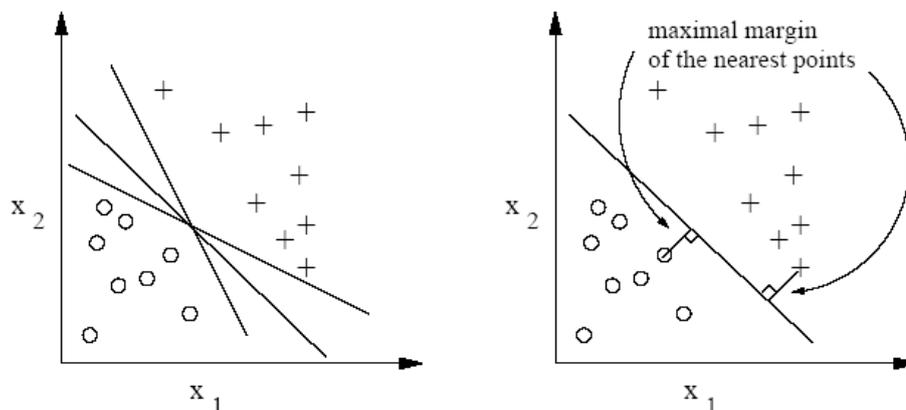


Figure B.1: Linear classification: (left) example of classification problem where the separating hyperplane is not unique, (right) example of a unique hyperplane which corresponds to a maximal margin of the closest points to the separating hyperplane.

B.1 Maximal Margin Classifiers

Consider the class of hyperplanes $w^T x + b = 0, w \in \mathbb{R}^n, b \in \mathbb{R}$, corresponding to a decision function.

$$f(x) = \text{sign}(w^T x + b) \quad (\text{B.1})$$

First, we consider the case of linearly separable data. A hyperplane can separate two classes of data in many possible ways (see figure B.1). There is no unique separating hyperplane, unless we add a criterion to decide which is the best or the optimal separating hyperplane.

Basically the idea of learning from examples is to recognize the pattern of a class by examining the training points corresponding to that class. New data points are assumed to lie somewhere around the known training data. Therefore, a hyperplane should be chosen such that a small shift of the data does not result in prediction change. If the distance between the separating hyperplane and the training points becomes too small, even test examples very close to the training samples may be classified incorrectly.

Based on this idea, Vapnik and Chervonenkis presumed that the generalisation ability depends on the distance between the hyperplane and the training points. They introduced the Generalized Portrait, a learning algorithm for

separable problems, by constructing a hyperplane which maximally separates the classes (maximum margin):

$$\max_{w,b} \min\{\|x - x_k\| : x \in \mathbb{R}^n, w^T x + b = 0, k = 1, \dots, N\} \quad (\text{B.2})$$

To show how this hyperplane can be constructed in an efficient way, we need to start with some definitions.

Definition B.1.1 *Separability*

A training set $D = \{(x_1, y_1), \dots, (x_N, y_N) : x_k \in \mathbb{R}^n, y_k \in \{-1, +1\}\}$ is called separable by a hyperplane $w^T x + b = 0$ if there exist both a unit vector w ($\|w\| = 1$) and a constant b such that the following equalities hold:

$$w^T x + b \geq +1 \quad \text{for } y_k = +1. \quad (\text{B.3})$$

$$w^T x + b \leq -1 \quad \text{for } y_k = -1. \quad (\text{B.4})$$

The hyperplane defined by w and b is called a separating hyperplane.

Definition B.1.2 *Margin*

Consider separating hyperplane H as defined by $w^T x + b = 0$.

- the margin $\zeta_k(w, b)$ of a training point x_k is defined as the distance between H and x_k : $\zeta_k(w, b) = y_k(w^T x_k + b)$.
- the margin $\zeta_D(w, b)$ of a set of vectors $D = x_1, \dots, x_k$ is defined as the minimum distance from H to the vectors in D : $\zeta_D(w, b) = \min_{x_k \in D} \zeta_k(w, b)$.

Now consider the unit vector w^* and the constant b^* which maximize the margin of the training set $\zeta(w, b)$ and also satisfy the condition B.3 and B.4. This pair of (w^*, b^*) defines the hyperplane which separates the positive from the negative examples with the largest margin. This hyperplane is also called **maximal margin hyperplane or optimal separating hyperplane**.

Definition B.1.3 *Optimal separating hyperplane*

The Optimal hyperplane of a training set D is defined by:

$$(w^*, b^*) = \operatorname{argmax}_{w,b} \zeta_D(w, b). \quad (\text{B.5})$$

Vapnik proves on the uniqueness of the optimal separating hyperplane. With a unique w^* we can describe b^* by:

$$b^* = \frac{1}{2}(\min_{k \in I_+} w^{*T} x_k - \max_{k \in I_-} w^{*T} x_k). \quad (\text{B.6})$$

Where $I_+ = \{k | y_k = +1\}$ and $I_- = \{k | y_k = -1\}$.

B.2 Construction of the Optimal Hyperplane

Given a training set $D = \{(x_1, y_1), \dots, (x_N, y_N) : x_k \in \mathbb{R}^n, y_k \in \{-1, +1\}\}$, the optimal separating hyperplane is the solution to the optimization problem.

$$\begin{aligned} & \max \quad \zeta_D(w, b) \\ & \text{subject to} \quad \zeta_D(w, b) > 0 \\ & \quad \quad \quad \|w\| = 1 \end{aligned} \tag{B.7}$$

However, solving B.7 is not straightforward, it involves nonlinear constraints, while the objective function itself is neither linear nor quadratic. We can rewrite the optimization problem equivalently as:

$$\begin{aligned} & \min \quad 1/2\|w\|^2 \\ & \text{subject to} \quad w^T x + b \geq +1 \quad \text{for } y_k = +1. \\ & \quad \quad \quad w^T x + b \leq -1 \quad \text{for } y_k = -1. \end{aligned} \tag{B.8}$$

Theorem B.2.1 *Theorem (Vapnik)* Vector w_0 that solves problem B.8 is related to the vector w^* solving problem B.7 by the equality $w^* = \frac{w_0}{\|w_0\|}$.

This implies that the construction of the optimal hyperplane first needs to solve problem B.8 with linear constraints, where the constraints can be simplified as:

$$w^T x + b - 1 \geq 0 \quad , k = 1, \dots, N. \tag{B.9}$$

The Lagrangian for this problem is:

$$L(w, b, e; \alpha) = \frac{1}{2}w^T w - \sum_{k=1}^N \alpha_k \{y_k [w^T x + b] - 1\}. \tag{B.10}$$

with Lagrange multipliers $\alpha_k \geq 0$ for $k = 1, \dots, N$. The solution is characterized by the saddle point of the Lagrangian.

$$\max_{\alpha} \quad \min_{w, b} L(w, b; \alpha). \tag{B.11}$$

This leads to:

$$\begin{cases} \frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{k=1}^N \alpha_k y_k x_k. \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{k=1}^N \alpha_k y_k = 0. \end{cases}$$

with resulting classifier

$$y(x) = \text{sign}\left[\sum_{k=1}^N \alpha_k y_k x_k^T x + b\right]. \tag{B.12}$$

Elimination of w from above equations gives the following Quadratic Programming (QP) problem as the dual problem in the Lagrange multipliers α_k .

$$\begin{aligned} \max_{\alpha} J_D(\alpha) &= -\frac{1}{2} \sum_{k,l=1}^N y_k y_l x_k^T x_l \alpha_k \alpha_l + \sum_{k=1}^N \alpha_k & (B.13) \\ \text{such that} & \sum_{k=1}^N \alpha_k y_k = 0. \end{aligned}$$

Note that this problem is solved in $\alpha = [\alpha_1 \dots \alpha_N]^T$, and not in w . This QP problem has a number of interesting properties like global and unique solution, sparseness and geometric meaning of support vectors.

B.3 Optimal Hyperplane for Linearly Non-separable Case

In the previous section the SVM solution of a linearly separable classification problem is explained. However, in most real life problems we deal with noisy data which will render simple linear separation impossible. No feasible solution to the margin maximization problem can be found, due to the fact that the objective function (i.e. the dual Lagrangian) is growing arbitrarily large.

In the previous section the SVM solution of a linearly separable classification problem is explained. However, in most real life problems we deal with noisy data which will render simple linear separation impossible. No feasible solution to the margin maximization problem can be found, due to the fact that the objective function (i.e. the dual Lagrangian) is growing arbitrarily large.

Cortes and Vapnik in 1995 gave the extension of linear SVM to the non-separable case. Basically it is done by introducing positive slack variable ζ_k in the constraints. The inequalities are transformed to:

$$y_k [w_k^T + b] \geq 1 - \zeta_k, k = 1, \dots, N. \quad (B.14)$$

We are interested in the smallest slack variable satisfying:

$$\zeta_k = \max\{0, 1 - y_k [w^T x_k + b]\}. \quad (B.15)$$

It measures how many points fail to have a margin of $1/||w||$. The values of ζ_k indicate where x_k lies compared to the separating hyperplane.

- $\zeta_k \geq 1$: $y_k[w^T x_k + b] < 0$, misclassification.
- $0 < \zeta_k < 1$: x_k is classified correctly, but lies inside the margin.
- $\zeta_k = 0$: x_k is classified correctly, and lies outside the margin or exactly on the margin boundary.

In the primal weight space the optimization problem becomes

$$\begin{aligned} \min_{w,b,\zeta} \mathcal{J}P &= \frac{1}{2}w^T w + c \sum_{k=1}^N \zeta_k \\ \text{such that } y_k[w^T x_k + b] &\geq 1 - \zeta_k, k = 1, \dots, N. \\ \zeta_k &\geq 0, k = 1, \dots, N \end{aligned} \quad (\text{B.16})$$

where c is a positive real constant. We should then consider the following Lagrangian:

$$L(w, b, \zeta; \alpha, \nu) = \mathcal{J}P(w, \zeta) - \sum_{k=1}^N \alpha_k (y_k[w^T x_k + b] - 1 + \zeta_k) - \sum_{k=1}^N \nu_k \zeta_k. \quad (\text{B.17})$$

with Lagrange multipliers $\alpha_k \geq 0$, $\nu_k \geq 0$ for $k = 1, \dots, N$. The second set of Lagrange multipliers is needed due to the additional slack variables ζ_k . The solution is given by the saddle point of the Lagrangian:

$$\max_{\alpha, \nu} \min_{w, b, \zeta} L(w, b, \zeta; \alpha, \nu). \quad (\text{B.18})$$

In comparison with the linearly separable case B.14 this problem has additional box constraints.

B.4 Nonlinear SVM Classifiers

By combining the idea of an optimal separating hyperplane with a kernel induced mapping to a high dimensional feature space, we extend the idea from linear to nonlinear classifiers. One can formally replace x by $\varphi(x)$ and apply the kernel trick where possible. However, notice that $\varphi(x)$ can be infinite dimensional, and hence also the w vector. While for linear SVM one can in fact equally well solve the primal problem in w as the dual problem in the support values α , this is no longer the same for the nonlinear SVM case

because in the primal problem the unknown w can be infinite dimensional. With slight modification, for the nonlinear case we can write

$$w^T \varphi(x) + b \geq +1 \quad \text{for } y_k = +1. \quad (\text{B.19})$$

$$w^T \varphi(x) + b \leq -1 \quad \text{for } y_k = -1. \quad (\text{B.20})$$

which is equivalent to

$$y_k [w^T \varphi(x) + b] \geq +1, k = 1, \dots, N. \quad (\text{B.21})$$

in the case of separable data. The classification can be written as

$$y(x) = \text{sign}[w^T \varphi(x) + b]. \quad (\text{B.22})$$

The optimization problem becomes

$$\begin{aligned} \min_{w,b,\zeta} \mathcal{J}P &= \frac{1}{2} w^T w + c \sum_{k=1}^N \zeta_k \\ \text{such that } y_k [w^T \varphi(x_k) + b] &\geq 1 - \zeta_k, k = 1, \dots, N. \\ \zeta_k &\geq 0, k = 1, \dots, N \end{aligned} \quad (\text{B.23})$$

The Lagrangian is constructed:

$$L(w, b, \zeta; \alpha, \nu) = \mathcal{J}P(w, \zeta) - \sum_{k=1}^N \alpha_k (y_k [w^T \varphi(x_k) + b] - 1 + \zeta_k) - \sum_{k=1}^N \nu_k \zeta_k. \quad (\text{B.24})$$

with Lagrange multipliers $\alpha_k \geq 0$, $\nu_k \geq 0$ for $k = 1, \dots, N$. The solution is given by the saddle point of the Lagrangian:

$$\max_{\alpha, \nu} \min_{w, b, \zeta} L(w, b, \zeta; \alpha, \nu). \quad (\text{B.25})$$

After the aggregation of the equation B.25, In the quadratic form, the kernel trick is applied

$$K(x_k, x_l) = \varphi(x_k)^T \varphi(x_l) \quad (\text{B.26})$$

for $k = 1, \dots, N$. Finally the nonlinear SVM classifier takes the form

$$y(x) = \text{sign} \left[\sum_{k=1}^N \alpha_k y_k K(x, x_k) + b \right]. \quad (\text{B.27})$$

with α_k positive real constants which are the solution to a QP problem. The next problem is the determination of the constant b . Karush-Kuhn-Tucker (KKT) complementarity conditions state that the product of the

dual variables and the constraints should be zero at the optimal solution. Therefore, using the KKT conditions, it yields

$$\left\{ \begin{array}{l} \frac{\partial L}{\partial w} = 0 \rightarrow w = \sum_{k=1}^N \alpha_k y_k \varphi(x_k). \\ \frac{\partial L}{\partial b} = 0 \rightarrow \sum_{k=1}^N \alpha_k y_k = 0. \\ \frac{\partial L}{\partial \zeta_k} = 0 \rightarrow c - \alpha_k - \nu_k = 0. \\ \alpha_k \{y_k [w^T \varphi(x_k - 1 + \zeta_k)]\} = 0, k = 1, \dots, N. \\ \nu_k \zeta_k = 0, k = 1, \dots, N. \\ \alpha_k \geq 0, k = 1, \dots, N. \\ \nu_k \geq 0, k = 1, \dots, N. \end{array} \right.$$

From $\nu_k \zeta_k = 0$ we have for the solutions $w^*, b^*, \zeta_k^*, \alpha_k^*, \nu_k^*$ to this problem that $\zeta_k^* = 0$ for $\alpha_k^* \in (0, c)$. Hence

$$y_k [w^T \varphi(x_k + b)] - 1 = 0 \quad \text{for } \alpha_k \in (0, c). \quad (\text{B.28})$$

which means that one can take any training data point for which $0 \geq \alpha_k \geq c$ and use that equation to compute the bias term b .

