Data Fusion in Health Smart Home: Preliminary Individual Evaluation of Two Families of Sensors

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***Abstract*— Life expectancy is nowadays increasing thanks to major improvements in medicine. Thus, modern societies are facing the great challenge to care after a fast growing population of elderly people. For that reason, researchers work on solutions to maintain, as long as possible, elderly persons safely in their own home, with efficient systems to detect abnormal trends and to launch alarms. This project deals with the development of indicators to detect the loss of autonomy. A flat was equipped with different sensors to classify the activities of daily living of the patient in his own environment. This paper describes the installation of the different sensors and the results of the preliminary individual evaluation of two of them (a sound and speech recognition system and an inertial/magnetic kinematic sensor). The first system classifies the sounds produced in the flat in eight classes and differentiates the normal sentences with the distress sentences uttered by the subject. The second analyzes the signal from the accelerometers and magnetometers to identify the posture and the level of activity. The algorithms were tested with two scenarios performed by ten subjects.**

I. INTRODUCTION

AGEING comes with a natural process in the loss of autonomy which reduces the chance for an independent living at home. For this reason, methods to help dependant people to stay at home have to be invented. Researchers and geriatrics now agree on the kind of information to be monitored and lots of research projects aims at the implementation of a home monitoring system able to deliver suitable information to detect the loss of autonomy of an elderly people at home.

Indeed, this is actually a real social problem. With more than 1.3 million people over 85 nowadays in France and a prevision of more than 2 millions for 2015, loss of autonomy (for elderly or handicapped persons) will threaten in the next years a non negligible part of the population. The gain of time before the entrance is one of the solution to regulate the lack of places in such in equipped institution.

Smart sensors and smart homes have been intensively explored to resolve this problem [1]. The former, such as embedded accelerometers, magnetometers and gyroscopes are used to deliver information on the posture and movements of the person (walking, sitting down…) [2], [3] or to try to automatically detect a fall [4], [5]. The latter are used to measure the activity of the person in his environment [6], [7] or to help people with cognitive impairments executing the principle task of the daily life [8]. Microphones can also be used into speech recognition in smart homes for automation purposes [9]. Despite interesting results, it is now quite evident that no individual system will cover all the needs. Therefore, new approaches are in the fusion of several modalities.

This article presents our work into Health Smart Homes and a preliminary evaluation in real and unsupervised conditions of an embedded sensor measuring activity and of a complete sound and speech recognition system included in the real flat.

II. MATERIALS AND METHODS

A. The Health Smart Home

To monitor the activity of the person, the Health Smart Home of Grenoble (named 'HIS'), a real flat of 47m² inside the faculty of medicine of Grenoble, was equipped with several sensors (as shown on Fig. 1):

- Six presence infra-red sensors deliver the information on the displacements of the person (each movement in a room is detected), wirelessly linked to a CAN bus,
- Eight microphones, linked to the analog channels of an acquisition board on a computer, with a program that classifies the different sounds in the flat in eight classes and recognizes the speech enounced,
- A weather station records the inside temperature and hygrometry,
- ACTIM6D, an inertial and magnetic kinematic sensor embarked on the subject,
- Five large angle webcams for further indexation of the activities performed and to use supervised classification algorithms.

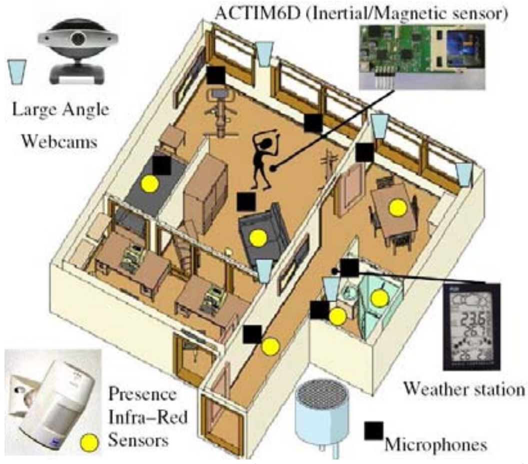

Fig. 1. The Health Smart Home of the TIMC-IMAG and its set of sensors

Manuscript received on January 31, 2008.

