Medical Remote Monitoring using sound environment analysis and wearable sensors

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1. Introduction

The developments of technological progress allow the generalization of digital technology in the medicine area, not only the transmission of images, audio streams, but also the information that accompany them. Many medical specialties can take advantage of the opportunity offered by these new communication tools which allow the information share between medical staff. The practice of medicine takes a new meaning by the development and diffusion of Information and Communication Technologies (ICT). In the health field, unlike other economic sectors, the technical progress is not necessarily generating productivity gains but generate more safety and comfort for patients.

Another fact is that 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[i]. Moreover, the elderly prefer to preserve their independence, autonomy and way of life living at home the longest time possible. The number of medical specialists decreases with respect to the increasing number of elderly fact that allowed the development of technological systems to assure the safety (telemedicine applications).

The elderly living at home are in most of the cases (concerning Western and Central Europe and North America) living alone and with an increased risk of accidents. In France, about 4.5 % of men and 8.9% of women aged of 65+ years has an everyday life accident[ii]. Between these everyday life accidents, the most important part is represented by the domestic accidents; about 61% (same source) and 54% of them take place inside the house. In France, annually, 2 millions of elderly falls take place, which represent the source of 10 000 deaths[iii]. Between 30% and 55% of falls cause bruises and only 3% to 13% of falls are the causes of serious injuries such as fractures, dislocation of a joint, or wounds. Apart from physical injury and hospitalization, a fall can cause a shock (especially if the person cannot recover only after the fall). This condition can seriously affect the senior psychology, he might looses the confidence in his abilities and can result in a limitation of daily activities and, consequently, in a decrease of the life quality.

In order to improve the quality of life of elderly several applications has been developed: home telemonitoring in order to detect distress situations and audio-video transmission in order to allow specialists to diagnose patient at distance.

This chapter describe a medical remote monitoring solution allowing the elderly people to live at home in safety.

2. Telemedecine applications

The term ″telemedicine″ appears in a dictionary of the French language for the first time in the early 1980′s, the prefix ″tele″ denoting ″far away″. Thus, telemedicine literally means remote medicine and is described as ″part of medicine, which uses telecommunication transmission of medical information (images, reports, records, etc.) in order to obtain remote diagnosis, a specialist opinion, continuous monitoring of a patient, a therapeutic decision.″
Using a misnomer, one readily associates the telemedicine to the generic term ″health telematics″. This term has been defined by the World Health Organization in 1997 and ″refers to the activities, services and systems related to health, performed remotely using information technology and communication needs for global promotion of health, care and control of epidemics, management and research for health.″

The interest of telemedicine is far from being proved and is not without stimulating reflection, particularly in the areas ethical, legal and economic. The main telemedicine applications are:

- **Telediagnostic** = The application which allow a medical specialist to analyze a patient at distance and to have access to different medical analysis concerning the patient. A specific case can be if a specialist is at the same place with the patient but need a second opinion from another one.
- **Telesurgery** = technical system allowing a surgery at distance for spatial or military applications. Also in this category we can have the distant operation of a complex system like an echograph or the augmented reality in order to help the medicine in the framework of a surgery.
- **Telemonitoring** = an automatic system which survey some physiological parameters in order to monitor a disease evolution and/or to detect a distress situation.
- **Tele-learning** = teleconferencing systems allowing medical staff to exchange on medical information.

Among the main telemedicine applications, telediagnostic and telemonitoring are more investigated solutions. The telediagnostic allows medical specialist to consult the elderly through audio video link in order to avoid unnecessary travel for both patient and medical staff. Several systems were currently developed between hospital and nursing home, or between medical staff and a mobile unit. The main challenges are the audio-video quality, the possibility to transmit also other medical data (ECG, medical records) and data security. In order to guarantee a good audio-video quality a high bandwidth network is needed.

The medical remote monitoring or telemonitoring can prevent or reduce the consequences of accidents at home for elderly people or chronic disease persons. The increase of aging population in Europe involves more people living alone at home with an increased risk of home accidents or falls. The remote monitoring aims to detect automatically a distress situation (fall or faintness) in order to provide safety living to elderly people.