Appendix C

Dempster-Shafer Theory

C.1 Les fondamentaux de la Théorie de Dempster-Shafer

Dans cette théorie probabiliste introduit par Dempster, travers ses fonctions de probabilité inférieure et probabilité supérieure auxquelles Shafer attribue respectivement la fonction de croyance et la fonction de plausibilité, l'on prend en compte l'extension de la théorie des probabilités subjectives. Les applications ne concernent que des ensembles de définition discrets au niveau credal et pignistic. Se basant sur une distribution de masse d'évidence m définie sur l'ensemble des propositions Ω (espace de mondes possibles de cardinal fini), elle associe des degrés de croyance et de plausibilité des parties de A (groupe de propositions ou d'informations) de Ω .

C.1.1 La fonction de croyance et la fonction de plausibilité

La fonction de croyance ou de plausibilité est une fonction qui, pour une information ou proposition émise ou déduite d'une analyse, permet d'attribuer des degrés de croyance ou de plausibilité comprise entre 0 et 1.

Soit Ω un ensemble d'hypothèses $\{H_1, H_2, \dots, H_n\}$ mutuellement exclusives, appelé cadre de discernement. L'ensemble des parties A de Ω est noté 2^Ω .

Si on définit la fonction $m : 2^\Omega \rightarrow [0,1]$ une distribution d'évidence sur les parties Ω (ou la partition de Ω), alors $A \rightarrow m(A)$ représente la distribution d'évidence sur la partie A .

- $m(A)$ est la confiance portée strictement dans A sans que celle-ci puisse être répartie sur les hypothèses qui la composent.
- A est un élément focal si $m(A) \neq 0$.

Dans le cas où pour $m : 2^\Omega \rightarrow [0,1]$ les deux conditions suivantes sont remplies: $m(\emptyset) = 0$ et $\sum_{A_i \subset \Omega} m(A_i) = 1$, il est appelé fonction de masse sur Ω .

La fonction de croyance $Bel(A)$ (croyance que la vérité est dans A) est par conséquent la somme des masses des propositions incluses dans A . Elle est définie par la formule suivante: $Bel(A) = \sum_{B_i \subset A} m(B_i)$.

La fonction de plausibilité $Pl(A)$ (la plausibilité que la vérité est dans A) est la somme des masses des propositions dont l'intersection avec A n'est pas nulle, elle est donnée par la formule: $Pl(A) = \sum_{A \cap B_i} m(B_i)$.

C.2 Combinaison d'information avec la théorie de l'évidence

La théorie de Dempster-Shafer permet de combiner des informations issues de source différente, car d'après Shafer, si deux fonctions de croyance sont définies sur un même cadre de discernement alors ce cadre de discernement distingue l'interaction pertinente entre deux informations. De ce fait les informations doivent être définies sur un même cadre de discernement de façon que l'on puisse en déduire leur somme orthogonale suivant la règle de combinaison Dempster. Cette somme est toujours une fonction de croyance et prend en compte l'influence de toutes les autres. Cette règle peut s'énoncer comme suit:

Soit m_1 et m_2 deux jeux de masses associées aux fonctions de croyance Bel_1 et Bel_2 respectivement, sur le même cadre de discernement Ω . On note $Bel = Bel_1 * Bel_2$ la somme orthogonale de Bel_1 et Bel_2 , et A_1, A_2, \dots, A_l les éléments focaux de Bel_1 ainsi que B_1, B_2, \dots, B_n ceux de Bel_2 .

De ce fait: Si $\sum_{A_i \cap B_j} m_1(A_i)m_2(B_j) < 1$ alors la fonction $Bel : 2^\theta \rightarrow [0, 1]$ est définie par:

$$Bel(\emptyset) = 0 \quad \text{et} \quad Bel(C) = \frac{\sum_{A_i \cap B_j = C} m_1(A_i)m_2(B_j)}{1 - \sum_{A_i \cap B_j = \emptyset} m_1(A_i)m_2(B_j)} \quad (\text{C.1})$$

Il est à noter que cette règle de combinaison de combinaison donne lieu des propriétés de symétrie, d'associativité, d'élément neutre. Elle permet aussi

de combiner des fonctions bayésiennes pour créer d'autres fonctions bayésiennes et donne aussi lieu la règle de conditionnement.

Règle de conditionnement répond la définition:

Soit $Bel(A/B)$ la croyance en A sachant B , alors:

$$Bel(B/A) \approx (Bel \oplus 1_B)(A) \approx \sum_{B \subseteq A} \frac{\sum_{A_i \cap B = A} m(A_i)}{\sum_{A_i \cap B = \emptyset} m(A_i)} \quad (C.2)$$

$$Bel(B/A) = \frac{Bel(A \cup C_{\Omega}^B) - Bel(C_{\Omega}^B)}{1 - Bel(C_{\Omega}^B)} = 1 - \frac{Pl(C_{\Omega}^A \cap B)}{Pl(B)}. \quad (C.3)$$

C.3 Synthèses

La théorie de l'évidence, partir des mathématiques probabilistes, présente un cadre formel de raisonnement dans l'incertain, un modèle qui permet de modéliser la connaissance. Car à travers les fonctions de croyance qui sont des outils de mesure de la probabilité subjective, l'on peut valuer le degré de vérité d'une affirmation, d'un avis d'expert. Avec l'introduction des masses d'évidence, des coefficients d'affaiblissement de ces masses et aux moyens de la règle de combinaison elle permet de traiter l'information au point d'aboutir à sa fiabilité. Ce qui aide grandement dans la prise de décision, ou dans d'autres domaines (tel que la télédétection).

Toutefois, certains analystes et utilisateurs (tels que F. Voorbraak, H. Hyburg) relèvent des difficultés d'application de cette théorie en raison : " de la sensibilité de la méthode de combinaison sur les petites valeurs de masses de croyance, des grands temps de calcul qu'elle demande en comparaison aux autres méthodes, de l'absence de sémantique claire, de la difficulté de suivre une méthode systématique et quelque peu générique ".

Tenant compte de toutes informations, il est conseillé à un utilisateur d'analyser de façon judicieuse la portée de cette théorie dans le domaine d'application dont il veut en faire usage.

Appendix D

Particular Format File

D.1 SAM Indexing File

LHD: Format name plus version

FIL: File specification

TYP: Specific file type

VOL: Database volume ID DIR: Signal file directory

SRC: Signal file name

BEG: Labelled sequence start position

END: Labelled sequence end position

SYS: Labelling system

DAT: Date of completion of labelling

LBD: Label body keyword

LBA: labelling for sound event, begin, ,end, orthographic text prompt

LBB: labelling for speech event, begin, ,end, orthographic text prompt

CMT: Comment for description

ELF: End of label file

D.1.1 SAM indexing file example for a given ANA-SON file

LHD: V1.1

FIL: Sound

TYP: Phonemic sound

VOL: m: \ mes applications et developpements \ FL-EMUTEM.3.1 \ HOMECAD
\ TelesurveillanceAMC1-15-10-2008-16-28-01.sam

DIR: m: \ mes applications et developpements \ FL-EMUTEM.3.1 \ HOMECAD
\ TelesurveillanceAMC1-15-10-2008-16-28-01.wav

SRC: m: \ mes applications et developements \ FL-EMUTEM.3.1 \ HOMECAD
\ TelesurveillanceAMC1-15-10-2008-16-28-01.sam
BEG: 0
END: 32503808
EXP: Hamid MEDJAHED
SYS: FL-EMUTEM,Simpling rate is 44100Hz
DAT: 11-04-2008,13:34:01
SPA:
LBD:
LBE:
LBA: 511488, ,514048,Shouting
LBB:
CMT: SNR=3.448828, LLH=-24.917087
CMT: Tout les LLH, Door Lock(-57.149976),Dishes(-31.058402), Shouting(-
24.917087),Sons de pas(-81.754784),Phone ringtone(-28.562985),Breaking Glass
(-42.304129), Door slamming(-37.477431),Son(-28.508718),Speech(-42.859083),
CMT: LLK is the Likelihood
ELF:

D.2 WAV Audio File Format

WAV is an audio file format that was developed by Microsoft. It is so wide spread today that it is called a standard PC audio file format. A Wave file is identified by a file name extension of WAV (.wav). Used primarily in PCs, the Wave file format has been accepted as a viable interchange medium for other computer platforms, such as Macintosh. This allows content developers to freely move audio files between platforms for processing, for example.

The Wave file format stores information about the file's number of tracks (mono or stereo), sample rate, bit depth, as well as the uncompressed raw audio data.

D.2.1 Basics of digital audio and sound

First, some basics. Sound is air pressure fluctuation. Digitized sound is a graph of the change in air pressure over time. That's all there is to it.

For a good picture of this, open up Windows Sound Recorder and record a short sound, then look at the green bars it shows. When they're wide, there's a lot of air pressure, which your ear detects as a loud noise. When

they're flat in the middle, there's no change in air pressure, which your ear detects as silence. The faster they go up and down, the higher the sound you hear.

When you record a sound, your microphone changes the air pressure fluctuations into electrical voltage fluctuations, which your sound card measures every so often and changes into numbers, called samples. When you play a sound back, the process is reversed, except that the voltage fluctuations go to your speakers instead of your microphone, and are converted back into air pressure by the speaker cone.

The speed with which your sound card samples the voltage is called the sample rate, and is expressed in kilohertz (kHz). One kHz is a thousand samples per second.

It's important to note that digitized audio stores nothing directly about a sound's frequency, pitch, or perceived loudness. You can run certain algorithms on the samples to determine these values approximately, but you can't just read them from the file.

D.2.2 What is RIFF?

RIFF is a file format for storing many kinds of data, primarily multimedia data like audio and video. It is based on chunks and sub-chunks. Each chunk has a type, represented by a four-character tag. This chunk type comes first in the file, followed by the size of the chunk, then the contents of the chunk.

The entire RIFF file is a big chunk that contains all the other chunks. The first thing in the contents of the RIFF chunk is the "form type," which describes the overall type of the file's contents.

D.2.3 What is WAVE?

The WAVE format is a subset of RIFF used for storing digital audio. Its form type is "WAVE", and it requires two kinds of chunks:

- The `fmt` chunk, which describes the sample rate, sample width, etc., and
- the data chunk, which contains the actual samples.

WAVE can also contain any other chunk type allowed by RIFF, including LIST chunks, which are used to contain optional kinds of data such as the copyright date, author's name, etc. Chunks can appear in any order.

The WAVE file is thus very powerful, but also not trivial to parse. For this reason, and also possibly because a simpler (or inaccurate?) description of the WAVE format was promulgated before the Win32 API was released, a lot of older programs read and write a subset of the WAVE format, which I refer to as the "canonical" WAVE format. This subset basically consists of only two chunks, the fmt and data chunks, in that order, with the sample data in PCM format.

Appendix E

Author's Publications

Book Chapter

- Dan Istrate, Jerome Boudy, Hamid Medjahed, Jean Louis Baldinger, << Medical Remote Monitoring using sound environment analysis and wearable sensors >>, In- Tech, Recent Advances in Biomedical Engineering, ISBN 978-953-7619-X-X, October 2009.
- H.Medjahed, D.Istrate, J.Boudy, F.Steenkeste, J.L. Baldinger and B.Dorizzi, << A Multimodal Database for a Home Remote Medical Care Application >> , LNCS 4901,,Springer, 2008, ISBN 978-3-540-77410-5, pp. 99-106.

International conference with lecture committee and proceedings

- H. Medjahed, D. Istrate, J. Boudy and B. Dorizzi, << Human Activities of Daily Living Recognition Using Fuzzy Logic For Elderly Home Monitoring >>, FUZZ-IEEE 2009, ISBN 978-1-4244-3597-5, pp. 2001-2006, 20-24 August 2009, Jeju Island, Korea.
- H. Medjahed, D. Istrate, J. Boudy and B. Dorizzi, << A Fuzzy Logic System for Home Elderly People Monitoring (EMUTEM) >>, Fuzzy Systems 2009, ISBN 978-960-474-066-6, pp. 69-75, 23-25 Mach 2009, Prague, Czech Republic.
- W. Soudene, D. Istrate, H. Medjahed, J. Boudy, J.L. Baldinger, I. Belfeki and J.F.Delavaut, << Multi-Modal Platform for In-Home Healthcare Monitoring (EMUTEM) >>, International Conference on Health Informatics (HEALTHINF 2009), pp.381-386, January 14-17, 2009, Porto, Portugal.

- W. Soudene, D. Istrate, H. Medjahed, J. Boudy, J. L. Baldinger, I. Belfeki and J.F. Delavaut, << Une Plateforme Multimodale pour la Télévigilance Médicale >>, AMINA 2008, 13-15 November 2008.
- H.Medjahed, D.Istrate, J. Boudy, F.Steenkeste, J.L. Baldinger, I. Belfeki, V. Martins and B.Dorizzi, << A Multimodal Platform for Database Recording and Elderly People Monitoring >>, BIOSIGNALS 2008, pp.385-392, 28-31 January 2008, Funchal-Madeira, Portugal.