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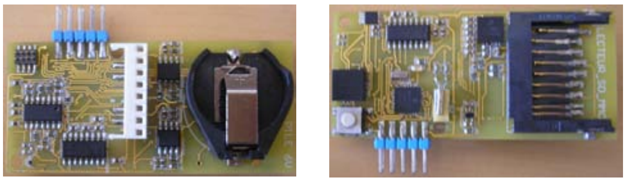


Fig. 2. The ACTIM6D circuit board

The data collected by all these sensors are spread and acquired on four different computers in the technical room of the HIS. For indexation convenience, the five webcams acquired videos are automatically time-stamped (by an acquisition filter of the video software) and the four computers that acquire the sensors are synchronized by NTP.

B. ACTIM6D

1) System Description

ACTIM6D (Fig. 2) is a home-made circuit board of reduced size (6.5cm x 3cm) that can be embedded on the subject, worn into a pocket under his left armpit (Fig. 3.b). It integrates a thermal sensor, a tri-axis ± 1.5g to ± 6g accelerometer (MMA7260Q, Freescale) and a tri-axis ± 6 Gauss magnetometer (HMC1053, Honeywell). These sensors are conditioned by an adapted circuitry (without any filtering process – this part is done further under Matlab), acquired by a 10 bits ADC on a microchip PIC microcontroller (18LF2580) at a frequency of 20 Hz and finally stored on a MMC (or SD) card. It is powered by two coin cells batteries (CR2025) that permit, with the average consumption of the board, an autonomy of about 20 hours. The SD Card (with 1GB) allow about 24 days of autonomy with 1 sector (512 bytes) is written each seconds. For testing purposes, we also placed a connector (white female 8 pins connector, on the left of Fig. 2) to plug another tri-axis digital compass (HMR3300, Honeywell) able to deliver, at 8 Hz, magnetometers raw data or compass information.

These tri-axis sensors provides a 3D axis set (Fig. 3. a) centered on the subject. We can then analyze the variation of the projection of the fixed vectors (gravitation and magnetic field of the earth) into a moving axis set. We save, for each experimental session, a 6D raw data signal made of the three axis for the accelerometers and the three axis for the magnetometers.

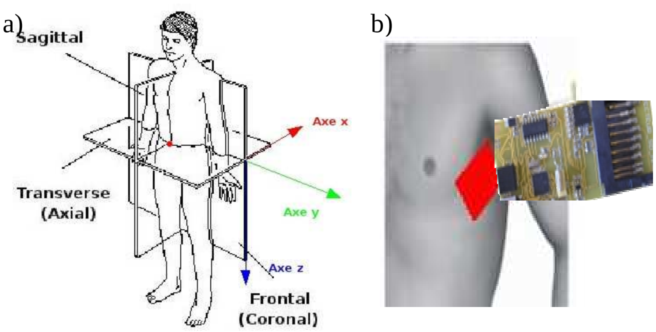


Fig. 3. (a) 3D Axis set of the subject and (b) Placement of the sensor on the subject

2) Information Extraction

We studied these signals to extract usable information in our data fusion algorithms. We determined that the information we want was:

- A representation of the level of activity of the person, to know if she is active or not,
- The percentage of time spent being sit down, stand-up, and lie down,
- The percentage of time spent walking.

Few algorithms can produce the information about walking, analyzing the frequencies within the signal with wavelets or Fourier transform [10].

The activity of the person can be deduced from an integration of the movement given by the six signals. This activity will depend of the subject, but we can compare them from one period of time to another for the same subject.

The interesting part of our work was to find the exact moment of the change in posture of the person (sitting down, standing up, lying down…). This is performed in searching for particular patterns within the signal that represent these actions.

