SVM-Based Multimodal Classification of Activities of Daily Living in Health Smart Homes: Sensors, Algorithms, and First Experimental Results

Anthony Fleury, *Member, IEEE*, Michel Vacher, and Norbert Noury, *Senior Member, IEEE*

***Abstract*—By 2050, about one third of the French population will be over 65. Our laboratory's current research focuses on the monitoring of elderly people at home, to detect a loss of autonomy as early as possible. Our aim is to quantify criteria such as the international activities of daily living (ADL) or the French Autonomie Gerontologie Groupes Iso-Ressources (AGGIR) scales, by automatically classifying the different ADL performed by the subject during the day. A Health Smart Home is used for this. Our Health Smart Home includes, in a real flat, infrared presence sensors (location), door contacts (to control the use of some facilities), temperature and hygrometry sensor in the bathroom, and microphones (sound classification and speech recognition). A wearable kinematic sensor also informs postural transitions (using pattern recognition) and walk periods (frequency analysis). This data collected from the various sensors are then used to classify each temporal frame into one of the ADL that was previously acquired (seven activities: hygiene, toilet use, eating, resting, sleeping, communication, and dressing/undressing). This is done using support vector machines. We performed a 1-h experimentation with 13 young and healthy subjects to determine the models of the different activities, and then we tested the classification algorithm (cross validation) with real data.**

***Index Terms*—Activity of daily living (ADL), classification, health smart home, machine learning, support vector machines (SVMs).**

I. Introduction

THE AVERAGE age of the population in developed countries is increasing due to improvements in medicine. The United Nations predicts 22% of people over 65 years of age in the world, by 2050. Nations have to be prepared to face this demographic modification to allow elderly people to live their life in the best possible conditions.

Researchers are working on telemedicine and telemonitoring solutions to allow elderly people to stay at home as long as they can. Mobility, which is currently a common request of companies, adds distance between family members. Elderly people often live alone and have to be autonomous. Moreover, with the increase of life expectancy, diseases such as Alzheimer's are more and more prevalent. All this leads to telemonitoring solutions, able to detect a distress situation (fall for instance), or a significant change in the habits or behavior of the person, which could indicate a problem.

Several solutions are studied by laboratories and companies to monitor people at home. These solutions include different levels of complexity and technological challenges. At the lowest complexity level, we find alarm systems. A personal help button is given to the person to keep close to him at all times (for instance around the neck); it is linked to a medical alarm system that is able to call an emergency center in case of problem. If the person presses the button, a connection is enabled to someone, who is able to primarily diagnose the importance of the problem and send help if needed. Such systems are commercialized in the U.S. by Alert-one or in France by Intervox, for example.

The next level of technology is to monitor changes in the person's habits. This has been done with various sensors and systems. In France, Edelia monitors water consumption and its possible variation to detect behavior modification. In Japan, Zojirushi Corporation is interested by the use of the electric water boiler. Drinking tea is a way to stay healthy for most people in this country, thus consumption is a relevant variable to monitor. Some researchers also worked on modification of rhythms concerning the activity "watching TV" in Japan [1].

These research projects focused on only one "variable" of the person's life. To improve the detection of behavioral changes, several teams have been working on Health Smart Homes equipped with various sensors [2]. With these sensors data, it is then mandatory to develop data fusion algorithms that can detect abnormal situations or evolutions inside the large set of information. The Massachusetts Institute of Technology (MIT) (Cambridge, MA) project House_n is one of them. In this project, a flat was equipped with hundreds of sensors [3], [4]. These sensors are used to help people in activities of daily living (ADL) to propose them human–machine interfaces to control of their environment. This will help people to stay physically and mentally active and keep them healthy. The Georgia Institute

Manuscript received November 22, 2008; revised July 23, 2009 and November 2, 2009. First published December 11, 2009; current version published March 17, 2010. This work was supported by the French Ministry of Research and Technology.