National Conferences

- H.Medjahed, D.Istrate, J. Boudy, F.Steenkeste and B.Dorizzi, << Environnement Multimodal pour la Télévigilance Médicale à Domicile EMUTEM >>, SFTAG Novembre 2009, Troyes, France.
- J. Boudy, J.L. Baldinger, F. Delavault, I. Belfeki, B. Dorizzi, I. Farin, R. Andreao, S. Müller, V. Ruiz-Martins, F. Steenkeste, D. Istrate, H. Medjahed, F. Rocaries, C; Dietrich, A. Lacombe, M. Baer, A. Ozguler, A. d'Escatha, << Télévigilance médicale au service du patient à domicile >>, conférence ASSISTH'07, pp. 397-401, Toulouse 19-21 novembre 2007, France.

Appendix F

Abbreviations

*

ADL: Activities of Daily Living
ANN: Artificial neural network
ATA: American Telemedicine Association
BIC: Bayesian Information Criterion
BOA: Bisector of area
CT: Computer Tomography
COA: Centroid of area
DR: Digital Radiology
ECG: Electrocardiographie
EHR: Electronic Health Records
EMR: Electronic Medical Records
EMUTEM: Environnement Multimodal Pour la Télévigilance Médicale
FIS: Fuzzy Inference System
FL: Fuzzy Logic
FL-EMUTEM: Fuzzy Logic Environnement Multimodal Pour la Télévigilance Médicale
FN: False Negative
FP: False Positive
FTP: File Transfer Protocol
GMM: Gaussian Mixture Model
HMM: Hidden Markov Model
HOMECAD: Home Remote Medical Care Database
ICTS: Information and Communication Technologies
IP: Internet Protocol
LFCC: Linear Frequencies Cepstral Coefficients
LOM: Largest of Maximum

MOM: Mean of Maximum
MRI: Magnetic Resonance Imaging
M-FIS: Mamdani Fuzzy Inference System
NCT: Norwegian Centre for Telemedicine
SAMU: Service d'Aide Médicale Urgente
SAOP: Simple Object Access Protocol
SE: Sensitivity
SNR: Signal-to-Noise Ratio
SOM: Smallest of Maximum
SP: Specificity
SVM: Support Vector Machine
SVC: Support Vector Classification
TCP: Transmission Control Protocol
TN: True Negative
TP: True positive
TS-FIS: Takagi Sugeno Fuzzy Inference System
UML: Unified Modeling Language
WMA: World Medical Association
XML: Extensible Markup Language

Résumé

**Identification de Situation de Détresse par la Fusion de Données
Multimodales pour La Télévigilance Médicale à Domicile**

**Par
Hamid MEDJAHED**

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I. Le contexte de la thèse

1/ Introduction

Aujourd'hui, la proportion des personnes âgées devient importante par rapport à l'ensemble de la population, et les capacités d'admission dans les hôpitaux sont limitées. En conséquence, plusieurs systèmes de télévigilance médicale ont été développés, mais il existe peu de solutions commerciales. Ces systèmes se concentrent soit sur la mise en œuvre d'une architecture générique pour l'intégration des systèmes d'information médicale, soit sur l'amélioration de la vie quotidienne des patients en utilisant divers dispositifs automatiques avec alarme, soit sur l'offre de services de soins aux patients souffrant de certaines maladies comme l'asthme, le diabète, les problèmes cardiaques ou pulmonaires, ou la maladie d'Alzheimer. Dans ce contexte, un système automatique pour la télévigilance médicale à domicile est une solution pour faire face à ces problèmes et ainsi permettre aux personnes âgées de vivre en toute sécurité et en toute indépendance à leur domicile.

Dans cette thèse, qui s'inscrit dans le cadre de la télévigilance médicale, un nouveau système de télévigilance médicale à plusieurs modalités nommé EMUTEM (Environnement Multimodale pour la Télévigilance Médicale) est présenté. Il combine et synchronise plusieurs modalités ou capteurs, grâce à une technique de fusion de données multimodale basée sur la logique floue. Ce système peut assurer une surveillance continue de la santé des personnes âgées.

L'originalité de ce système avec la nouvelle approche de fusion est sa flexibilité à combiner plusieurs modalités de télévigilance médicale. Il offre un grand bénéfice aux personnes âgées en surveillant en permanence leur état de santé et en détectant d'éventuelles situations de détresse.

2/Le contexte de recherche

La télémédecine, et plus particulièrement la télévigilance médicale, constitue aujourd'hui une solution pour pallier le manque de professionnels de santé face au fort accroissement de la population âgée en Europe. De plus, elle apporte à la fois une réduction des coûts d'hospitalisation et un meilleur

confort au malade. La télémédecine est l'utilisation des nouvelles techniques de l'information et de la communication pour des applications médicales et inclut les applications de télédiagnostic, télésurveillance, télé-opération, télé-éducation.

Les travaux de cette thèse de doctorat s'effectueront dans le cadre d'une collaboration entre le département EPH de Telecom Sud Paris, le laboratoire LRIT-ESIGETEL et l'Unité 558 de l'INSERM. Cette collaboration s'inscrit dans le cadre du projet européen **CompanionAble** qui vise à fournir une synergie entre la robotique et l'intelligence ambiante, leur intégration sémantique pour fournir l'assistance aux aides soignants. Cela permettra de soutenir la stimulation cognitive et la thérapie de gestion du bénéficiaire de soins. C'est par la médiation d'une assistance automatique (robotique et intelligence ambiante) travaillant en collaboration avec le milieu familial que CompanionAble aidera les personnes âgées atteintes de troubles cognitifs.

Cette thèse est aussi le fruit d'une collaboration dans le cadre d'un projet national **QuoVADis** qui répond au besoin de compensation des difficultés de communication dues aux pertes des capacités cognitives qui génèrent l'isolement social, la dépression, l'insécurité et l'inconfort dans la vie quotidienne. Le système vise d'une part à rétablir le lien affectif avec les proches, aidants et soignants par un système mobile interactif accompagnant la personne en difficulté, et d'autre part à lui permettre de se repérer dans son environnement et de le contrôler. Il a pour but de faciliter la prise en charge des pathologies cognitives (Maladie d'Alzheimer ou apparentées) et d'alléger le fardeau des aidants.

3/ La télévigilance médicale à domicile

Les travaux de recherche effectués au cours de cette thèse de doctorat se situent dans le cadre de la télévigilance médicale des personnes à domicile, qui est une des dimensions de la télémédecine. Cette application prend en particulier en compte des éléments de télésurveillance, de téléconsultation et de télé-assistance. La télévigilance médicale d'une personne à domicile s'appuie sur un système global comprenant les éléments suivants (voir Fig. 1.1) :

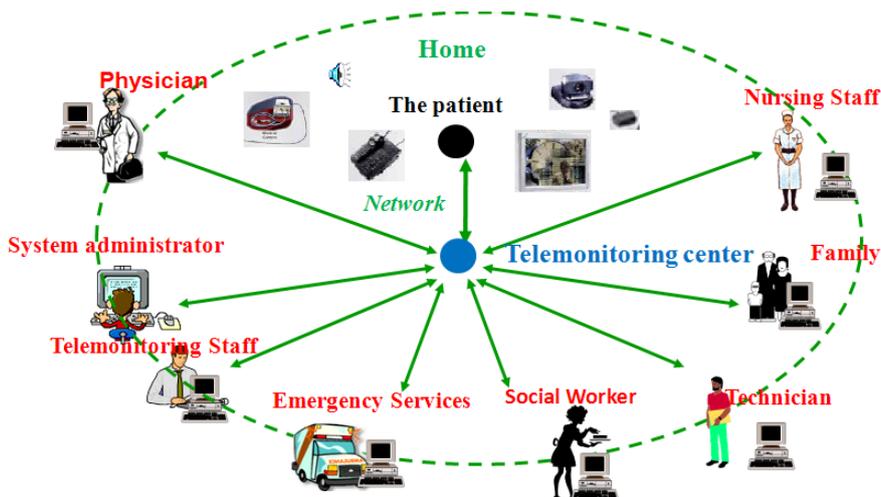


Fig. 1.1 : Système de la télésurveillance médicale à domicile.

- **Un ensemble de capteurs** de différents types (physiologie, environnement, activité) installés dans l’habitat ou portés par la personne, reliés en réseaux pour la collecte en temps réel de données, et d’appareillages automatiques (domotique) pour adapter l’environnement de vie de la personne à ses capacités personnelles, motrices et cognitives .
- **Une unité locale de traitement**, au niveau de chaque habitat, responsable du stockage et du traitement des signaux reçus des capteurs, de la gestion d’une base de connaissances relative à la personne télésurveillée, et de l’émission de messages et d’alarmes.
- **Un centre de télévigilance** pour le traitement des messages et alarmes reçus des habitats.
- **Un ensemble d’acteurs** (personnel médical, personne télésurveillée et membres de sa famille) peuvent accéder à tout moment, après authentification et selon leurs privilèges, aux données du système, au niveau de l’unité locale de traitement.

4/ Les objectifs et la contribution de la thèse

Le problème de détection de situations critiques d’une personne à partir des données collectées à domicile concerne en particulier la conception d’agents intelligents. De grandes quantités de données temporelles, hétérogènes, sont analysées en temps réel pour l’identification des situations inquiétantes ou critiques. Les projets développés et les plus avancés jusqu’à présent dans ce contexte s’intéressent souvent à une pathologie particulière, ou bien à un ensemble restreint ou spécifique de paramètres.

En se basant sur ces effets, nous avons concentré nos travaux de recherche sur cette thématique de télévigilance médicale à domicile, étant donné aussi la mise au point d’une quantité considérable de capteurs, qui peuvent être installés à la maison. Afin d’apporter des éléments de réponse à cette problématique, nous avons développé une plateforme (EMUTEM) à plusieurs modalités qui permet de répondre aux besoins ci-dessus identifiés. Cette plateforme administre un système constitué,

- D’un ensemble de microphones répartis dans les pièces du domicile de la personne âgée.
- D’un dispositif portable qui permet de mesurer la fréquence cardiaque, de détecter la posture et les mouvements ainsi que la chute de la personne équipée.
- D’un ensemble de détecteurs infrarouges qui détectent la présence de la personne dans une pièce donnée et également la position debout de cette personne.

L’objectif principal de cette thèse est d’étudier la fusion multimodale entre les différents capteurs afin d’augmenter la fiabilité de l’ensemble du système. Dans le cas d’une situation ambiguë de chute ou de malaise par exemple, il est essentiel de confirmer la détection de l’événement en utilisant plusieurs modalités. La fusion multimodale qui peut prendre en compte le mauvais fonctionnement des capteurs peut accroître la fiabilité du système et sa robustesse. Ainsi les données fournies par ces trois modalités hétérogènes sont recueillies, traitées et fusionnées par le biais d’une approche basée sur la logique floue. Cette plateforme assure la surveillance à distance de l’état de santé du patient/personne âgée et elle permet de détecter les situations de détresse.

II. L'acquisition des données pour la télévigilance médicale à domicile

Dans le domaine de la télévigilance médicale à domicile, la nécessité de disposer des bases de données multimodales a émergé ces dernières années, sous la poussée des systèmes de télévigilance fondée sur la décision et l'apprentissage. Par ailleurs le problème majeur de ces systèmes est le manque de données expérimentales bien indexées pour leur évaluation et amélioration. Pour cela on a développé une plate forme multi-capteurs pour l'acquisition, l'enregistrement et l'indexation d'une base de données médicale multimodale avec la possibilité de simuler quelques données médicales.

Nous avons développé un environnement pour l'acquisition et l'enregistrement d'une base de données multimodale où l'utilisateur peut interpréter les activités du patient en suivant un scénario qui résume la vie quotidienne de ce patient. Cette plateforme rassemble trois sous-systèmes qui ont été validés sur le plan technique de bout en bout, du point de vue matériel et logiciel. Cette plateforme est multimodale car elle nous permet d'enregistrer des données physiologiques par le sous-système RFpat [1], des informations audio par le sous-système Anason [2] et la localisation du patient par l'intermédiaire des capteurs infrarouges utilisés par le sous système Gardien [3]. En tenant en compte du caractère multimodal des données, un processus multidimensionnel d'indexation est utilisé pour obtenir une description complète de l'ensemble des données. D'autre part un processus de simulation est actuellement intégré dans notre plateforme comme un moyen de pallier le problème de manque de données expérimentales et la difficulté d'enregistrement de certaines données médicales telles que le pouls au cours des situations de détresse.

1/ La plateforme EMUTEM

Nous définissons un environnement intelligent celui qui est en mesure d'acquérir et d'appliquer les connaissances de ses habitants et de leur entourage afin de les adapter aux besoins de ces habitants et ainsi améliorer leur confort. Pour l'enregistrement de la base de données médicale multimodale notre premier objectif est la mise en place d'un tel environnement. Nous considérons notre environnement comme un agent intelligent, qui perçoit l'état de l'environnement en utilisant des capteurs et agit sur ce dernier en utilisant différents dispositifs comme des contrôleurs.

1.1/ Architecture matérielle

Notre plateforme est installée dans notre laboratoire et elle consiste en un appartement de 20 m² de surface arrangé en deux zones : la première contient les zones d'habitation habituelles (séjour, cuisine, salle de bain, chambre), la seconde un domaine technique afin d'évaluer et de superviser les expériences. Elle intègre des capteurs intelligents (infrarouges, audio, physiologique) reliée à un PC. La figure 2.1 illustre cette architecture.

Les deux microphones pour la surveillance sonore sont reliés au PC via une carte son externe, et l'ensemble peut être interprété comme un seul capteur audio par le logiciel Anason.

Des capteurs infrarouges sont fixés dans des endroits spécifiques dans la première zone (murs et plafond), ils sont reliés à une carte d'acquisition (ADAM) [4], qui est connectée au port série du PC. Des capteurs de contact (ouverture/fermeture) sont aussi fixés sur les portes et les fenêtres. Des capteurs de changement d'état sont associés à des appareils électroménagers.

Le sous-système RFpat est composé de deux modules principaux: (1) un terminal portable porté par le patient qui enregistre en continu ses données physiologiques et (2) une base de réception reliée au PC par liaison série RS232 qui reçoit les informations issues du portable toutes les 30 secondes.