The medical remote monitoring consists in establishing a remote monitoring system of one or more patients by one or more health professionals (physician, nursing...). This monitoring is mainly based on the use of telecommunication technology (ie the continuous analysis of patient medical parameters of any kind: respiratory, cardiac, and so on...). This technique is used in the development of hospitalizations at home, ie where the patient is medically monitored at home, especially in cases of elderly people. In addition, this method avoids unnecessary hospitalizations, increasing thus the patient comfort and security. The main aim of remote monitoring systems is to detect or to prevent a distress situation using different types of sensors.

In order to improve the quality of life of elderly several research teams have developed a number of systems for medical remote monitoring. These systems are based on the deployment of several sensors in the elderly home in order to detect critical situations. However, there are few reliable systems capable of detecting automatically distress situations using more or less non intrusive sensors. Monitoring the activities of elderly people at home with position sensors allows the detection of a distress situation through the circadian rhythms (Bellego et al., 2006). However, this method involves important data bases and an adaptation to the monitored person (Binh et al., 2008). Other studies monitor the person activity through the use of different household appliances (like oven or refrigerator) (Moncrieff et al., 2005). More and more applications use embedded systems, like smart mobile phones, to process data and to send it trough 3G networks (Bairacharya et al., 2008). In order to detect falls, several wearable sensors was developed using accelerometers (Marschollek et al., 2008), magnetic sensors (Fleury et al., 2007) or data fusion with smart home sensors (Bang et al., 2008).

There are many projects which develop medical remote monitoring system for elderly people or for chronic disease patient like TelePat project[iv] which was aimed at the realization of a service of remote support in residence for people suffering of cardiac pathologies (Lacombe et al., 2004). Other National projects like RESIDE-HIS and DESDHIS[v] have developed different modality to monitor like infra-red sensor, wearable accelerometer sensor and sound analysis. At European level (FP6) several projects has investigated the domain of combination of smart home technologies with remote monitoring like SOPRANO project which aims at the design of a system for the assistance of the old people in the everyday life for a better comfort and safety (Wolf et al., 2008).

Consequently, devices of the ambient intelligence are connected continuously to a center of external services as in the project EMERGE[vi]. This last aims by the behavior observation through holistic approach at detecting anomalies, an alarm is sent in the case of fall, faintness or another emergency.

Three institutions (TELECOM & Management SudParis, INSERM U558 and ESIGETEL) have already developed a medical remote monitoring modality in order to detect falls or faintness. The TELECOM & Management SudParis has developed a mobile device which detects the falls, measures the person pulse, movement and position and is equipped with panic button (Baldinger et al., 2004). The ESIGETEL has developed a system which can recognize abnormal sounds (screams, object falls, glass breaking, etc.) or distress expressions (Help!, A doctor please! etc.) (Istrate et al., 2008).

Each remote monitoring modality, individually, present cases of missed detections and/or false alarms but the fusion of several modalities can increase the system reliability and allow a fault tolerant system (Virone et al., 2003). These two modalities and others are combined in the framework of CompanionAble project.

3. CompanionAble Project

A larger telemedicine application which includes sound environment analysis and wearable sensor is initiated in the framework of a European project. CompanionAble[1] project (Integrated Cognitive Assistive & Domotic Companion Robotic Systems for Ability & Security) provides the synergy of Robotics and Ambient Intelligence technologies and their semantic integration to provide for a care-giver's assistive environment. CompanionAble project aims at helping the elderly people living semi or independently at home for as long as possible. In fact the CompanionAble project combines a telemonitoring system in order to detect a distress situation, with a cognitive program for MCI patient and with domotic facilities. The telemonitoring system is based on non intrusive sensor like: microphones, infra-red sensors, door contacts, video camera, pills dispenser, water flow sensor; a wearable sensor which can detect a fall and measure the pulse and a robot equipped with video camera, audio sensors and obstacles detectors.

4. Proposed telemonitoring system

Two modalities sound and wearable sensors are presented by following. A multimodal data fusion method is proposed in the next section.