A. Fleury was with the AFIRM Team, Techniques de l'Ingénierie Médicale et de la Complexité – Informatique, Mathématique et Applications, Grenoble (TIMC-IMAG) laboratory, Unité Mixte de Recherche (UMR) 5525, Centre National de la Recherche Scientifique (CNRS)/Université Joseph Fourier (UJF), Faculté de Médecine de Grenoble, F-38706 La Tronche Cedex, France and now with Ecole des Mines de Douai, Computer Science and Automation Department, F-59508 Douai Cedex, France (e-mail: fleury@ensm-douai.fr).

M. Vacher is with the GETALP Team, Laboratoire d'Informatique de Grenoble (LIG), UMR 5217 CNRS/UJF, 38041 Grenoble Cedex 9, France (e-mail: Michel.Vacher@imag.fr).

N. Noury is with the AFIRM Team, TIMC-IMAG laboratory, UMR 5525, CNRS/UJF, Faculté de Médecine de Grenoble, F-38706 La Tronche Cedex and also with the Institut des Nanothechnologies de Lyon – Institut National des Sciences Appliquées (INL-INSA) Lyon Laboratory, MMB Team, UMR 5270 CNRS/Ecole Centrale de Lyon (ECL)/INSA/Université Claude Bernard Lyon I (UCBL), University of Lyon, F-69621 Villeurbanne, France (e-mail: Norbert.Noury@insa-lyon.fr).

Color versions of one or more of the figures in this paper are available online at http://ieeexplore.ieee.org.

Digital Object Identifier 10.1109/TITB.2009.2037317

of Technology works on "The Aware Home Research Initiative" [5], a two-floor home that was designed to consider the different generations of the family. The ground floor is designed for the elderly person running an independent life at home. The first floor is for children with mental disabilities and their parents that have to educate and care for them even with a full-time job. This house is equipped with motion and environmental sensors, video cameras (for fall detection and activity recognition [6], for short-term memory help [7]), and finally, RF identification (RFID) tags to find lost objects easily. All this, plus other assistance devices and systems, allow researchers to explore ways to help people living independently at home when they are old or handicapped. Both floors are linked with flat screens to allow intergeneration communication. In France, the researchers of both AILISA [8] and PROSAFE [9] projects work on monitoring the activities of the person with presence infrared sensors to raise alarms in case of problem (changes in the level of activities). In the PROSAFE project, ERGDOM has, for objective, to monitor the comfort of the person inside the flat (temperature, light, etc.). The AILISA project was the starting point for our research. Our experimentations took place in a modified version of the flat setup.

This paper presents our research and contribution to the automatic recognition of ADL in a Smart Home. Section II presents the results of related works in detection and classification of ADL. Our project was divided in three parts. The first was choosing sensors adapted to the activities we want to monitor and their implementation in a real flat, at the Grenoble School of Medicine. This step is described in Section III. The second part was, using these sensors, choosing the discriminatory features and implementing the classification based on support vector machines (SVMs). This second stage of the project is described in Section IV. The last part of the project was to test the whole system in real conditions on 13 individuals, to evaluate the accuracy of the classification process. This last step is described in Section V. Finally, in Section VI, the results are discussed and compared to the previously quoted related research.

II. Related Research

As far as activity classification is concerned, few articles have been published on the subject and few experiments made in real conditions. This thematic was explored by [10] using RFID tags on a large number of home objects (108) to identify the activity that was performed by detecting contacts with objects using a glove-equipped RFID receiver. Fourteen activities (hygiene, washing, housework, preparing a snack, etc.) were chosen because of their interaction with various objects. Fourteen individuals were monitored for 45 min and the global results were 88% of detection accuracy for the various activities. The classification was performed using dynamic Bayesian networks trained for each activity, considering the time necessary for a given activity (a Gaussian curve) and also what objects were necessary to perform it.

Similar research is presented in [11] using homemade ON–OFF sensors. These sensors are simple switches that detect the use of a particular object at home. These switches can transmit their data and also their identifier (which corresponds to a location and an object). From this data, for each activity recorded, we build a vector of features, which takes into account the use of a sensor or not, the way it is used, and if another sensor has been used before. The sensors are used on various doors, on specific objects such as cabinets, and also on electrical devices (microwave oven, TV, etc.). The authors tried to learn models for 35 activities using Naive Bayes network with the described features. The results are presented for activities with a minimum number of occurrences (at least six) and for two individuals. The maximum number of activities was eight. The results presented ranged from 7% to 30% of adequate classification, depending on the activity. Better results are presented for the activity detected in the "best interval" (with a confidence interval of time before and after activity).