For the accelerometers, the patterns are easily obtained but for the magnetometers, they are more complex as they depend of the orientation of the subject regarding the magnetic field of the Earth. To overcome this difficulty, we will analyze the signal into the quaternion space. The quaternion [11] gives us a different representation of the transformation between two moments of the signal with two information: (1) the rotation axis and (2) the angle of the transformation. Analyzing this signal instead of the magnetometers raw signals prevent us from being dependant of the orientation and having to construct patterns for each angle. Given two vectors (representing two moments of the signal), we will be able to construct a quaternion representing the transformation between the vectors whose expression is (where $\mathbf{k} = \begin{pmatrix} k_x & k_y & k_z \end{pmatrix}$ is the rotation axis and ϑ the rotation angle):

$$Q = \begin{pmatrix} \cos\left(\frac{\vartheta}{2}\right) \\ \sin\left(\frac{\vartheta}{2}\right) k_x \\ \sin\left(\frac{\vartheta}{2}\right) k_y \\ \sin\left(\frac{\vartheta}{2}\right) k_z \end{pmatrix} \qquad (1)$$

The next stage of the analysis is to design a pattern for each movement we want to recognize. To do so, we will construct adapted wavelets and perform a wavelet transform on our signal. For a signal x(t), given a wavelet g(t), the continuous wavelet transform is a matrix of values $C_{a,b}$ defined by the equation:

$$C_{a,b} = \frac{1}{a} \int_{-\infty}^{+\infty} x(t) \cdot g\left(\frac{t-b}{a}\right) dt \qquad (2)$$

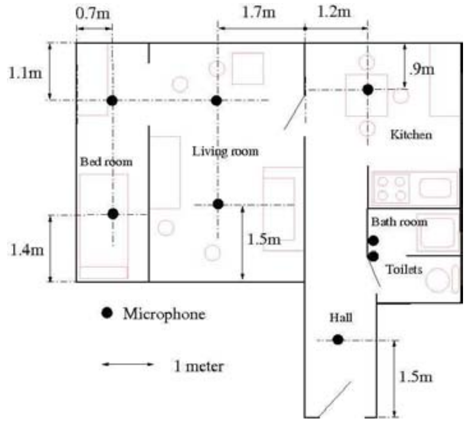


Fig 4. Repartition of the microphones inside the Health Smart Home

With this method, we can localize, the time ("b") of the modification of posture and the speed at which was performed (the scale parameter "a" of the wavelet transform) in comparison with the model.

C. Sound and Speech Recognition

1) System Installation

Eight microphones have been integrated and hidden into the flat ceil. The disposition of the microphone is shown on Fig 4.

Each microphone has been plugged on an analog input channel of a National Instrument PCI-6034E, connected to a computer running GNU/Linux. On this computer, a software application developed by the LIG laboratory is in charge of the recognition of sounds and speech. A synopsis of this application is presented on Fig 5.

As shown on this figure, the system is a multi-threaded application, connected to the eight microphones. This application is responsible of:

- Detecting a sound that occurs in the signal using an adaptative threshold that consider, at any moment, the noise level for this microphone,
- Segmenting it in speech or everyday life sound,
- If it is an everyday life sound, classifying it in one of the eight classes known by the system,
- Else, recognizing of the French sentence by an independent ASR application,
- For each event, an independent XML file is created including the results of the different stages of the process.

These different stages of the sound and speech analysis system are presented in the following sections.

2) Detection

The first stage of the sound and speech analysis is the sound detection. The eight analogue input channels are continuously and simultaneously sampled by the system at 16 kHz. The noise level is evaluated and the detection of the beginning and the end of the signal uses an adaptive threshold. When the beginning and the end of the signal have been isolated, a sound file (in classical wav format) is created, ready to be used by the next thread of the application in charge with the segmentation.