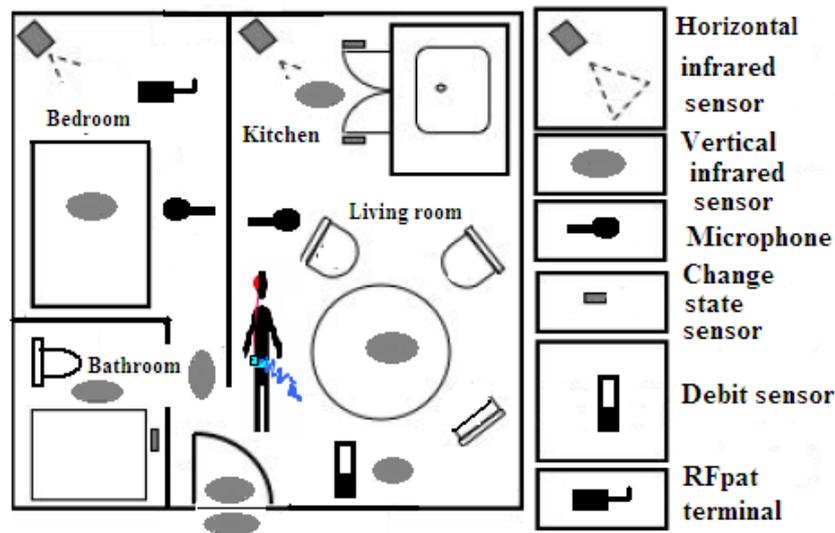


Fig. 2.1 : Le dispositif général de l'environnement de la plateforme EMUTEM.

2.2/ Architecture logicielle

Le système multimodal a trois sous-systèmes principaux comme le montre la Figure 2.2 et il prévoit une interface graphique qui encapsule le sous-système Anason. Cette interface est implémentée sous LabWindows/CVI et elle communique avec RFpat et Gardien par le protocole TCP/IP. Gardien est implémenté en C++ et il récupère les données toutes les 500 ms. RFpat est également implémenté en C++ et il reçoit les données de récepteur toutes les 30 s.

L'utilisation du module de communication à travers le protocole TCP/IP permet à chaque module (sous-système) d'être exécuté sur un autre ordinateur, et de synchroniser les trois modalités de télévigilance.

L'utilisateur peut interagir avec le système via le navigateur Internet et superviser les différentes applications. Nous utilisons ce serveur Web pour communiquer avec la personne qui interprète le rôle de patient affichant un scénario de référence à suivre sur des écrans aménagés pour cette tâche.

Cette plateforme utilise aussi un web service via le protocole SOAP. La flexibilité du système obtenu grâce au protocole de communication TCP/IP nous permet d'ajouter d'autres capteurs potentiels, par exemple un capteur d'ECG.

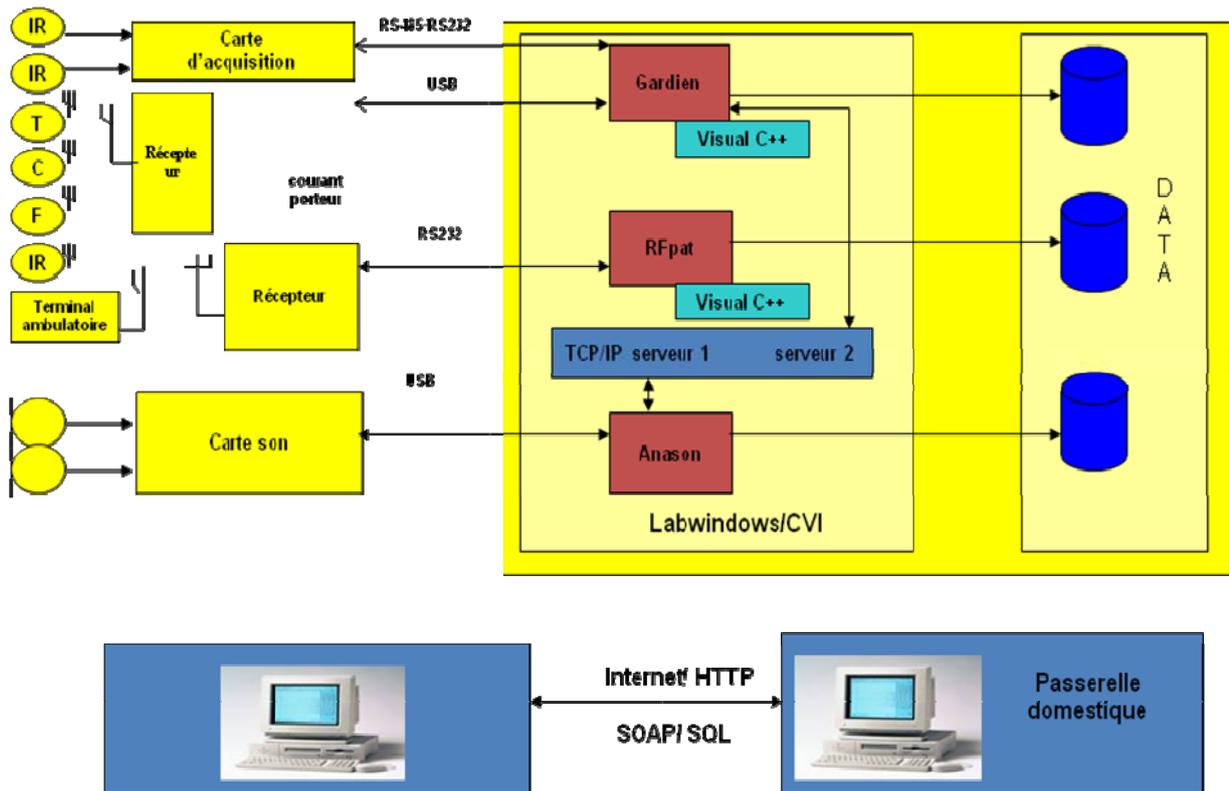


Fig. 2.2 : L'architecture logicielle de la plateforme EMUTEM

2. /Les sous systèmes de la plateforme EMUTEM

Cette plateforme gère trois systèmes hétérogènes, un système sonore, un équipement portable pour les données physiologiques et actimétriques et des détecteurs infrarouges plus des capteurs de contact et de changement d'état.

2.1/ Le capteur sonore intelligent (ANASON)

Aujourd'hui les dispositifs de télévigilance et de soins à distance font face à un réel problème d'acceptation et d'adoption par les utilisateurs finaux et les soignants. En effet, ce genre de systèmes est souvent jugé comme intrusif et non respectueux de la vie intime des personnes équipées. Les capteurs sonores, quant à eux, sont plus facilement acceptés par patients et/ou personnes âgées, leur famille et les soignants. Ils sont considérés comme moins intrusifs que les caméras, les vêtements intelligents, etc.

Ainsi, afin de préserver la vie privée et l'intimité du patient et/ou personne âgée tout en assurant sa sécurité, nous nous proposons d'équiper sa maison avec un certain nombre de microphones. Dans ce contexte, l'environnement sonore n'est pas enregistré en continu. Ces microphones permettent le contrôle à distance de l'environnement acoustique de la personne équipée. Le principal avantage de ce système consiste dans l'exécution en temps réel. Ainsi, nous analysons en permanence l'environnement sonore afin de détecter des situations de détresse et/ou des appels à l'aide.

Ce capteur décrit dans [1] est composé de quatre modules comme le montre la Figure 2.3 :

- **Module M1:** détection et extraction d'évènements sonores. Le premier module M1 est en permanence à l'écoute de l'environnement sonore dans le but de détecter et d'extraire des sons ou des phrases utiles. Le signal extrait par le module M1 est traité par le module M2.
- **Module M2:** module de classification son/parole. Le deuxième module M2 est un module de classification à bas niveau (parole/son). Il traite le son reçu par le module M1 afin de séparer les signaux de parole des signaux de son. A titre d'exemple un discours prononcé par le patient sera classé comme 'parole' mais un claquement de porte ou des sons de pas seront classés comme 'son'.

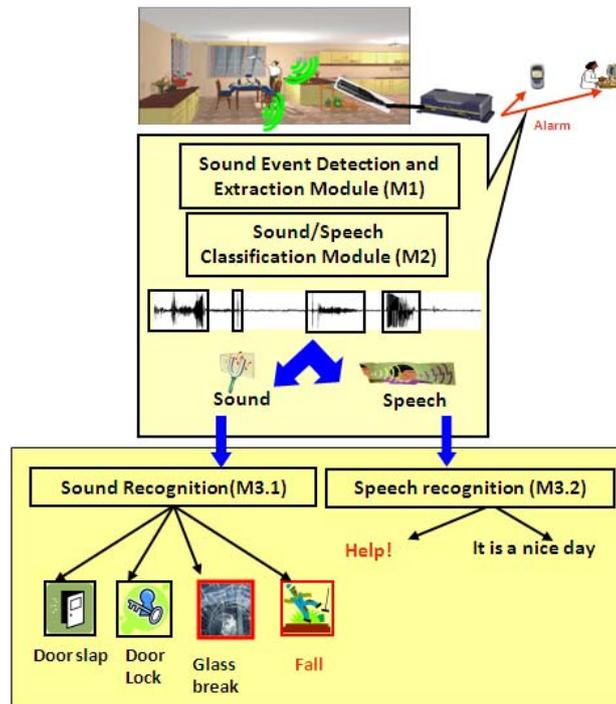


Fig. 2.3 : Architecture du capteur intelligent ANASON

- **Module M3:** étape de classification haut niveau [4]. Ce module traite chaque classe déterminée par le module M2. Il consiste en deux sous-modules. Dans le cas où un label de son a été attribué au signal par le module M2, le sous-module de reconnaissance des sons (M3.1) classe le signal parmi huit classes sonores prédéfinies [5] (bris de verre, claquement de porte, bruit de vaisselle, etc.). Dans le cas de l'attribution d'une étiquette de parole, le signal extrait est analysé par un moteur de reconnaissance vocale (module M3.2) en vue de détecter les expressions de détresse (« A l'aide ! », « Un docteur ! », « A moi ! », « Aidez-moi ! », etc.).

2.2/Le terminal portable RFpat

Le terminal portable est constitué :

- D'un terminal mobile : il s'agit d'un boîtier que le patient ou la personne âgée porte en permanence à la ceinture lorsqu'elle est chez elle. Il mesure les données vitales de la personne et les transmet à une station réceptrice
- D'un terminal fixe : il s'agit d'une station de réception.

Ce terminal a un triple rôle :

- Il mesure les données physiologiques du patient, notamment le pouls ambulateur de manière permanente.
- Il détecte avec une grande sensibilité les mouvements du patient et il indique son activité.
- Il détecte la chute du patient.

Toutes les données recueillies par les différents capteurs RFpat [2] sont traitées dans le dispositif portable sans fil. Pour assurer une autonomie optimale de ce dernier, nous avons mis en œuvre une conception électronique à faible consommation. Ainsi, l'architecture du système est basée sur 2 microcontrôleurs qui assurent l'acquisition et le traitement du signal et son émission vers le terminal fixe. Précisément, le terminal mobile (boîtier portable) comporte un certain nombre de traitements :

- Il enregistre les différents signaux physiologiques et actimétriques de la personne équipée
- Il effectue un prétraitement de ces signaux en vue de réduire l'impact du bruit d'environnement et du bruit résultant de l'usage ambulateur. En effet, la lumière et les mouvements du patient perturbent la mesure de la fréquence cardiaque.

Ce dernier point est très important pour la conception et la fiabilisation des systèmes de télévigilance à domicile. En effet, la mesure fiable des signaux physiologiques d'une personne en mode ambulateur est une tâche difficile à réaliser. Pour le système RFpat, nous avons fait le choix de résoudre le problème du bruit dans la phase d'acquisition. De plus, certains filtres numériques et algorithmes de réduction du bruit ont été mis en œuvre dans le terminal portable. Ces filtres et algorithmes ont été appliqués à tous les signaux acquis: les données relatives au mouvement, celles concernant la posture et les données physiologiques, ici la fréquence cardiaque.

Les données de mouvement retracent l'activité de la personne « télévigilée ». Elles nous donnent des informations comme: « la personne est allongée », « elle est immobile », « elle est assise /debout », etc. Ces données nous renseignent également sur l'état d'agitation de la personne. En effet, nous calculons le pourcentage de temps durant lequel la personne est en mouvement et ce toutes les 30 secondes (de 0 à 100% pendant 30 secondes).

Les données sur la posture nous disent si la personne est debout / assise ou allongée. Ceci est intéressant dans la mesure où cela nous renseigne sur l'activité de la personne. Grâce à un dispositif actimétrique intégré dans le terminal portable, nous pouvons détecter les situations où la personne s'approcherait du sol très rapidement. Cette information est interprétée comme une "chute" quand l'accélération dépasse un certain seuil dans une situation spécifique donnée.

Le signal de pouls est fourni par un capteur photo-pléthysmographique connecté à l'appareil portable. Il est pré-conditionné et débruité au niveau du terminal mobile, ce qui nous donne des informations sur la fréquence cardiaque toutes les 30 secondes. Pour le mode ambulateur, le défi consiste en la réduction du bruit. Nous avons pu réduire l'erreur des variations de mesure du pouls à 5% (mesure sur 1 minute

rafraîchie toutes les 30 secondes), ce qui reste en conformité avec les recommandations des professionnels de santé.