4.1 ANASON

The information from the everyday life sound flow is more and more used in telemedical applications in order to detect falls, to detect daily life activities or to characterize physical status. The use of sound like an information vector has the advantage of simple and cheapest sensors, is not intrusive and can be fixed in the room. Otherwise, the sound signal has important redundancy and need specific methods in order to extract information. The definition of signal and noise is specific for each application; e.g. for speech recognition, all sounds are considered noise. Between numerous sound information extraction applications

[1] *www.companionable.net*

we have the characterization of cardiac sounds (Lima & Barbarosa, 2008) in order to detect cardiac diseases or the snoring sounds (Ng & Koh, 2008) for the sleep apnea identification. Using sound for the fall detection has the advantage that the patient not need to carry a wearable device but less robust in the noise presence and depend from acoustic conditions (Popescu et al., 2008), (Litvak et al., 2008). The combination of several modalities in order to detect distress situation is more robust using the information redundancy.

The sound environment analysis system for remote monitoring capable to identify everyday life normal or abnormal and distress expressions is in continuous evolution in order to increase the reliability in the noise presence. Currently in the framework of the CompanionAble project a coupled smart sensor system with a robot for mild cognitive impairment patients is being developed. The sound modality is used like a simplified patient-system interface and for the distress situation identification. The sound system will participate to the context awareness identification, to the domotic vocal commands and to the distress expressions/sounds recognition. This system can use a classical sound card allowing only one channel monitor or an USB acquisition card allowing a real time multichannel (8 channels) monitoring covering thus all the rooms of an apartment.

Current systems use mainly the speech information from sound environment in order to generate speech command or to analyze the audio scene. Few studies investigate the sound information. The (Moncrieff et al., 2005) uses the sound level coupled with the use of household appliances in order to detect a threshold on patient anxiety. In (Stagera et al., 2007) some household appliances sounds are recognized on an embedded microcontroller using a vectorial quantization. This method was used to analyze the patient activities, a distress situation being possible to be detected through a long time analysis. In (Cowling & Sitte, 2002) a statistical sound recognition system is proposed but the system was tested only on few sound files.

The proposed smart sound sensor (ANASON) analyzes in real time the sound environment using a first module of detection and extraction of useful sound or speech based on the Wavelet Transform (Istrate et al., 2006). The module composition of the smart sound sensor can be observed in the Fig.1. This module is applied on all audio channels simultaneously, in real time. Only extracted sound signals are processed by the next modules. The second module classifies extracted sound event between sound and speech. This module, like the sound identification engine, is based on a GMM (Gaussian Mixture Model) algorithm. If a sound was detected the signal is processed by a sound identification engine and if a speech was detected a speech recognition engine is launched. The speech recognition engine is a classical one aiming at detecting distress expressions like ″Help!″ or ″A doctor, please!″.

Signal event detection and extraction. This first module listen continuously the sound environment in order to detect and extract useful sounds or speech. Useful sounds are: glass breaking, box falls, door slap, etc. and sounds like water flow, electric shaver, vacuum cleaner, etc. are considered noise. The sound flow is analyzed through a wavelet based algorithm aiming at sound event detection. This algorithm must be robust to noise like neighbourhood 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 even at signal to noise ratio (SNR) of 0 dB. The signals extracted by this module are recorded in a safe communication queue in order to be processed by the second parallel task.