With this adaptive threshold, we now miss no event and we reduce the number of unwanted ones.

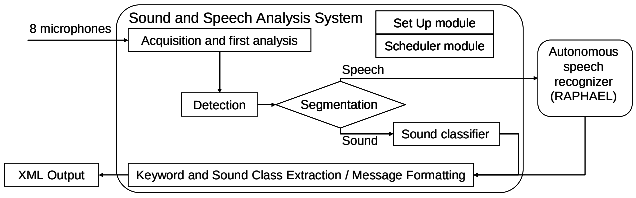


Fig 5. Global organization of the sound and speech recognition system

3) Segmentation

This stage has to classify a given sound into speech type or sound of daily life type. Segmentation is achieved through a Gaussian Mixture Model (GMM) classifier trained with the everyday life sound corpus and the normal/distress speech corpus which have been recorded in the LIG laboratory. Acoustical features are Linear Frequency Cepstral Coefficients (LFCC) with 16 filter banks and the classifier uses 24 Gaussian models. These features were used because life sounds are better discriminated from speech with constant bandwidth filters than with Mel Frequency Cepstral Coefficients (MFCC) and Mel scale. Frame width is 16 ms with an overlap of 50%.

The validation of this segmentation module was made by mixing the sounds and speech records from the corpora and adding them noise recorded in the HIS at 4 Signal to Noise Ratios (training was performed on pure sounds). In these "laboratory" conditions, we obtained a Segmentation Error Rate of 17.3% for a Signal to Noise Ration (SNR) of 0 dB, 5.1% at 10 dB, 3.8% at 20 dB and finally 3.6% at 40 dB. We can notice that SER remains quite constant with a 5% value above 10 dB.

4) Sound Classification

When segmented as sounds, the wav file is then processed by the classification stage of the application. Everyday life sounds are classified using a GMM classifier. This classifier was trained with the eight classes of the everyday life sound corpus using LFCC features (24 filter banks) and 12 Gaussian models. The every day life sounds are divided into 8 classes corresponding to 2 categories: normal sounds related to usual activities of the patient (door clapping, phone ringing, step sounds, dishes sounds, and door lock), abnormal sounds related to distress situations (breaking glass, fall of an object, screams). This corpus contains some records made at LIG laboratory (61%) using super-cardioids microphones (eW500, Sennheiser), some files coming from a preceding corpus recorded at the time of former studies in the CLIPS laboratory and some files obtained from the Web. The corpus is constituted of 1,985 audio files for a total duration of 35 min 38 s, each file contains one sound.

We also evaluated the performances of this classification, in the same conditions as for segmentation, using different SNR. With the 12 GMM models and 24 LFCC, the Classification Error Rate is 36.6% at 0 dB, 21.3% at 10 dB, 12% at 20dB and finally 9.3% at 40 dB. We notice again that the error is highly dependant of the SNR.

5) Speech Recognition

The autonomous speech recognizer RAPHAEL [10] is running as an independent application and analyzes the speech events resulting from the segmentation module through a file exchange protocol. As soon as the requested file has been analyzed, it is deleted and the 5 best hypotheses are stored in a hypothesis file. This event allows the scheduler to send another file to be analyzed.

For speech recognition, the training of the acoustic models was made with large corpora in order to insure good speaker independence. They were recorded by 300 French speakers in the CLIPS laboratory and LIMSI laboratory. All corpora were recorded using the same 16 kHz sampling rate as the analysis system.

In order to validate the system we have recorded an adapted corpus: the normal/distress speech corpus in French. This corpus is made of 66 normal and 60 distress sentences [13].

The language model of this system is a medium vocabulary statistical system (around 10,000 words in French). This model was obtained by extraction of textual information from the Internet and from the French journal "Le Monde" corpora and from the normal/distress speech corpus.