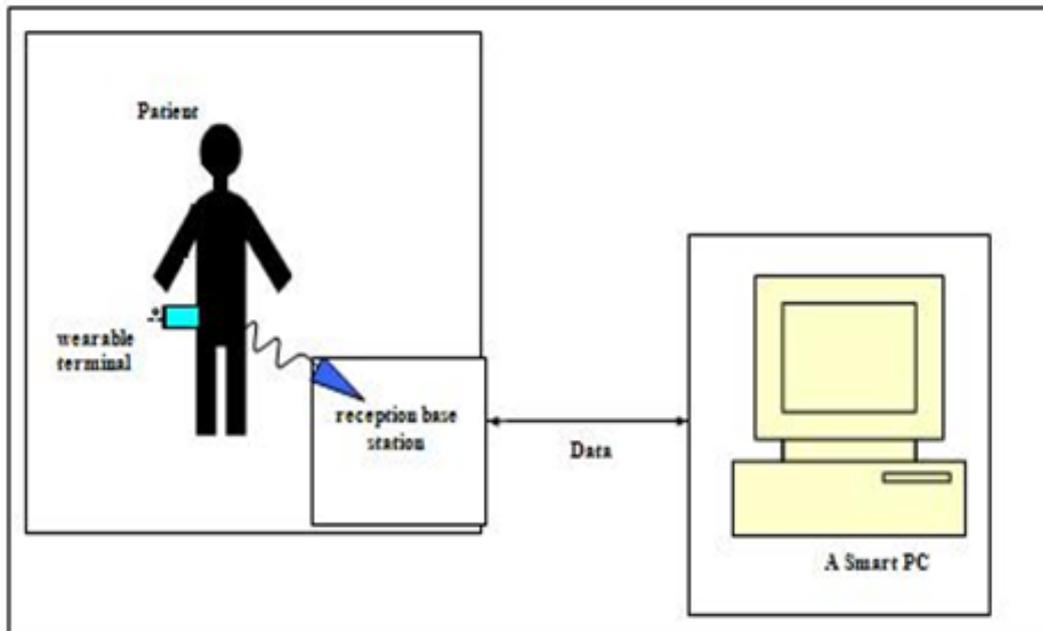


Fig.2.4 : Configuration du module RFpat

Une fois toutes ces données recueillies, pré-conditionnées et traitées par les algorithmes embarqués, elles sont transmises depuis le terminal mobile vers la station fixe. La configuration actuelle du module RFpat est présentée sur la figure 2.4. Le terminal mobile, détecte également la chute éventuelle de la personne et transmet l'alarme correspondante vers le PC de contrôle après validation algorithmique embarquée.

2.3/Gardien

Dans la même optique de sauvegarde de la vie privée du patient, nous avons développé un système de télévigilance par infrarouge géré par notre plateforme multimodale. Ainsi, un ensemble de capteurs infrarouges ont été déployés dans l'appartement test avec des capteurs de contact et de changement d'état. Ces capteurs ont deux fonctionnalités:

- Localiser la personne à domicile: les capteurs sont activés par la présence de la personne dans une chambre donnée. Seules les salles de séjour et la chambre à coucher sont équipées.
- Détecter la position verticale de la personne: Un capteur infrarouge est installé dans les pièces à vivre de l'appartement (salle de séjour et / ou cuisine) afin de détecter si la personne est debout ou pas. En fait, il s'agit d'un capteur à champ horizontal qui détecte les mouvements dans un plan horizontal à une hauteur d'un mètre et demi du sol.

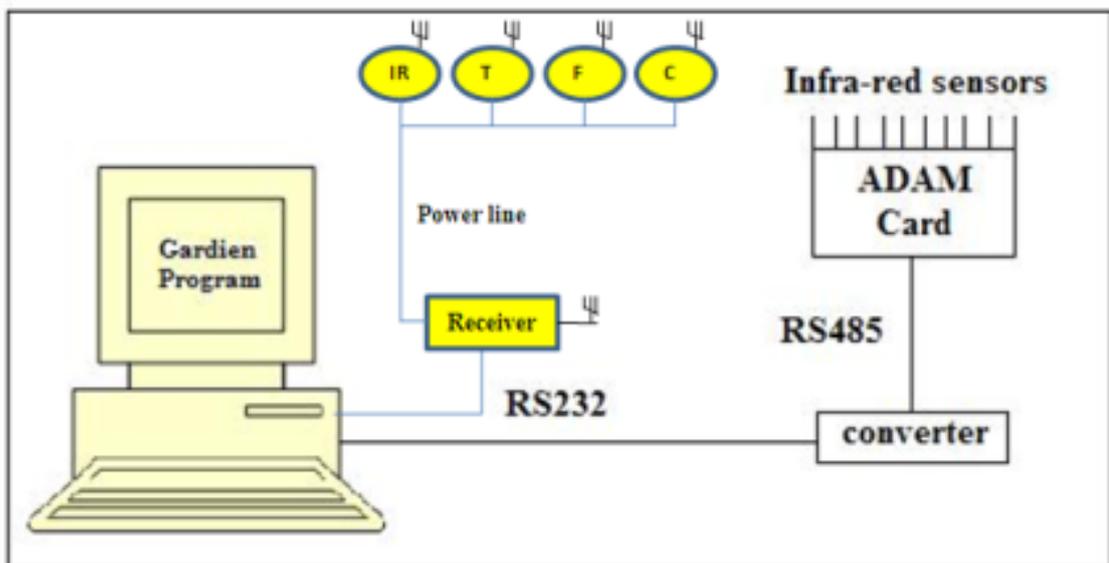


Fig.2.5 : Le système GARDIEN

Cette seconde fonctionnalité est très utile afin de confirmer ou d'infirmer une détection de chute par les modules RFPAT ou ANASON. L'ensemble de ces capteurs et des logiciels et du matériel utilisé pour la détection infrarouge forme le système baptisé GARDIEN. La figure 2.5 représente le système GARDIEN.

3/Enregistrement de la base de données multimodale

La construction d'une plateforme d'acquisition, d'enregistrement, de simulation et l'indexation d'une base de données médicale multimodale nous semble être un grand bénéfice et avantage pour l'évaluation et l'amélioration des systèmes de télévigilance médicale. Pour réaliser cette base de données une stratégie d'enregistrement a été adoptée. On utilise des scénarios de référence qui reflète les activités quotidiennes d'une personne âgée et des personnes avec des profils différents.

3.1. Les scénarios

Afin d'aider la personne interprétant le rôle du patient, l'enregistrement s'effectue à l'aide des scénarios de référence qui sont affichés sur des écrans au cours de processus d'enregistrement.

Le logiciel permet d'écrire ou de modifier un scénario sur une interface graphique et les enregistrer dans un fichier XML. Cette interface graphique est composée de deux parties: la première concerne les informations personnelles relatives à la personne qui va interpréter le rôle de patient, la deuxième partie est consacrée à l'édition de scénario à l'aide d'un tableau composé de colonnes dédiées à chaque capteur et une dernière colonne pour le résumé des actions à suivre.

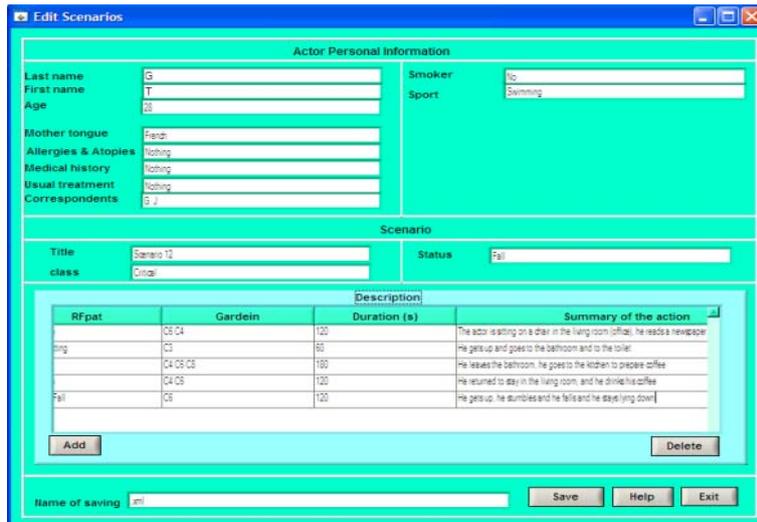


Fig.2.6 : L'interface graphique pour l'éditition des scénarios

Ces scénarios de référence sont fondés sur des situations réelles et ils visent à refléter la vie quotidienne d'un patient ou d'une personne âgée. Les scénarios sont divisés en deux catégories: des scénarios critiques avec un ou plusieurs événements de détresse, et des scénarios normaux. Ces scénarios sont automatiquement affichés sur des écrans de contrôle au cours d'enregistrement figure 2.7.

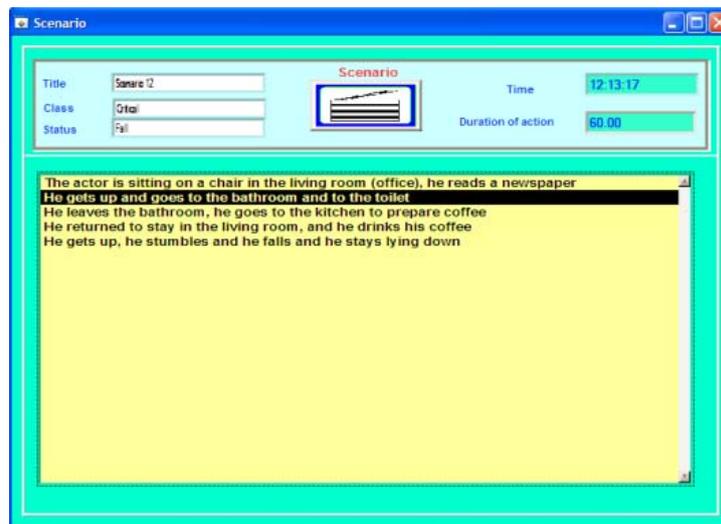


Fig.2.7 : L'interface graphique pour l'affichage des scénarios

3.2/ La base de données médicale multimodale

Les données acquises par le patient sont stockées dans un dossier nommé avec un code correspondant à la personne qui a interprété le rôle de patient. Chaque enregistrement est composé de cinq fichiers correspondant aux différents sous systèmes. Le premier, nommé personnel.xml, contient l'identifiant du patient et certaines informations personnelles comme l'âge, la langue maternelle, médicaux habituel, etc. Le second nommé scenario.xml, décrit le scénario de référence. Toutes ces données sont protégées. Les données sonores sont enregistrées en temps réel, dans un fichier wav avec une résolution de 16 bits et

une fréquence d'échantillonnage de 16 kHz. Les données vitales issues de RFpat sont enregistrées dans un fichier texte qui contient des informations sur l'attitude du patient (allongé ou debout/assis), son agitation (entre 0% et 100%), sa fréquence cardiaque, les événements de chute et les appels l'urgence. La fréquence d'échantillonnage est de 0,03 Hz. Les données acquises toutes les 500 ms par Gardien sont sauvegardées dans un fichier texte. Chaque ligne de ce fichier contient les capteurs infrarouges qui sont excités (ils sont représentés par des nombres hexadécimaux de 1 à D).

Pour compléter cette base de données un processus de simulation est intégré à cette plateforme. Il est dédié à la simulations de la fréquence cardiaque pour les situations de détresse.

Ainsi, notre plateforme d'acquisition prévoit une base de données multimodale qui sera très utile pour l'évaluation des méthodes de fusion. L'état brut de ces données sera aussi utile pour le développement et l'évaluation des algorithmes de traitement propres à chaque modalité.

Pour indexer notre base de données multimodale, nous avons retenu la norme SAM [6] généralement utilisé pour la description des bases de données de parole et de son. Ce fichier SAM va décrire les données enregistrées par la délimitation de la partie utile pour l'analyse et le traitement. A chaque modalité de la base de données va correspondre un fichier d'indexation, nous avons adapté ce standard SAM aux spécificités de chaque modalité, et nous avons ajouté un autre fichier d'indexation globale pour toute la base.

III. La fusion de données multimodale

Après la présentation de la base de données hétérogène enregistrée par la plateforme EMUTEM, pour traiter ces données issues de différentes modalités, la fusion de données multimodale est étudiée dans ce chapitre. Depuis les dix dernières années, il a été démontré que la multimodalité est une alternative qui permet d'améliorer les performances par rapport aux dispositifs ne faisant appel qu'à une seule modalité

1/ La fusion de données

Les premiers travaux d'analyse discriminante (AD) ont commencé dans les années 1920 et ont été inspirés par des études concernant la reconnaissance de races humaines à partir de mesures crâniennes ([7]). On appelle classifieur un algorithme capable d'attribuer à tout individu une classe (éventuellement cette classe peut être la classe de rejet). Ce classifieur peut ainsi déterminer la classe pour de nouveaux individus pour lesquels l'information de classe est :

- Perdue (déterminer le sexe à partir d'ossements),
- Inaccessible (décider d'une opération ou non en fonction des diagnostics cliniques),
- Accessible à l'homme mais pas à la machine (reconnaissance de forme)
- Ou inexistante (prédire la réussite ou l'échec d'une opération chirurgicale).

La fusion d'informations peut prendre différentes formes selon le moment auquel elle est effectuée. La figure 3.1 montre trois possibilités de fusion à différents stades de la reconnaissance. Il est possible de fusionner les données directement après extraction des signaux, on peut également fusionner les scores provenant des différentes modalités et enfin fusionner les informations durant la phase de décision. Certaines méthodes produisent même des modèles uniques à partir de données extraites séparément.

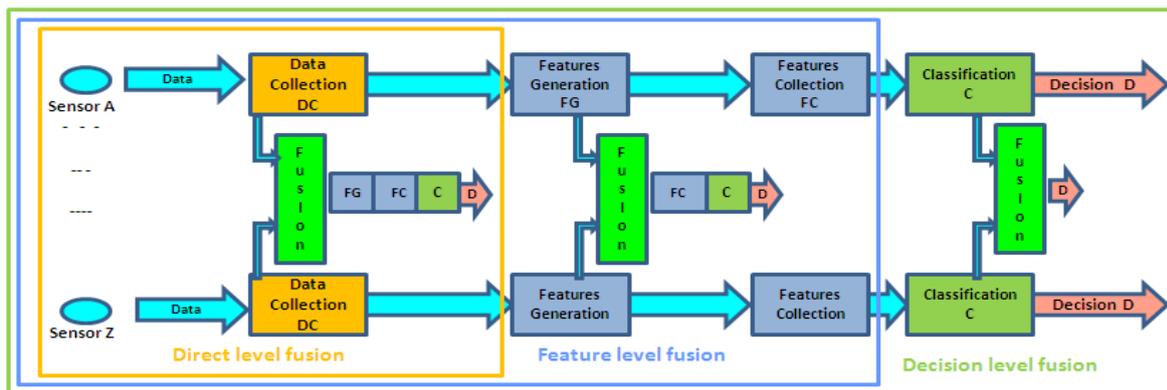


Fig.3.1 les niveaux de fusion

2/ Discussion

Pour former l'architecture générale de fusion à implémenter sur la plateforme EMUTEM, on s'est basé sur les niveaux de fusion présenté précédemment. Chaque niveau de fusion à ses avantages et il est choisi selon la nature des données a traité. De ce fait le module de fusion à intégrer sur la plateforme EMUTEM regroupe les trois niveaux de fusion comme le montre la figure 3.2.