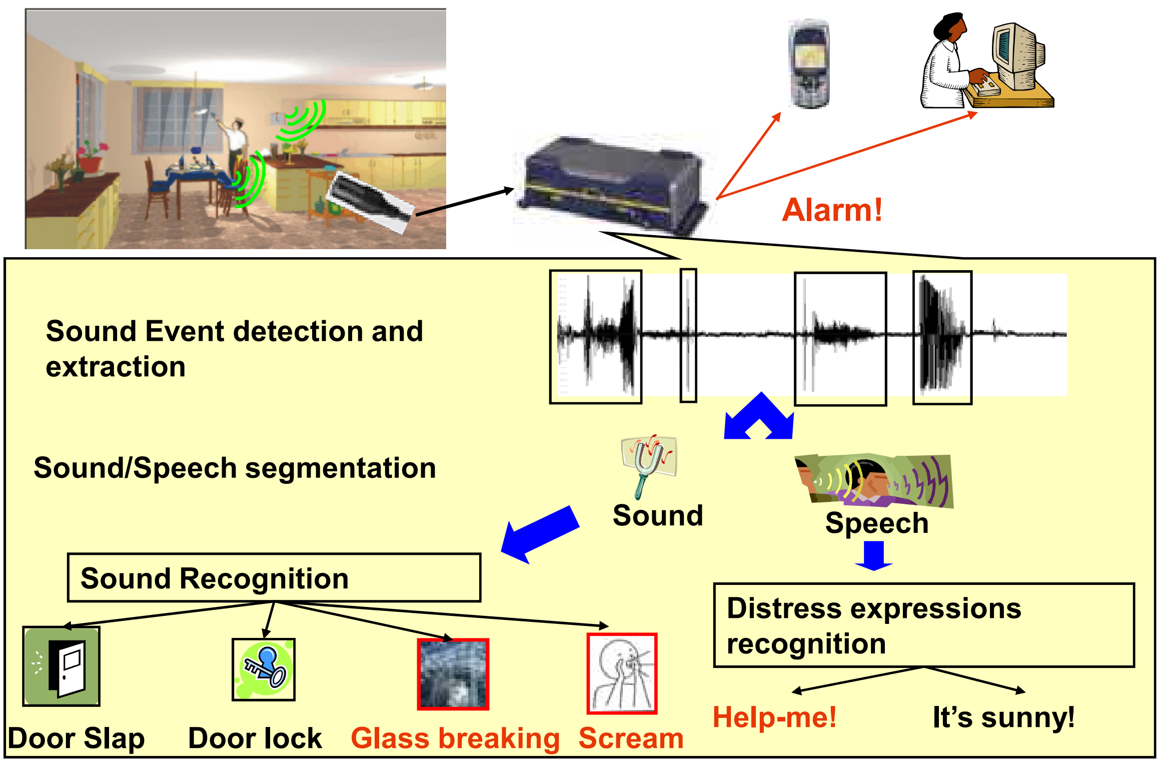

Fig. 1. Sound environment analysis system (ANASON)

Sound/speech segmentation. The second module is a low-stage classification one. It processes the extracted sounds in order to separate the speech signals from the sound ones. The method used by this module is based on Gaussian Mixture Model (GMM). 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. Other types of acoustical parameters like zero crossing rate, roll-off point, centroid or wavelet transform based was tested with good results.

Sound recognition. This module composes with the previous one the second parallel task and classifies the signal between several predefined sound classes. This module is based, also, on a GMM algorithm. The 16 MFCC (Mel Frequency Cepstral Coefficients) acoustical parameters have been used coupled with ZCR (Zero crossing rate), Roll-off Point and Centroid. The MFCC parameters are computed from 24 filters. A log-likelihood is computed for the unknown signal according to each predefined sound classes; the sound class with the biggest log likelihood constitute the output of this module.

In the current version, the number of Gaussians is optimized according to data base size which allows having different number of Gaussians for each sound class. Taking into account that for some sounds, especially for abnormal ones, is difficult to record an important number, we have chosen to allow a variation between 4 and 60 Gaussians for the sound models.

Distress expressions recognition. In order to detect distress expressions two possibilities can be considered: the use of a classical speech recognition engine followed by a textual detection of distress expressions or a word spotting system. The first solution has tested with good results through a vocabulary optimization with specific words.

If an alarm situation is identified (the sound or the sentence is classified into an alarm class) this information and the sound signal are sent to the data fusion system. In the case of a typical everyday life sound, only the extracted information (and not the sound) is sending to the data fusion system.