The speech recognition system was evaluated with the sentences from 5 speakers of our corpus (630 tests). In 6% of the cases, for normal sentences, an unexpected distress keyword is detected by the system and leads to a False Alarm Sentence. In 16% of the cases, for distress sentences, the distress keyword is not recognized (missed): this leads to a Missed Alarm Sentence. This often occurs in isolated words like "Aïe" (Ouch) or "SOS" or in syntactically incorrect French expressions like "Ça va pas bien" (I don’t feel well).

The global Speech Recognition Error Rate is then 11%.

6) Data post-processing

Every audio signal is recorded by the application, analyzed on the flow and finally stored on the hard drive of a computer. For each detected signal, it is first segmented (as sound or speech) and then classified (as one of the eight classes) or in case of speech the 5 more probable sentences are written. For each sound, an XML file is generated containing all the important information. Afterwards, these collected data are processed using Matlab™.

They are classified using a simple rule: for a sound that will be done in the flat, we will take the SNR of the best sound (named x), and keep all the microphones that have a SNR greater than $0.8 \cdot x$. We will take our decision with a vote between these different decisions, with two rules in case of equality: (1) if a distress speech is detected, we will keep this decision and (2) in case of equality with another decision than a distress speech, we keep the decision of the microphone that has the best SNR.

This Matlab script generates a text file (CSV format with tabulations between the different columns) that can be automatically processed by another application, with the timestamp information and the decision taken (with a sum-up of the decision of the different microphones). This file allows the realization of a diagram with the time, the room and the type of sound captured in the flat.

III. Experimental Results

To test these two sensors and their associated algorithm, we realized two scenarios that were all recorded by the webcams of the HIS. The protocols are described in the following sections, followed by results.

A. Experimental Protocols

1) ACTIM6D

To test the circuit, five people volunteered to reproduce a scenario. The flat was especially equipped with two chairs (firm, without armrest, height of the sit: 45 cm, angle sit/back: 10°), placed at 90° one with respect to the other) and a bed (firm, height: 46 cm). The two chairs are used to show the independence of the algorithm against the position of the chair. The tests have been performed using the HMR 3300 as magnetometers system and the ACTIM6D for accelerometers.

The scenario was the following:

- Perform five Up & Go from the chair number one (an Up & Go is defined as follow: the subject is sat down on the chair, he stand up, walk for 4 m, turn around, come back, turn around the chair and sit down again),
- A succession of five sequences of walk: the subject is sat down on the chair number two, he stands up, walk for few seconds (the order was to walk to the door and come back to the chair) and sit down again,
- Five sequences on the bed: the subject walk to the bed, lye down (on the back), stay in this position a few seconds, move on the bed on the left and on the right, stay immobile on the back and then stand up,
- Stand-up in the living room, the subject has to tie up his two shoes and pick-up a pen from the floor.

2) Sound and Speech Recognition

To validate the sound and speech recognition system, every subject had to pronounce 45 sentences (20 distress sentences, 10 normal sentences and 3 phone conversations of 5 sentences each). For this experimentation, 10 subjects volunteered, 3 women and 7 men (age: 37.2 ± 14 years, weight: 69±12 kg, height: 1.72±0.08m). The number of sounds collected during this experimentation was 3, 164 (2, 019 had an SNR lower that 5 dB), with an SNR of 12.65 ± 5.6 dB. After classification, we kept 1, 008 sounds with a mean SNR of 14.4 ± 6.5 dB.

The experimentation took place during the day – so we do not control the environmental conditions of the experimental session (such as noises occurring in the hall). The sentences were uttered in the flat, with the subject sat down or stood up. He was situated between 1 and 10 meters away from the microphones and had no instructions on his orientation with respect to the microphones (he could choose to turn his back to the microphone direction). Microphones are set on the ceiling and directed vertically to the floor. The phone is on a table in the living room.