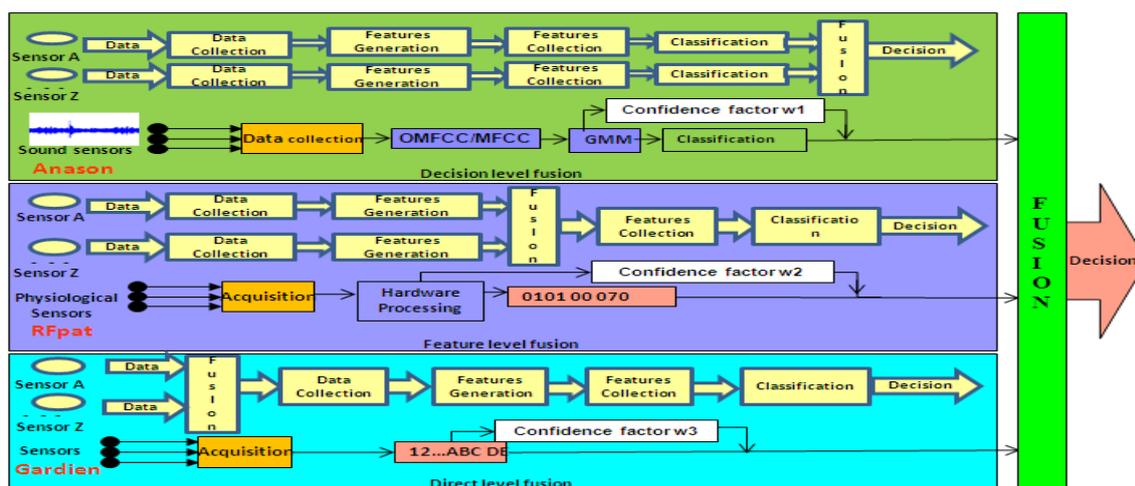


Fig.3.2 : L'architecture de fusion de la plateforme EMUTEM

3/La recherche des outils adaptés

Pour résoudre un problème de fusion, et tenant compte de la nature de données traitées par notre plateforme EMUTEM, dans le domaine statistique, on a identifié des méthodes linéaires généralisées basées sur les probabilités bayésiennes [8,9,10], puis les modèles statistiques telle que les modèles de Markov cachés (HMM) [11] et aussi les modèles graphiques basés sur les réseaux bayesiens, mais il s'est avéré que les performances peuvent être remises en cause dès que les données sont trop complexes (présentant des imbrications, hétérogène, de grande taille). Par ailleurs, les valeurs des coefficients de ces modèles peuvent être difficiles à relier à la réalité des besoins des médecins. Donc ils ne remplissent pas l'exigence d'intelligibilité.

A l'opposé de ces modèles linéaires, on a étudié les modèles connexionnistes (ANN [12]) très performants puisqu'ils parviennent à modéliser des non-linéarités fortes mais au prix d'une architecture complexe et, là encore, ils ne remplissent pas l'exigence d'intelligibilité (les poids associés aux connexions d'un MLP ne sont pas reliés à une réalité physique). Les SVM [13], malgré le transit dans l'espace des caractéristiques qu'est déconnecté de toute réalité physique, pourraient remplir cette exigence d'intelligibilité puisque seule la détermination des vecteurs supports des frontières entre classes est nécessaire.

La logique floue introduite par L.A. Zadeh [14] qui traite l'incertitude et l'imprécision répond aux exigences de performance et d'intégrabilité de la plateforme EMUTEM et elle est plus en adéquation avec le raisonnement humain.

En se basant sur ces constats et compte tenu de la complexité des données à traiter (mesures audio, physiologiques et multi-sensoriel) et la difficulté de modéliser statistiquement une situation anormale relative aux personnes âgées, la logique floue a été jugé utile pour être le module de décision de notre plateforme multimodale EMUTEM. La logique floue peut répondre à la fois aux critères de performance et d'intelligibilité, de plus elle permet de traite l'imprécision et l'incertitude. Elle repose un historique d'application pour les problèmes cliniques y compris l'utilisation dans le diagnostic automatique.

4/ La logique floue

En 1965, Zadeh [14] introduit le concept de la logique floue et depuis ce temps plusieurs applications basées sur ce concept ont été développées. Ce concept reflète le raisonnement humain basé sur l'incertitude et l'imprécision en introduisant la notion d'appartenance partielle d'un élément 'x' à un ensemble 'A'. La figure 3.3 résume le fonctionnement d'un système d'inférence floue.

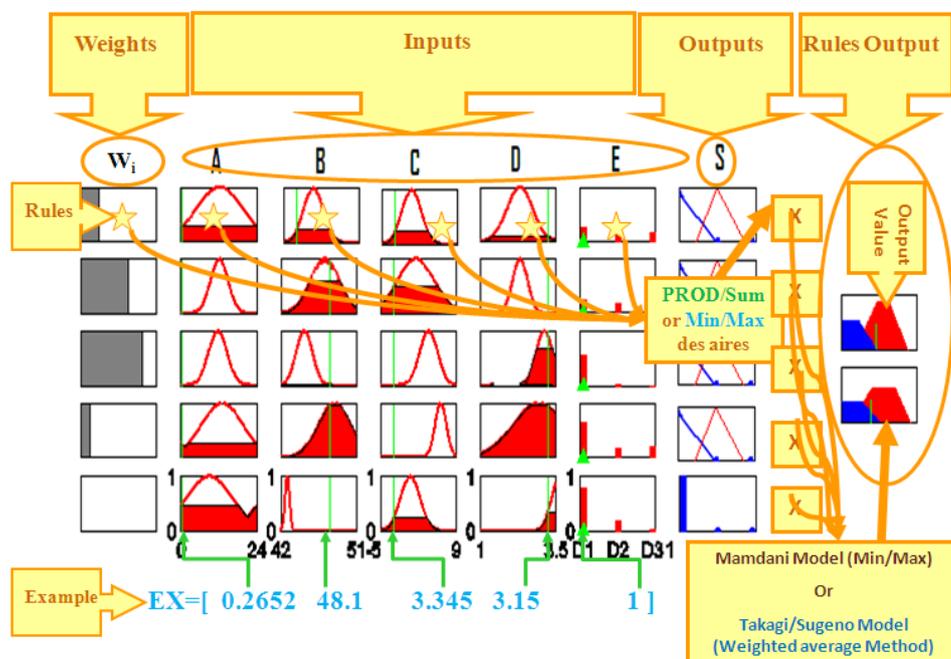


Fig.3.3 Un système d'inférence floue

La « fuzzification » est la première étape de la logique floue. Elle convertit les données à un ensemble de variables floues en associant à chaque entrée et sortie de système un ensemble de fonctions d'appartenances. Le système d'inférence flou utilise des règles basées sur des opérateurs logiques qui relient les entrées aux sorties. Il y a plusieurs types de règles floues, parmi eux Mamdani [15] et Takagi/Sugeno [15] qui sont intégrés sur la plateforme EMUTEM. La « defuzzification » est la dernière étape de système d'inférence floue, elle transforme les ensembles flous engendrés par les règles floues en valeurs réelles à l'aide de fonctions de defuzzification telles que le « Centre de gravité », le « Plus petit des Max »...ect.

5/ La place de la logique floue dans les systèmes de classification

D'un point de vue global, l'utilisation d'ensembles flous peut se faire essentiellement à deux niveaux :

- **La représentation des attributs:** il peut arriver que des données soient incomplètement spécifiées ou fortement bruitées, peu fiables, ou encore que certains attributs soient difficilement mesurables avec précision ou difficilement quantifiables numériquement. A ce moment-là, il est naturel de recourir à des ensembles flous pour décrire la valeur de ces paramètres. Les attributs sont alors des variables linguistiques, dont les valeurs sont construites avec des adjectifs et des adverbes du langage courant : *grand, petit, très, un peu*, etc.
- **La représentation des classes:** les classes ne forment plus une partition nette de l'espace, mais une partition floue où le recouvrement est autorisé. De cette façon, un même individu peut appartenir à plusieurs classes. Un bon nombre de méthodes floues de reconnaissances des formes sont en fait des extensions de méthodes classiques basées sur l'idée de partition floue : c-moyennes floues, K- plus proches voisins flous, etc.

Plutôt que de créer de nouvelles méthodes de reconnaissance basées sur des approches entièrement différentes, les ensembles flous s'insèrent naturellement dans l'expression même du problème de la reconnaissance, et vont apporter soit une généralisation des méthodes qui existent déjà soit un procédé de combinaison avec ces méthodes.

- **Description des données :** La logique floue est utilisée pour décrire les données syntaxiques [16], les données numériques et contextuelles, les données conceptuelles ou des données basée sur des règles, cela est la contribution la plus signifiante pour la description des données.
- **Analyse des paramètres discriminants:** C'est l'ensemble des méthodes qui à partir des données brutes tentent de les raffiner pour améliorer les performances ou diminuer la charge de calcul, la taille mémoire, etc. en ne gardant que l'essentiel. On peut distinguer deux types de méthodes : le prétraitement qui représente toutes les méthodes qui "nettoient" les données brutes (normalisation, filtrage, lissage, etc.), En traitement d'image, il existe un bon nombre de techniques à base de logique floue pour des opérations de segmentation, détection de bords, amélioration du contraste, égalisation d'histogramme [17], extraction : toutes les manipulations qui abaissent la dimension du vecteur de caractéristiques, allant de la simple sélection aux techniques plus sophistiquées de recherche d'axes (analyse en composante principale, analyse factorielle, etc.). Là aussi, il existe des techniques basées sur la logique floue, bien que ce domaine ait été encore peu exploré jusqu'à présent. Citons une méthode utilisant la version floue des c-moyennes [18], ainsi que [19], basée sur des mesures de « fuzziness ».

- **Algorithmes de regroupement:** Les algorithmes de regroupement ont pour but de partager un ensemble de données non étiquetées en groupes, de telle sorte que les groupes obtenus contiennent des individus les plus semblables possible, tandis que des individus de groupes différents sont le plus dissemblables possible. Les algorithmes classiques les plus utilisés sont l'algorithme des c -moyennes où on suppose le nombre de classes connu, et sa généralisation, l'algorithme « ISODATA [20] », où est obtenu automatiquement à l'aide d'un critère heuristique de validité des groupes.
- **Conception du discriminateur:** Le discriminateur est conçu pour produire une partition floue ou un nette, décrivant les données. Cette partition correspond aux classes à viser par le système de discrimination. En effet, l'algorithme « fuzzy ISODATA » est adapté pour cette étape.

IV. Implémentation et les détails de mise en œuvre

Après avoir sélectionné la logique floue pour être le noyau de l'approche de fusion à implémenter sur le module de décision de la plateforme EMUTEM, on procède à l'implémentation de cette nouvelle approche de fusion. La plateforme est nommée maintenant FL-EMUTEM.

1/ Le désigne de l'architecture de fusion

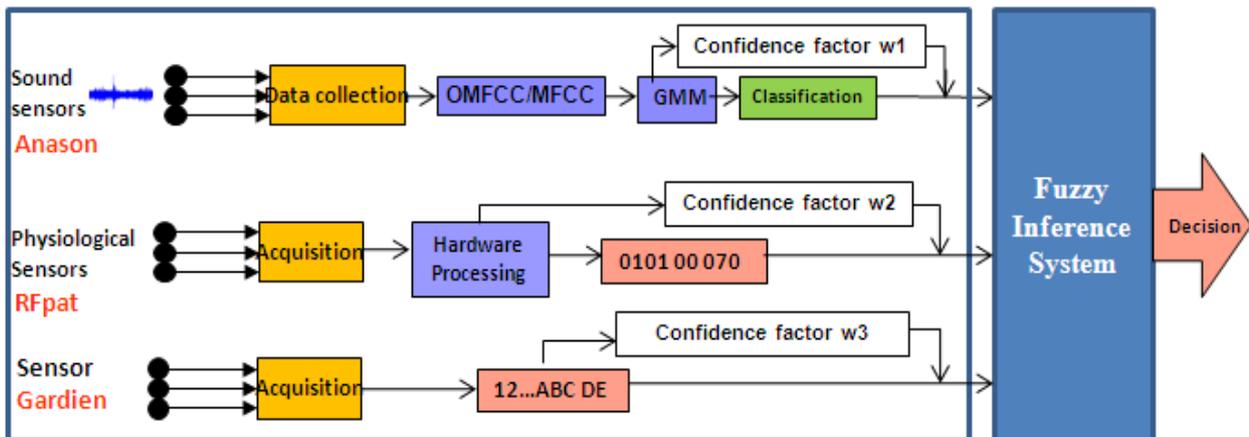


Fig.4.1 : Le désigne de l'architecture de fusion

La figure 4.1 montre le désigne de l'architecture de fusion incorporée dans la plateforme FL-EMUTEM. Le facteur de confiance $w1$ issu d'Anason correspond à la vraisemblance associée à chaque classification. Pour RFpat le facteur de confiance $w2$ est calculé durant la phase de débruitage des signaux vitaux. Pour Gardien le facteur de confiance est calculé en fonction de nombre de capteur activé reçu sur une trame de donnée et aussi leur position dans l'appartement, le idéal est quand on reçoit une trame avec deux capteurs activé, un horizontal et l'autre vertical alors la valeur 1 est attribuée pour le facteur de confiance $w3$.