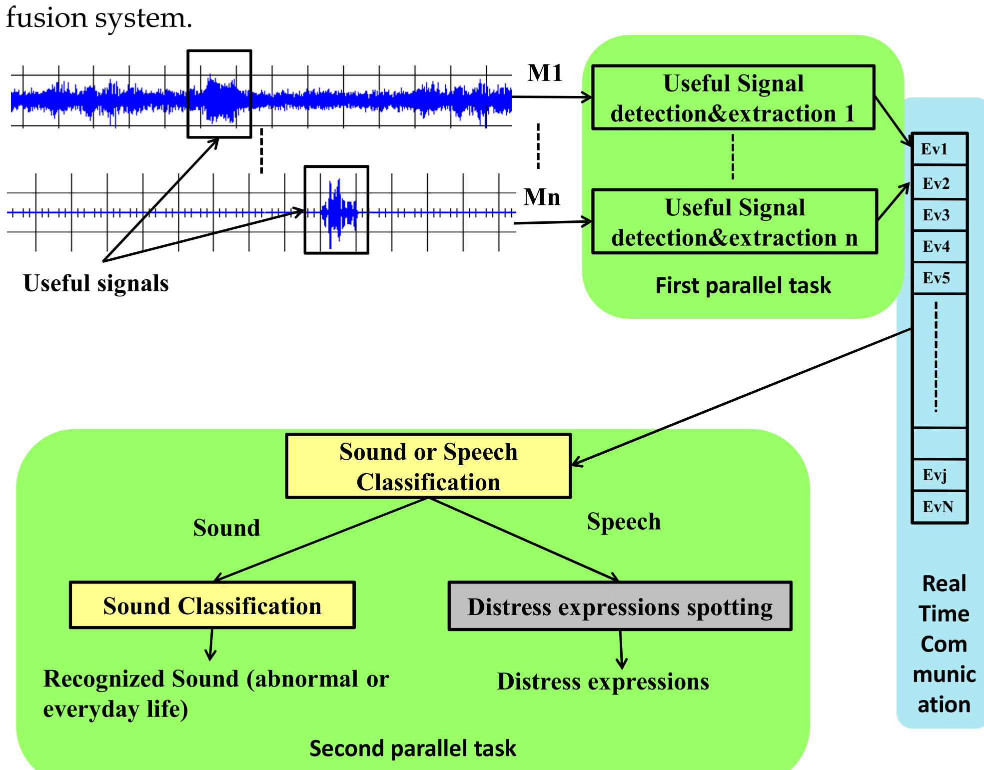

Fig. 2. ANASON real time implementation

ANASON system has been implemented in real time on PC or embedded PC using three parallel tasks (Fig. 2.):

1. Sound Acquisition + Sound Event Detection & Extraction

2. Hierarchical Sound Classification
3. Graphical User Interface and Alarm management

ANASON modality carries out also localization information concerning the microphone which has been used to recognize the abnormal sound or speech and a confidence measure in the output (SNR value).

The speech monitoring allows the system to detect a distress request coming from the patient, if the patient in the distress situation is conscious (the same role that panic button of RFPAT).

Globally, ANASON software has no false alarms and 20 % of missed detections for signals with SNR between 5 and 20 dB (real test conditions). The Useful signal detection and extraction module and the Sound or Speech Classification module work correctly even for signals with a SNR about 10 dB but the sound or speech recognition modules need at least a SNR of 20 dB. We work currently to ameliorate these performances by adding specific filtering and noise adaptation modules.

Fig. 3. Example of sound/speech detection and recognition

Fig.3. shown the ANASON algorithm application on a signal recorded in our laboratory. In the second window the blue rectangle represent the automatic output of ANASON and the gray ones the reference labels (manually labels). We can observe some reduced errors on the start/stop time of each event. All detected events were correctly classified.

4.2 RFPAT

The remote monitoring modality RFPAT consists in two fundamental modules (Fig. 2.):

- A mobile terminal (a waist wearable device that the patient or the elderly clips to his belt, for instance, all the time he is at home; it measures the person's vital data and sends it to a reception base station)

- A fixed reception base station (a receiver connected to a personal computer (PC) through a RS232 interface; it receives vital signals from the patient's mobile terminal, analyzes and records them).

