Elderly People Telemonitoring in an Integrated Smart House Environment

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Abstract: In this paper, 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 ensures a pervasive in-home health monitoring for elderly people based on fuzzy logic.

Keywords: Data fusion, Fuzzy logic, Healthcare telemonitoring, Telemedicine, Signal processing.

1. INTRODUCTION

Elderly people are living longer and more fulfilled lives, and they desire to maintain their independent living as long as possible. Studies reveal that they prefer an independent lifestyle (Hareven, 2001). But independent lifestyles come with risks and challenges. It is therefore our duty of scientists to provide the necessary devices to allow them to live at home while being safe and in good condition. Thus, the next generation of smart in-home systems must include automatic healthcare telemonitoring system in order to enable elderly people to lead a healthier life. These healthcare telemonitoring systems have the potential to improve the quality of older adults' life through the use of smart technologies to sense, alert and automate household priorities, as well as to provide home based healthcare.

For this reason we have developed a platform for several uses and to meet the needs identified above. This platform manages a system consisting in:

A set of microphones disposed in all rooms of the house of the elderly (Anason (Istrate *et al.*, 2008)).

A portable device (RFpat (Medjahed *et al.*, 2008b)) that can measure ambulatory pulse heart rate, detect posture, potential fall of the equipped person and his activity rate.

A set of infrared sensors (Gardien (Medjahed *et al.*, 2008b)) 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.

Outputs of these heterogeneous systems are collected processed and fused through a fuzzy inference decision module in our multimodal platform (FL-EMUTEM). Fuzzy logic has been found useful to be the decision module of our multimodal monitoring system FL-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, control systems (Mason *et al.*, 1997), image processing (Lalande, 1997) and pattern recognition (Zahlmann *et al.*, 1997). Some experts found it easier to map their knowledge onto fuzzy relationships than onto probabilistic relationships between crisply defined variables.

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

2. BACKGROUND ABOUT FUZZY LOGIC

2.1. *How to Build a Fuzzy Inference System*

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:

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

where $\mu_A(x)$ in (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 $x \in A$, or $\mu_A(x) = 1$ if $x \notin A$, 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. This description of membership function is the base of each fuzzy inference system (FIS).

FIS actually consists of a rule-base including a collection of fuzzy *If-Then* 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. This step is done by using membership functions which can take different shapes as it is on Fig. 1.
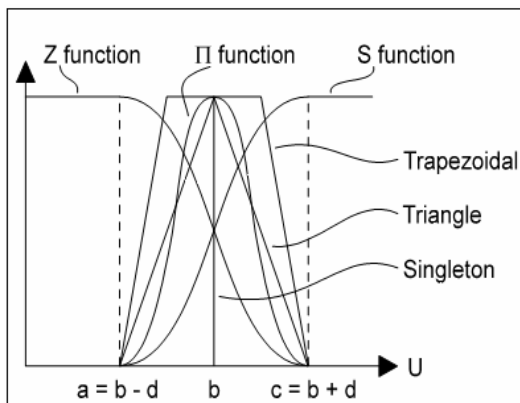

Fig. 1. Membership functions

Application of the fuzzy operators (AND and OR) in the antecedent part of all rules, using T-norm and T-conform (Klement *et a*l., 2000) 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 Takagui Sugeno model (Jang *et al.*, 1997): 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 Takagui Sogeno-FIS it is simply the weighted average of all output singletons as having the rules truth values as weights. In Mamdani-FIS one of defuzzification functions described in the defuzzification section is used. There are different defuzzification methods; in the EMUTEM 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). The following Equation illustrates them.

2.2. *Fuzzy Logic and Classification Methods*

The idea of fuzzy sets was originated by Zadeh (Zadeh, 1992), 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.

Rather than creating new methods of fusion and classification based on entirely different approaches, fuzzy logic fits 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 (Bezdek and Pal, 1992), fuzzy logic is very useful for these steps.

Data description: Fuzzy logic is used to descript syntactic data (Mizumoto *et al.*, 1972), numerical data and Contextual, conceptual data or data based on rules (Pao, 1989) 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 (Keller and Krishnapuram, 1992).There are also techniques based on fuzzy logic for extraction (Pal and Chakraborty, 1986).