2/ Architecture logicielle

La figure 4.2 montre l'architecture de notre plateforme. Elle est implémentée sous forme de composants associés à chaque tâche, en utilisant le langage C++ et LabWindowsCVI. On peut distinguer trois principales composantes, la partie acquisition qui encapsule les différents modules d'acquisition associés à chaque modalité, un composant multitâche pour la synchronisation et le module d'inférence floue.

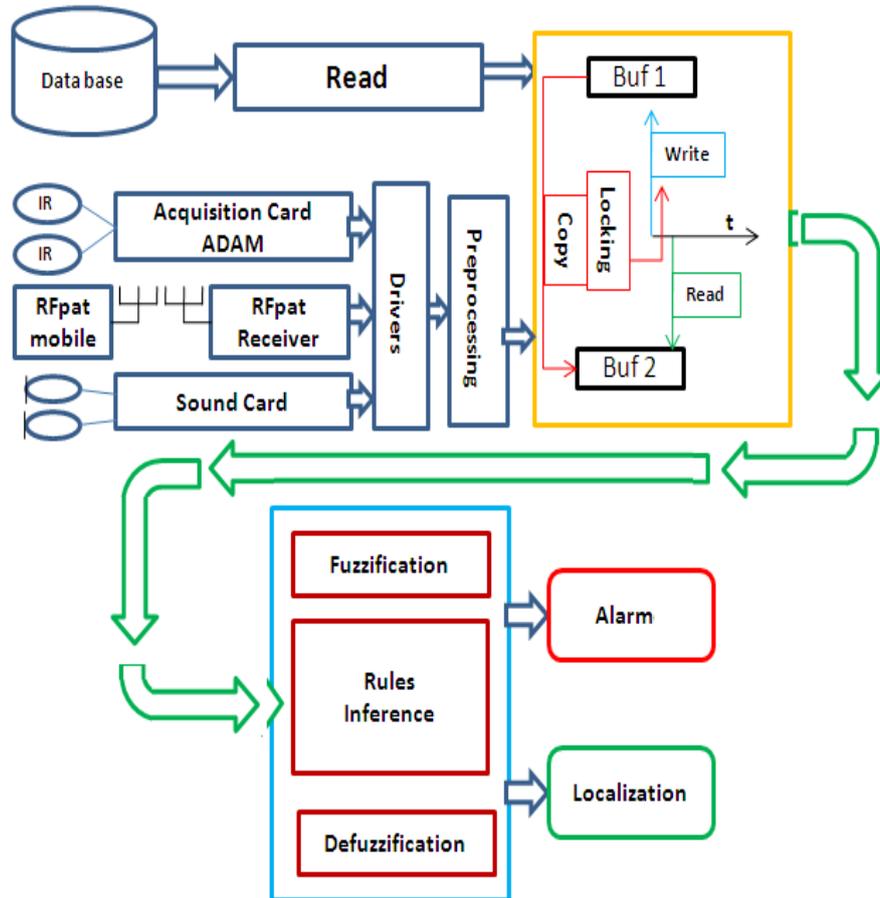


Fig. 4.2 : L'architecture logicielle de la plateforme FL-EMUTEM

3/ La fuzzification

Pour implémenter cette approche, les entrées et les sorties de notre plateforme FL-EMUTEM ont été « fuzzifiées »

3.1/ La fuzzification des sorties Anason

Anason produit trois entrées, la classification des événements sonores ou toutes les classes de son et les expressions de détresses à détecter sont numérisées sur une échelle numérique spécifique avec quatre fonctions d'appartenance en fonction de leurs degrés de détresse. Deux autres entrées sont issues des RSB (rapport signal à bruit) associés à chaque microphone avec trois fonctions d'appartenance. La figure 4.3 illustre cette fuzzification.

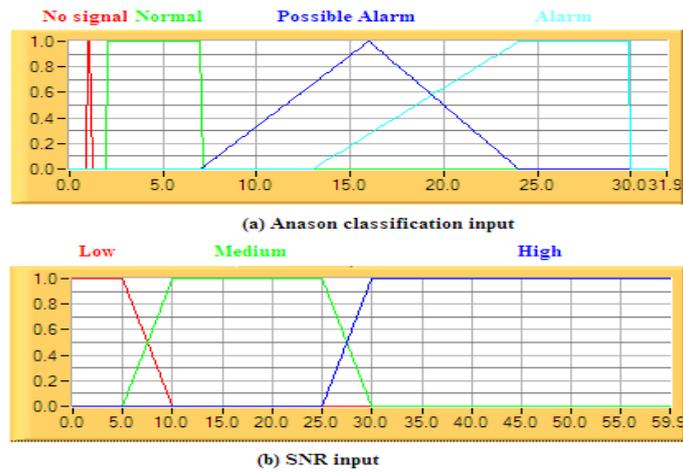


Fig.4.3 : la fuzzification des sorties Anason

3.2/ La fuzzification des sorties RFpat

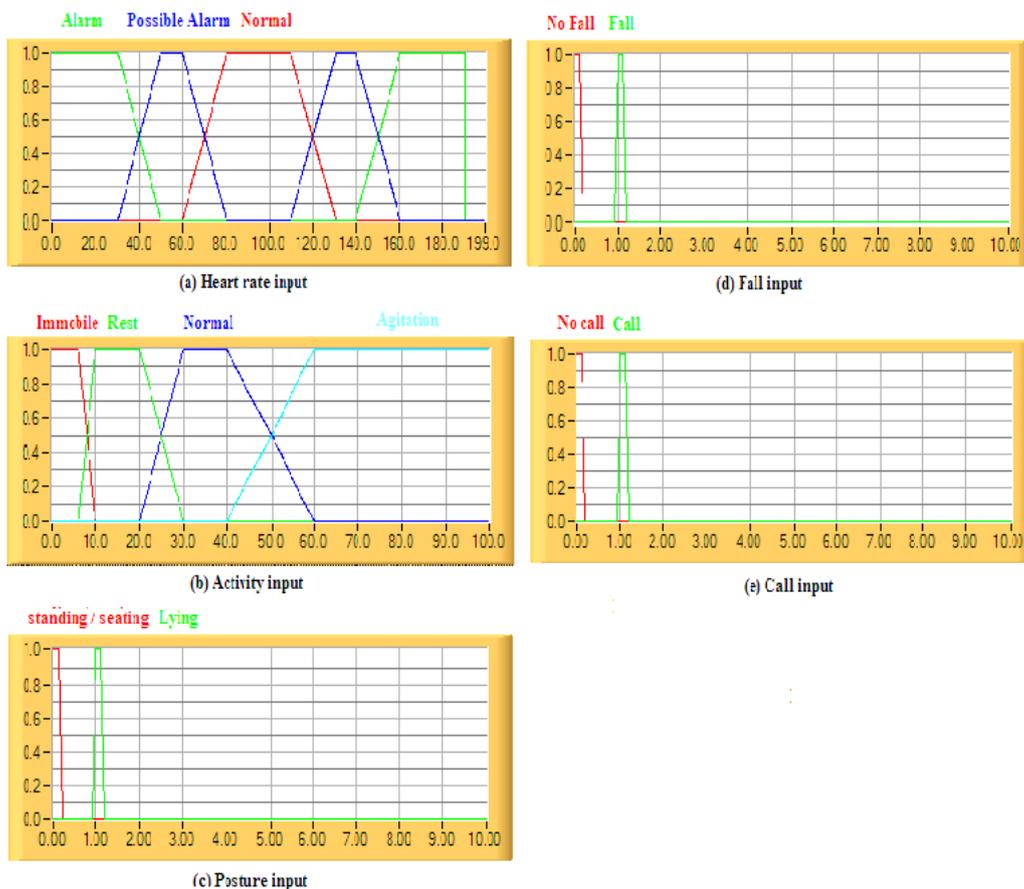


Fig.4.4 : La fuzzification des sorties RFpat

RFpat produit cinq entrées (Index chute, Inclinaison, Mouvement, Pouls et Autonomie) qui sont aussi fuzzifiées. La figure 4.4 montre les fonctions d'appartenance de chaque sortie.

3.3/ La fuzzification des données Gardien

Pour chaque capteur infrarouge un compteur de nombre de détections de présence est associé, avec trois fonctions d'appartenance. Une autre fonction d'appartenance est associée à un compteur de nombre de présence globale associé à l'ensemble des capteurs infrarouges. Une fonction d'appartenance de type singleton est aussi à chaque capteur de contact et de changement d'état.

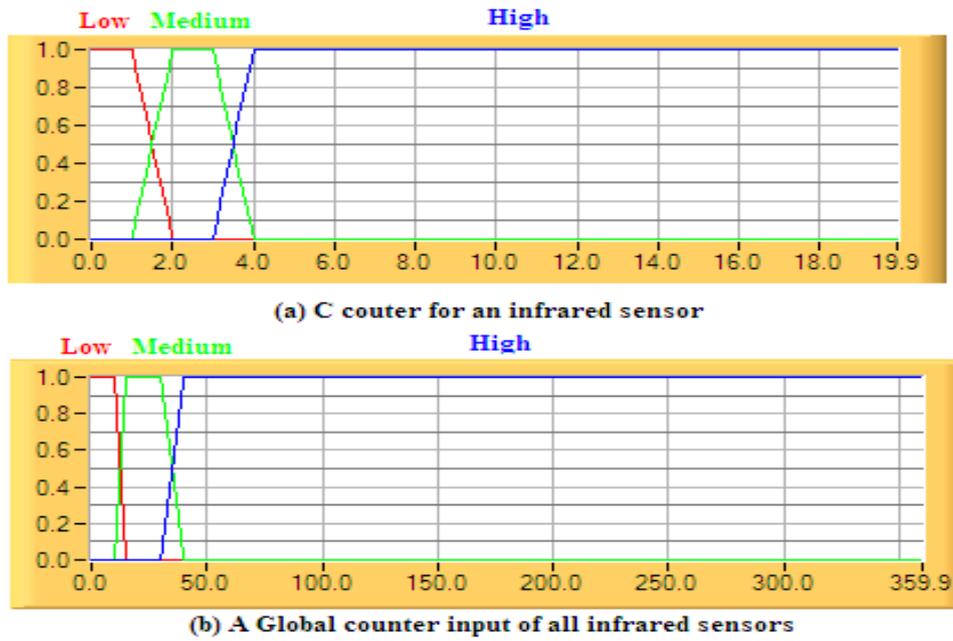


Fig4.5 : La fuzzification de sorties Gardien

3.5/ La fuzzification de la variable temps

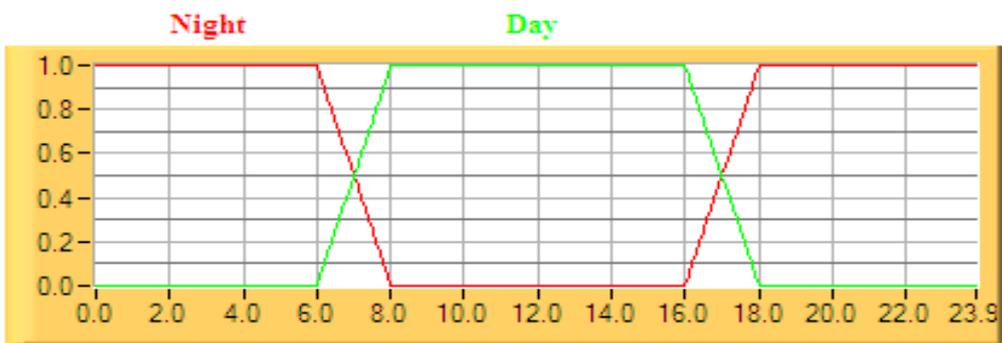


Fig4.6 : la fuzzification de temps

La dernière entrée est le temps (horaire dans la journée) avec deux fonctions d'appartenances jour et nuit.

3.6/ La fuzzification des sorties

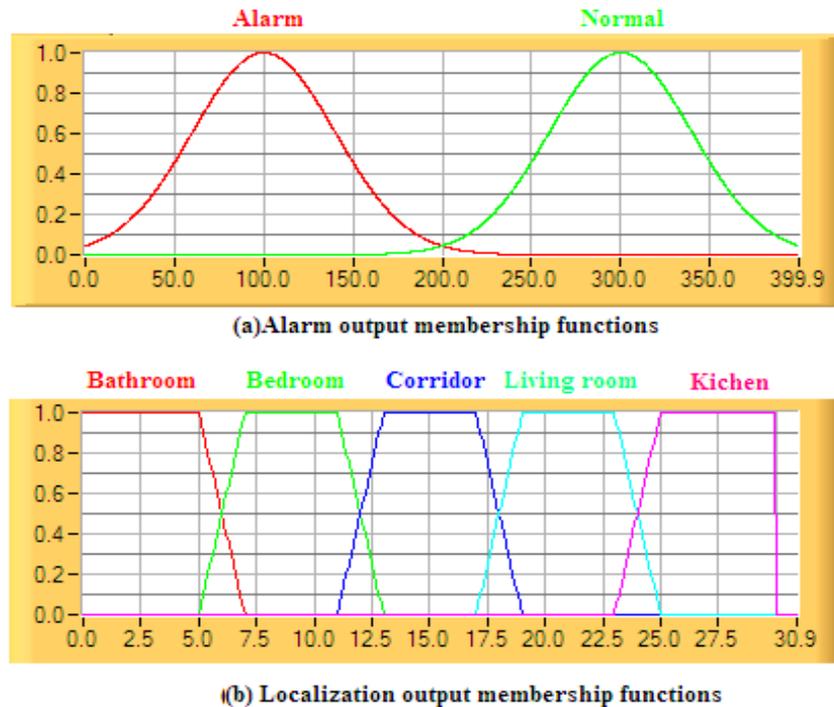


Fig.4.6 : La fuzzification des sorties de la plateforme FL-EMUTEM

FL-EMUTEM possède deux sortie une sortie « Alarme » avec deux fonctions d'appartenance et une sortie « Localisation » où les pièces d'appartement (ou zones) sont ces fonctions d'appartenance.