The protocol was quite simple. The subject was asked to first go in the flat and close the door, and then to make a little scenario (close the toilet door, make a noise with a cup and a spoon, let fall a box on the floor and scream ”Aie”). This whole scenario was repeated 3 times. Then, he had first to go to the living room and close the door and then to go to the bed room and read the first half of one of the five successions of sentences, compounded of 10 normal and 20 distress sentences.

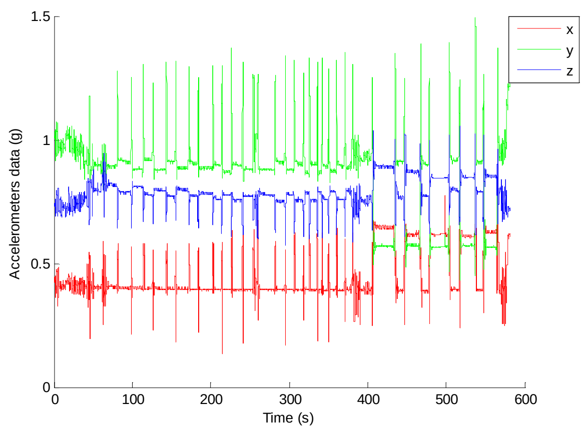
After, he had to go to the living room and had to utter the second half of the sequences. He was finally called 3 times and had to answer the phone and each time to read the phone conversation (5 sentences each). To realize these successions of sentences, we choose 30 representative sentences and realized 5 phone conversations, and then we scrambled the sentences five times, and we randomly chose 3 of the 5 conversations.

B. Results

1) ACTIM6D

To test the describe algorithms, the first stage was to learn the different patterns. This has been done using the experiment presented on Fig 6.

We can observe, on this figure, the phenomenon describe earlier. As far as accelerometers data are concerned, the patterns are the same for the two different chairs. The magnetometers data are different for this point, which is the reason why the quaternion transformation has been used on them.



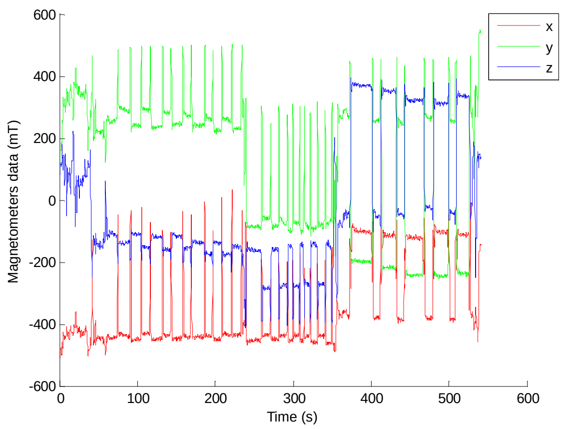


Fig 6. Accelerometers and magnetometers data from the ACTIM6D. This signal is from an session with 3 parts: (1) Sitting down and standing up from the first chair 5 times, (2) Sitting down and standing up from the second chair 5 times, (3) lying down and standing up from the bed 5 times.

These signals have been used to create wavelet patterns for both accelerometers and magnetometers and then we have tested the detection and classification of these patterns on the data from the experimental sessions of the five volunteers. We arrived, with filtering process on the signal to remove noise, to a first result of 72% of well-classified movements.

These first results show us that the method is correct for our use, and that the models of movements have to be improved. More experimental sessions should also demonstrate the validity of the model for more suitable results.

2) Sound and Speech Recognition

a) Speech (Normal/distress sentences) recognition

TABLE I. ERROR RATE OF THE SPEECH CLASSIFICATION SYSTEM (NORMAL VS DISTRESS SENTENCES)

	Segmentation	Classification
Global	6%	30.5%
Normal	6.9%	9.5%
Distress	4.3%	54.8%

The speech recognition results are presented in the Table I. This table gives us the segmentation and classification results for the sentences uttered in the flat. As we can see, the segmentation results are equivalent to those obtained in laboratory conditions at equal SNR. For the classification results, the global results are lowered by the distress sentences recognition error rate that is of only 46%. This is due to: (1) the model of language that have to be improved, to be more specific and less speaker dependant (the error rate is different from one speaker to another) and (2) the noise in the flat that can not be controlled, and the position of the speaker that can vary even within a sentence. The normal sentences are well-recognized by the system, that leads to a very low false alarm rate (but the missed-alarm rate need to be improved).

b) Sound recognition

The results of the sound recognition system are summed-up in the Table II, by the confusion matrix. This table gives us, for each type of sound realized in the flat, the result of the classification (in percent). Bold values represent the well-classified rate for each class.