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 (Dunn, 1973) algorithm are the famous in this category.

Design of the discriminator: The discriminator is designed to pro- duce 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.

3. APPROACH DESCRIPTIONS

The main advantages of using fuzzy logic system are the simplicity of the approach and the capacity of dealing with the complex data acquired from the three subsystems: Anason, RFpat and Gardien. Fuzzy set theory offers a convenient way to do all possible combinations 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. The data fusion is carried out at three different levels: for sound at decision level, for infrared system at input data level and for wearable physiological sensor at representation level.

3.1 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.

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 Fig. 2.
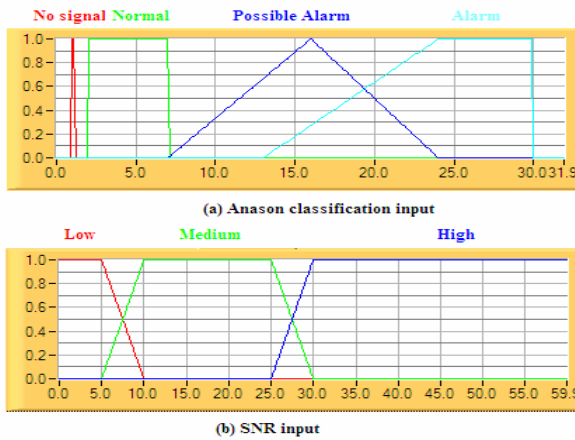

Fig. 2. Fuzzy sets defined for input variables produced by Anason.

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.*

RFpat provides physiological data to the FL-EMUTEM platform. 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 / seating 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.
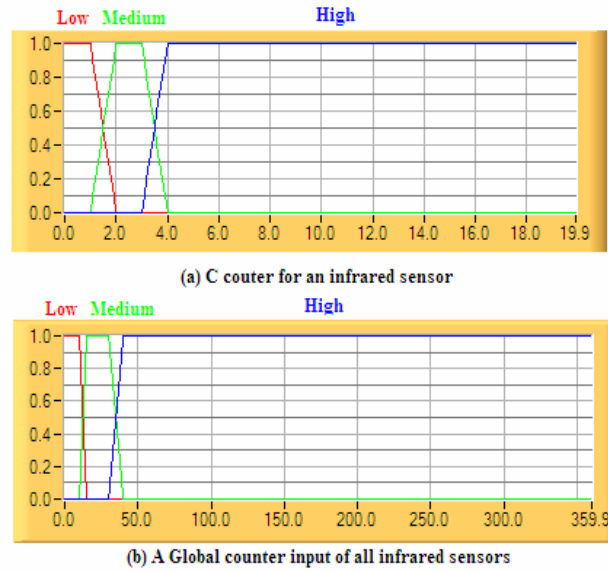

Fig. 3. Fuzzy sets defined for input variables produced by an infrared sensor.

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.

A singleton membership function is assigned to each change state sensor with two linguistic variables *On* and *Off.*

Fig. 4 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.
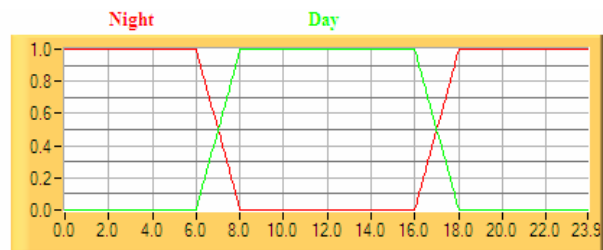

Fig. 4. Fuzzy sets defined for the time input

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 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.

Two membership function models are selected: Gaussian functions are 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.

3.2 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 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.

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 o_er 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.