4/ Agrégation des règles

Le module d'inférence flou d'EMUTEM est basé sur les règles de Mamdani et Sugeno, un exemple d'une règle pour la détection d'alarme est :

Si (Anason classification est absence de signal) et (pouls est alarme possible) et (Activité est immobile) et (Cc est bas) et (C8 est bas) et (Cg est bas) alors (Alarme est alarme).

Pour chaque règle un facteur de confiance est associé.

5/La defuzzification

Après l'agrégation des règles la defuzzification est effectuée en utilisant la méthode de plus petits des maximums pour la sortie alarme et la méthode de centre de gravité pour la sortie Localisation.

6/ Interface graphique de FL-EMUTEM

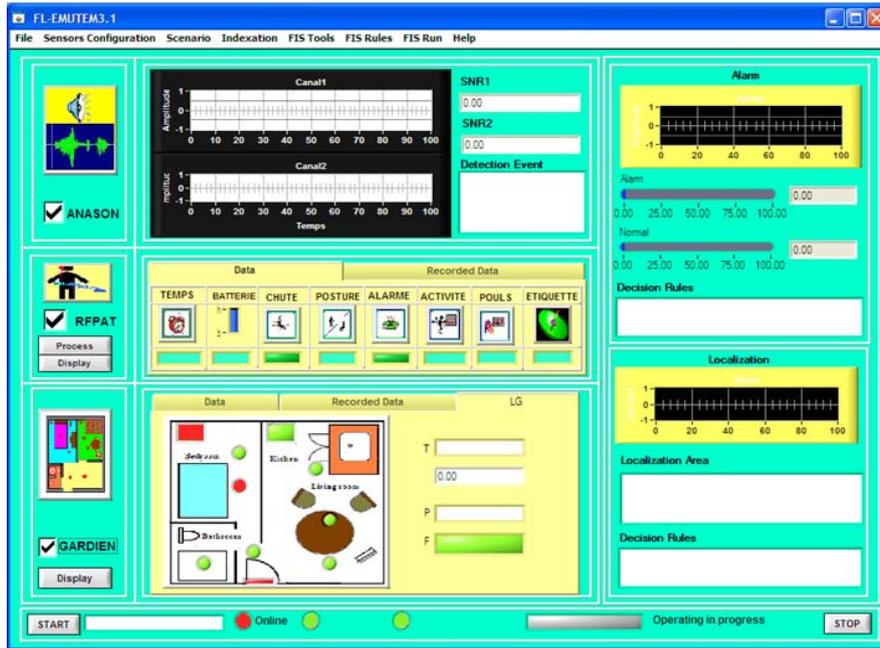


Fig. 4.7 : Interface graphique de la plateforme FL-EMUTEM

L'interface graphique de FL-EMUTEM facilite la configuration et la mise en œuvre du système d'inférence flou. Elle nous offre la possibilité de configurer chaque modalité et aussi la fuzzification de ses sorties. On a aussi le choix pour sélectionner la fonction d'appartenance associé à chaque fuzzification et aussi la méthode de defuzzification à utiliser pour chaque sortie. Une interface graphique pour éditer les règles associées pour le système d'inférence flou est aussi disponible sur cette interface (Figure 4.8).

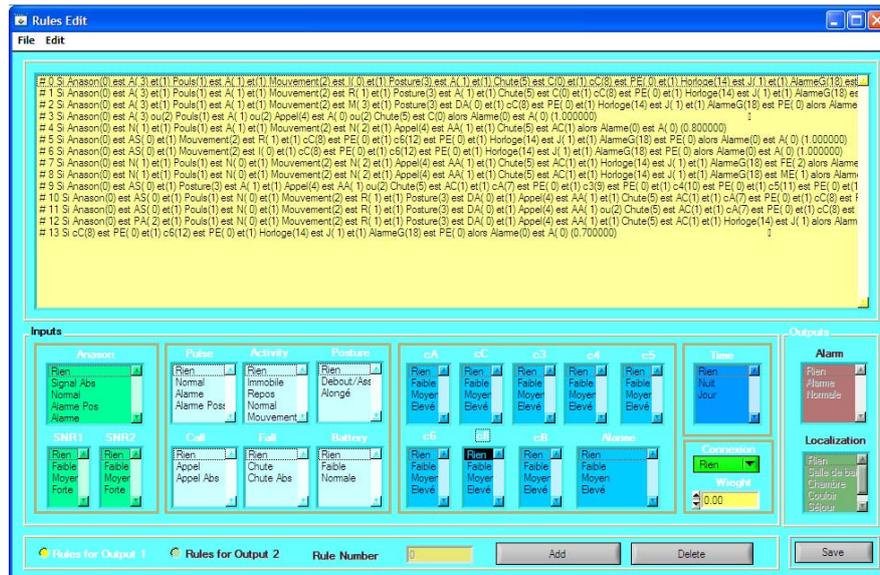


Fig.4.8 : Interface graphique pour l'édit des règles

V. Expérimentations et résultats

1/Généralité

La mise en place d'un processus expérimental nécessite la définition du contexte expérimental, de l'ensemble de données nécessaires à l'expérimentation, de la méthodologie d'expérimentation et des mesures de performances nécessaires à l'évaluation du système.

L'expérimentation de l'approche proposée pour la fusion de donnée multimodale est réalisée dans le cadre de la télévigilance médicale à domicile. Dans ce contexte, le système a pour objectif la détection des situations de détresse qui peuvent surgir chez une personne âgée dans son domicile.

Parmi les données expérimentales il y a les données issues de la base de données décrites précédemment dans le chapitre 2. Comme nous n'avons pas suffisamment de données représentant différentes situations de détresse, l'expérimentation est aussi effectuée à l'aide de données simulées. L'avantage de considérer les données simulées est leur capacité à générer des séquences qui représentent plusieurs situations, dont plusieurs profils de personnes âgées.

La mise en place d'un processus expérimental nécessite de disposer de critères appropriés à l'évaluation objective des performances du système. Pour cela on a retenu un ensemble de métriques à utiliser pour l'évaluation des résultats expérimentaux :

- La sensibilité $Sp(\%) = VP / (VP + FN) * 100$
- La spécificité $Se(\%) = VN / (VN + FP) * 100$
- L'erreur de classification $Err(\%) = (FN + FP) / (VN + FN + FP + VP) * 100$
- La bonne classification $Pc(\%) = (VN + VP) / (TN + FN + FP + TP) * 100$

Ou VP : vrai positif, VN: vrai négatif, FP : Faux positif, FN : Faux négatif.

2/ Résultats

Nous avons commencé les tests à l'aide de données simulées, afin de valider chaque règle. Cette simulation a donné des résultats très prometteurs pour la génération d'Alarme et la Localisation.

Après la validation des règles on a utilisé 100 séquence de simulation dont 70 représentent des situations de détresse et 30 des situations normales. Le tableau 5.1 représente les résultats obtenus.

		FL-EMUTEM Classification	
		Situation Anormale	Situation Normale
Séquences simulées	Situation Anormale	68	2
	Situation Normale	1	29

Tableau 5.1 : Matrice de confusion pour les données simulées

Le tableau 5.2 illustre les résultats issus de cette matrice de confusion.

Métrique	Valeur (%)
Sp	97
Se	96
Err	3
Pc	97

Tableau 5.2 : Le résultat des données simulées

Après cette validation avec la simulation, EMUTEM est testé sur une base de données issue de 20 scénarios qui reflète la vie quotidienne des personnes âgées, dont 10 scénarios contiennent des situations de détresse et 10 autres aucune situations de détresse. La stratégie utilisée consiste à réaliser plusieurs tests avec différentes combinaisons de règles et, en fonction des résultats obtenus, une ou plusieurs règles sont ajoutées à l'ensemble présélectionné de règles afin d'obtenir la détection manquée. Grâce à cette stratégie des résultats encourageants ont été obtenus pour les deux sorties.

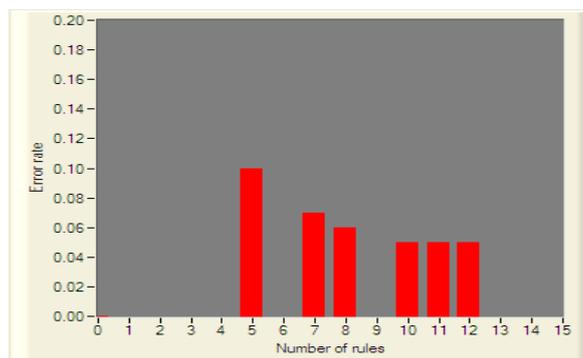


Fig.5.1 : Le taux d'erreur pour la sortie Alarme en fonction de nombre de règles

Figure 5.1 montre l'histogramme de taux d'erreur pour la sortie alarme en fonction au nombre de règles utilisées dans le système d'inférence flou, il diminue lorsque le nombre de règles augmente. Avec 10 règles pour la sortie alarme et 16 règles pour la sortie localisation on a obtenu environ 95% de bonne

détection pour la sortie alarme et 97% de bonne localisation pour la sortie localisation sont atteints. Le taux d'erreur pour la sortie alarme correspond à des situations qui ne sont pas détectables par les capteurs utilisés par FL-EMUTEM et aussi la difficulté à définir la bonne règle permettant de surmonter cette situation. Pour la sortie localisation le taux d'erreur pourrait être justifié par le fait que nous utilisons un local simulé en appartement et ainsi la difficulté de calibrer les capteurs infrarouges.

3/Synthèse

Selon la stratégie utilisée dans cette phase d'expérimentation et selon les résultats obtenus par le système d'inférence floue qui est utilisé dans la plateforme FL-EMUTEM, notre system a présenté quatre propriétés importantes:

- **Intelligibilité** : La description de modèle de décision utilisé dans la plateforme FL-EMUTEM, avec l'inférence floue devient relativement aisée puisqu'elle est principalement basée sur l'emploi de règles linguistiques décrivant l'expertise, les règles de décision étudiées, les règles floues s'avèrent commodes pour associer les actions opérées par l'agent décisionnaire aux conditions décrivant, même de façon partielle et vague, les situations rencontrées lors de la prise de décision. Cette simplification de l'architecture de modèle entraîne une plus grande simplicité de programmation, une plus grande flexibilité et de plus faible coûts de maintenance. En outre, par sa lisibilité et sa similarité avec le langage naturel, ce formalisme à base de règles facilite le dialogue entre ingénieurs et médecins, par exemple l'ingénieur n'a plus besoin d'expliquer qualitativement ce que modélise quantitativement une équation différentielle. L'interface graphique de FL-EMUTEM avec son architecture permet une bonne supervision des expériences par sa flexibilité dans l'ajout ou la suppression de règles et également la modification du poids de chaque règle, le choix des fonctions d'appartenance et le modèle d'agrégation des règles.
- **Localité** : Lors des expériences, nous avons vu que la décision de la plateforme FL-EMUTEM sur une situation donnée qui peut être décrite en termes vagues, incertaines et subjectives, est prise par des règles. La modification de la décision de FL-EMUTEM à propos d'une situation donnée est alors obtenue par la modification des règles locales qui sont associées à l'une de ces sorties de la plateforme. Cette modification des règles localement ne conduira pas à un changement global de la décision de la plateforme, mais elle ne produit que des changements dans le système de décision au sujet de la situation visée. Cette propriété de localité facilite la supervision des expérimentations.
- **Traçabilité** : Durant la phase expérimentale de la plateforme EMUTEM, on a eu la possibilité de tracer le chemin utilisé par le système d'inférence flou pour atteindre la décision finale en partant des entrées. Il suffit pour cela de lister les règles floues qui ont été déclenchées, avec leurs degrés d'activation. De ce fait, la validation du modèle flou s'en trouve facilitée.
- **Flexibilité** : La plateforme FL-EMUTEM nous permet d'ajouter d'autres modalités, et ainsi d'augmenter le nombre d'entrées pour le système d'inférence floue. Il est également possible d'affiner localement une règle, dont le comportement serait jugé grossier, en la remplaçant par un groupe de règles plus spécialisées. Une règle de localisation a été modifiée avec cette technique au cours des expériences.

VI. Conclusion

Dans ce travail de recherche, pour répondre au contexte de la thèse, nous avons développé une nouvelle plateforme représentant un environnement multi-capteurs pour l'acquisition de données fournies par des différents capteurs. Cette plateforme assure la surveillance de l'état de santé du patient/personne âgée et elle permet de détecter les situations de détresse. Nous avons réuni trois différentes modalités afin d'assurer une sécurité optimale du patient/personne âgée dans un cadre confortable et de façon non intrusive. Nous proposons un appareil portable capable d'acquérir et de traiter les signaux vitaux, un capteur intelligent analysant les sons de tous les jours en vue de détecter les situations de détresse et un réseau de capteurs infrarouges qui localise la personne dans son domicile et détecte sa position verticale, et qui est également composé de capteurs de contact et de changement d'état pour bien surveiller l'environnement de patient (ouverture fermeture de porte, température...etc.).

L'originalité de ce travail est la multimodalité issue de la synchronisation des différentes modalités. Un processus de simulation est intégré dans cette plateforme pour remédier au manque de données réelles correspondantes aux vraies situations de détresse. L'apport de cette plateforme a été valorisé par l'enregistrement d'une base de données médicale multimodale.

Pour traiter ces différentes données hétérogène, une nouvelle approche de fusion de données basée sur la logique floue est adoptée pour être le noyau de module de décision de la plateforme FL-EMUTEM. La plateforme FL-EMUTEM qui encapsule cette architecture a été mise en œuvre et validée par la simulation et l'expérimentation. Cette approche permet de combiner plusieurs modalités et aussi d'ajouter ou d'éliminer facilement une modalité, ce qui confère une très grande flexibilité à notre système de télévigilance.

Notre but ultime est de rendre ce système de télévigilance plus robuste pour aider le personnel médical à prendre en temps réel la bonne décision sur l'état de santé des personnes âgées.

Pour étendre cette approche de fusion basée sur la logique floue et pour qu'elle soit plus robuste, nous envisageons d'introduire la technique des arbres de décision flous sur cette méthode de fusion. Après cela, une mise en œuvre embarquée de la plateforme FL-EMUTEM conduira à un système fonctionnel en temps réel.

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