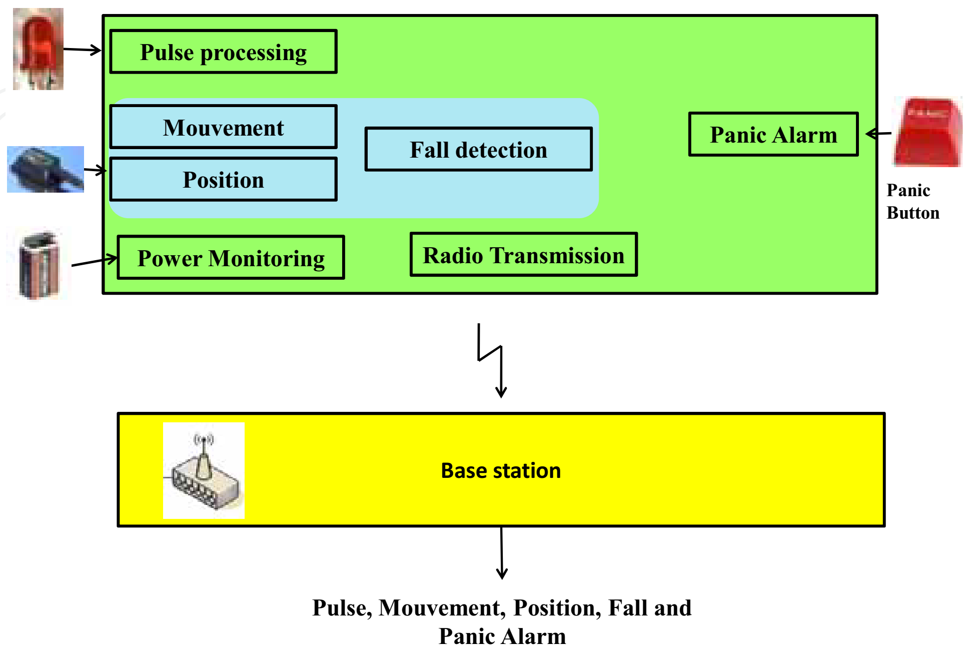

Fig. 4. Wearable device (RFPAT)

All the data gathered from the different RFPAT sensors are processed within the wireless wearable device. To ensure an optimal autonomy for the latter, it was designed 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 (Fig. 4.) encapsulates several signal acquisition and processing modules:

- to records pulse rate, actimetric signals (posture, movement) and panic button
- to pre-process the signals in order to reduce the impact of environmental noise or user motion noise.

This latter point is an important issue for in-home healthcare monitoring. In fact, monitoring a person in ambulatory mode is a difficult task to achieve. For the RFPAT system, the noise is filtered in the acquisition stage inside the wearable device using digital noise reduction filters and algorithms. These filters and algorithms were applied respectively to all acquired signals: movement data, posture data and namely the pulse signal (heart rate).

Movement data describes the movement of the monitored person. It gives us information like: "immobile", "normal life movements", "stressed person", 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 actimetric 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.

The pulse signal is delivered by a photoplethysmographic sensor connected to the wearable device. After pre-conditioning and algorithmic de-noising it gives us information about the heart rate every 30 seconds.

In the ambulatory mode, the challenging process consists in noise reduction (Baldinger et al., 2004). We afford 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 low power microcontroller based computing unit, embedded in the mobile terminal.

Currently, a fall-impact detector is added to this system in order to make the detection of falls more specific.

5. EMUTEM platform

A data synchronization and fusion platform, EMUTEM (Multimodal environment for medical remote monitoring), was developed (Medjahed et al., 2009).

In order to maximize correct recognition of the various activities daily live (ADL) like sleeping, cleaning, bathing etc..., and distress situation recognition, data fusion over the different sensors types is studied. The area of data fusion has generated great interest among researchers in several science disciplines and engineering domains. We have identified two major classes of fusion techniques:

- Those that are based on probabilistic models (such as Bayesian reasoning (Cowel et al., 1999) and the geometric decision reasoning like Mahanalobis distance), but their performances are limited when the data are heterogeneous and insufficient for the correct statistical modeling of classes, therefore the model is uncontrollable.
- Those based on connectionist models (such as neural networks MLP (Dreyfus et al., 2002) and SVM (Bourges, 1998)) 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 lack of training sets that reflect activities of daily living, fuzzy logic has been found useful to be the decision module of the multimodal ADLs recognition system. Fuzzy logic can gather performance and intelligibility and it deals with imprecision and uncertainty. It has a background application history to clinical problems including use in automated diagnosis (Adlassnig, 1986), control systems (Mason et al., 1997), image processing (Lalande et al., 1997) and pattern recognition (Zahlmann et al., 1997). For medical experts is easier to map their knowledge onto fuzzy relationships than to manipulate complex probabilistic tools.