4. IMPLEMENTATION

4.1 Software Architecture

Fig. 5 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.
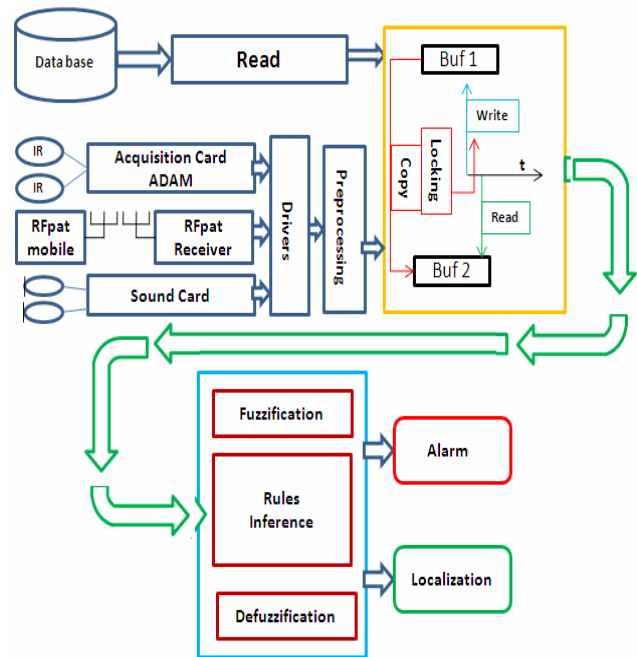

Fig. 5. FL-EMUTEM software architecture.

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). This 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 elderly person position detection.

4.2 Graphical Interfaces for Intelligibility

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.
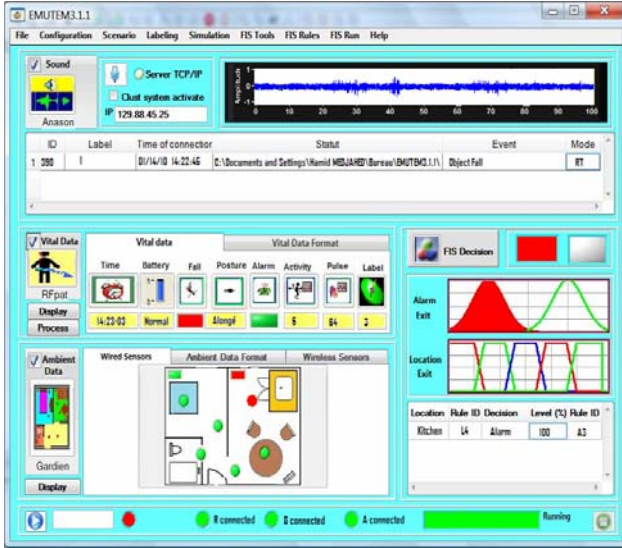
Fig. 6. FL-EMUTEM general graphical interface.

Fig. 6 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 this graphical interface. 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 simplicity for users and with a flexibility that allows adding other modalities. They allows expert to add their knowledge with a friendly user way.

5. EXPERIMENTAL RESULTS AND VALIDATION

To perform this experimental process we have selected appropriate metrics for evaluating the performance of the platform by comparing system's results to expected 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.

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:

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

$$Sp\ (\%) = \frac{TN}{TN + FP} \times 100 \tag{2}$$

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

$$Pc\ (\%) = \frac{TN + TP}{TN + FN + FP + TP} \times 100 \tag{3}$$

In order to demonstrate the effectiveness of this software, firstly we started by using simulated data in order to validate each rule. This first step of simulation gave very promising results for the alarm generation and localization without any false decision for each rule.

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.

	Normal_sequence	Distress_sequence
Normal_sequence	68	2
Distress_sequence	1	29

From this confusion matrix we can deduce some indices of performance which are displayed in table 1. The obtained results of FL-EMUTEM's performance are good and they demonstrate the reliability of the FL-EMUTEM platform.

Table 1. Performance indices for Alarm output obtained with simulated data by using 10 rules.

Se	Sp	Err	Pc
97%	96%	3%	97%

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.

Then FL-EMUTEM platform was tested with 20 scenarios selected from HOMECADE database (Medjahed et al., 2008), 10 scenarios with distress situations and 10 normal scenarios. 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 rules are 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, about 95% of good Alarm detection and 97% for good Localization. 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.

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. CONCLUSIONS

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 fuzzy logic decision module reinforces the secure detection of older per- son'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 and to build very reliable smart houses.

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