We also can deduce from it the classes that are close and difficult to differentiate automatically. This is the case for fall and door clapping (strong and short sounds) and also for normal sentences and dishes.

We have considered that when a distress sentence is uttered, a scream is neither a bad segmentation nor a bad classification. Indeed, distress sentences can be only a word like “Ouch” that is pronounced like a scream. The last noteworthy result is that the phone use is well recognized. However, a newer phone (with more sophisticated and unknown kind of ringing) should not allow such good results without learning them.

TABLE II. CONFUSION MATRIX FOR THE SOUND AND SPEECH RECOGNITION SYSTEM

		Results							
		Clap	Phone	Dishes	Break	Falls	Screams	Normal Speech	Distress Speech
Action	Doors Clapping	**80.1 %**	0 %	0 %	0 %	19.9 %	0 %	0 %	0 %
	Phone Ringing	0 %	**100 %**	0 %	0 %	0 %	0 %	0 %	0 %
	Dishes sounds	0 %	0 %	**51 %**	0 %	2.1 %	3.5 %	43.4 %	0 %
	Object Falls	21 %	0 %	0 %	2 %	**77 %**	0 %	0 %	0 %
	Screams	0 %	2.4 %	4 %	2.4 %	0 %	**78 %**	13.2 %	0 %
	Normal Speech	0.4 %	0 %	2.1 %	0 %	2.5 %	2.9 %	**90.5 %**	1.6 %
	Distress Speech	1.4 %	0 %	1 %	0 %	1.4 %	0 %	51 %	**45.2 %**

IV. DISCUSSION AND CONCLUSION

In this paper we have presented the individual evaluation of two sensors that are being used for latter data fusion algorithms in Health Smart Homes. The goal is to monitor the activity of elderly people in their own environment.

The first sensor is a home-made circuit board containing accelerometers, magnetometers, SD Card slot and coin cell battery (to be autonomous). It was designed to deliver information about change of posture of the person and level of activity (time spent to walk, sit down…). It has been primarily evaluated on the feasibility of pattern recognition for this kind of movements. Designing wavelet patterns, we obtained good results for classification.

We now work on the definition of better patterns, also on the signal filtering to remove a large part of the noise and eventually on reducing the computational time to make it possible to embed the algorithm on a microcontroller.

The second kind of sensors is a set of microphones distributed in the flat and connected to an acquisition board in a computer. We previously developed a software to detect the signals and then classify them into sound class or speech class (and for each class into sub-classes). To test it, volunteers performed a scenario with mixed sounds of daily life and also speech (with normal sentences and distress ones).

The results of this later part showed that the detection of sounds is efficient but also that we have to modify the speech corpus if we want to obtain a better recognition of the distress sentences. Indeed, the speech recognition faces two problems. First, the language model is perhaps not enough adapted to this kind of recognition. These models should be performed in increasing the number of sentences of our corpus. The second problem comes from the background noise in the flat which is a non-negligible perturbation in real conditions (contrary to the laboratory conditions). Future works also include: (1) the improvement of the filtering process to reduce the additive ambient noise, (2) the use of the collected data to improve the models and (3) the use of other data to learn more classes (especially water sounds for the bathroom and the toilets).

ACKNOWLEDGMENT

The authors would like to thank the volunteers from the both laboratories that spent time performing these two experimental protocols.

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