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 most easily recognized using sensors that are placed on the body (e.g. (Makikawa & Iizumi, 1995)(Himberg et al., 2001)(Lee and Mase, 2002)). 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 by using fuzzy logic. The use of fuzzy logic 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.
- Secondly, the history of fuzzy logic proves that it is used in many cases which are necessary for pattern recognition applications.

5.1 Fuzzy Logic

Fuzzy logic is a powerful framework for performing automated reasoning. It reflects human reasoning based on inaccurate or incomplete data. It uses the concept of partial membership, each element belongs partially or gradually to fuzzy sets that have been already defined. In contrast to classical logic where the membership function $m(x)$ of an element x belonging to a set S could take only two values: $m_S(x) = 1$ if $x \in S$ or $m_S(x) = 0$ if $x \notin S$, Fuzzy logic introduces the concept of membership degree of an element x to a set S and $m_S(x) \in [0, 1]$, here we speak about truth value.

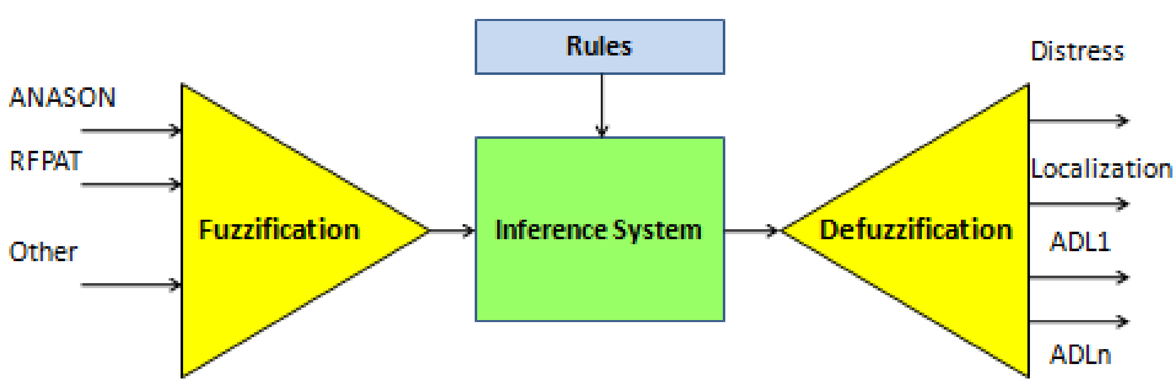

Fig. 5. Fuzzy Logic data fusion

The Fig. 5. shows the main fuzzy inference system steps:

- **Fuzzification**: First step in fuzzy logic is to convert the measured data into a set of fuzzy variables. It is done by giving value (these will be our variables) to each of a membership functions set. Membership functions take different shape: triangular, trapezoidal, Gaussian, generalized Bell, sigmoidally shaped function, single function etc. The choice of the function shape is iteratively determinate, according to type of data and taking into account the experimental results.

- **Fuzzy rules and inference system**: The fuzzy inference system uses fuzzy equivalents of logical AND, OR and NOT operations to build up fuzzy logic rules. An inference engine operates on rules that are structured in an IF-THEN format. The IF part of the rule is called the antecedent, while the THEN part of the rule is called the consequent. Rules are constructed from linguistic variables. These variables take on the fuzzy values or fuzzy terms that are represented as words and modelled as fuzzy subsets of an appropriate domain. There are several types of fuzzy rules, we mention only the two mains used in our system:
  - Mamdani rules (Jang et al., 1997) which is of the form: If x_1 is S_1 and x_2 is S_2 and...and x_p is S_p Then y_1 is T_1 and y_2 is T_2 and...and y_p is T_p. Where S_i and T_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 Tnorm and S-norm respectively, but there are many variations by using other operators.
  - Takagi/Sugeno rules (Jang et al., 1997): If x_1 is S_1 and x_2 is S_2 and...and x_p is S_p Then $y = b_0 + b_1x_1 + b_2x_2 +\ldots + b_px_p$. In the Sugeno model the conclusion is numerical. The rules aggregation is in fact the weighted sum of rules outputs.
- **DeFuzzification:** The last step of a fuzzy logic system 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; in our platform decision module we could use Centroid of area (COA), Bisector of area (BOA), Mean of Maximum (MOM), Smallest of Maximum (SOM) and Largest of Maximum (LOM).

5.2 Fuzzy Logic for medical telemonitoring

The first step for developing this approach is the fuzzification of system outputs and inputs obtained from each sensor and subsystem.

From ANASON subsystem three inputs are built. The first one is the sound environment classification; all sound class and expressions detected are labelled 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 1. N other inputs are associated to each SNR calculated on each microphone (N microphones are used in the current application), and these inputs are split into three fuzzy levels: low, medium and high.

RFPAT produce five inputs: heart rate for which three fuzzy levels are specified normal, low and high; activity which has four fuzzy sets: immobile, rest, normal and agitation; posture is represented by two membership functions standing up/setting down and lying; fall and call have also two fuzzy levels: Fall/Call and No Fall/Call. The defined area of each membership function associated to heart rate or activity is adapted to each monitored elderly person.

The time input has five membership functions morning, noon, afternoon, evening and night which are also adapted to patient habits.

Membership Function	Composition
Human Sound	snoring, yawn, sneezing, cough, cry, scream, laught
Speech	key words and expressions
Multimedia Sounds	TV, radio, computer, music
Door sounds	door claping, door knob, key ring
Water sounds	water flushing, water in washbasin, coffee filter
Ring tone	telephone ring, bell door, alarm, alarm clock
Object sound	chair, table, tear-turn paper, step foot
Machine sounds	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

Table 1. Fuzzy sets defined for the ANASON classification input

The output of the fuzzy logic ADL recognition contains some activities and distress situation identification. They are sleeping, getting up, toileting, bathing, washing hands, washing dishes, doing laundry, cleaning, going out of home, enter home, walking, standing up, setting down, laying, resting, watching TV and talking on telephone. These membership functions are ordered, firstly according to the area where they maybe occur and secondly according to the degree of similarity between them.

The next step of the fuzzy logic approach is the fuzzy inference engine which is formulated by a set of fuzzy IF-THEN rules. This second stage uses domain expert knowledge regarding activities to produce a confidence in the occurrence of an activity. Rules allow the recognition of common performances of an activity, as well as the ability to model special cases. A confidence factor is accorded to each rule and in order to aggregate these rules we have the choice between Mamdani or Sugeno approaches available under the fuzzy logic component. After rules aggregation the defuzzification is performed by the centroid of area for the ADL output.

The proposed method was experimentally achieved on a simulated data in order to demonstrate its effectiveness. The first study was 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 obtained results one rule is added to the selected set of rules in order to get the missed detection. With this strategy good results are reached for the ADL output (about 97% of good ADL detection).

6. Conclusions

This chapter has presented the usage of the sound environment information in order to detect a distress situation and the data fusion using Fuzzy Logic between sound extracted information and a wearable sensor. All presented system is the basis of the development of a complex companion system (CompanionAble project). The telemonitoring systems using redundant sensors in order to detect distress situation but also to prevent trough a long time analysis represents a solution to the lack of medical staff. These systems do not replace the care givers but represent only a help for them.

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8. ACKNOWLEDGMENTS

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Biomedical Engineering can be seen as a mix of Medicine, Engineering and Science. In fact, this is a natural connection, as the most complicated engineering masterpiece is the human body. And it is exactly to help our “body machine” that Biomedical Engineering has its niche. This book brings the state-of-the-art of some of the most important current research related to Biomedical Engineering. I am very honored to be editing such a valuable book, which has contributions of a selected group of researchers describing the best of their work. Through its 36 chapters, the reader will have access to works related to ECG, image processing, sensors, artificial intelligence, and several other exciting fields.