More recently, objects and food were tagged to create a model that distinguishes between preparing a drink (cold or hot) and hygiene activities [12]. The theory used to classify this data was evidential fusion (Dempster–Shafer theory). The results presented are the belief and mass functions, and their values that show the possibility to distinguish between activities with these sensors. Validations will be made later on real data. Nugent *et al.* [13] also tested the impact of the sensor failure on recognition using the evidential theory. They measured that up to three sensor failures were possible with their samples.

The CARE project [14] team also tried to differentiate between two activities using a lot of other sensors (switch, environmental, etc.). Due to hidden Markov models, activities could be differentiated, such as "going to the toilets" and "exit from the flat." The results are promising for these two activities; they are presented for two elderly people (contrary to other studies made on young individuals).

Electrical signatures are also another path being tested [15], [16] to detect different various ADL living. Indeed, by using pattern recognition on the electrical network, it is possible to infer what material is being used, and when it is turned on and off. In the first study, the sensor used detected a variation of the electromagnetic field emitted by the transformer of the various home electrical devices. The possibility to measure the use of these devices with this method was demonstrated. The second study implemented a different method to detect the use of devices by classifying events on the general power line of the flat to detect the turning on and off of devices. The flats of 18 aged people were monitored, and the results were presented for the detection of periods of activities and the detection of meal taking.

In this study, our goal was similar to previous studies: to recognize some ADL automatically, but we tried to use less sensors, to make scaling easier, and have learning algorithms adapted to all issues. No object was instrumented contrary to the study which equipped jars, food, etc. This made it simpler to implement in a lot of flats. Indeed, equipping only the flat and not the devices inside (except for the fridge and cupboard that are commonly present in every house) is simpler and the algorithm is more generic. Nevertheless, we introduced a sensor relatively less used, except in home automation, i.e., sound. This new modality is very informative and can also be used

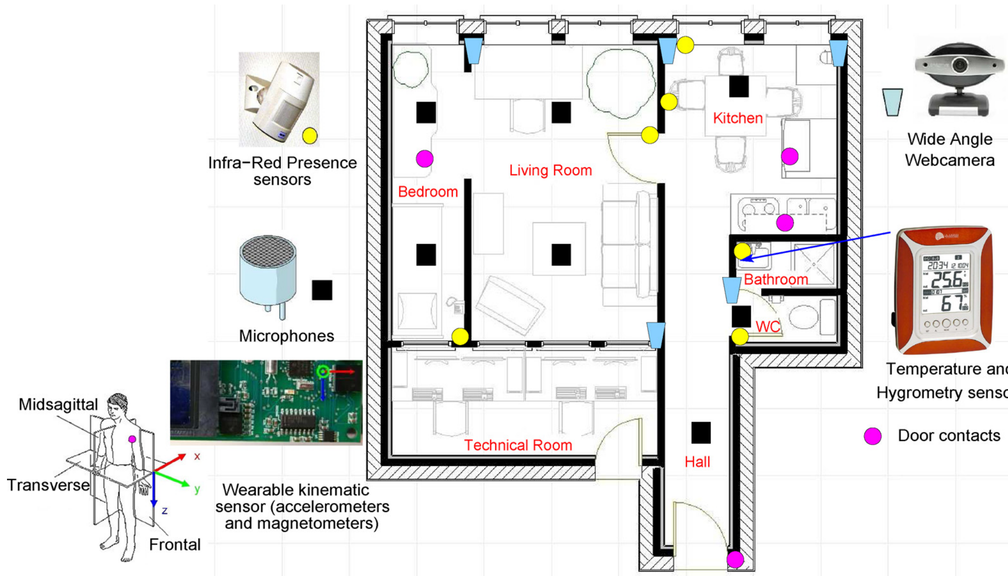


Fig. 1. Map and location of the sensors inside the Health Smart Home of the TIMC-IMAG Laboratory in the Faculty of Medicine of Grenoble. For the wearable sensor, the point shows the location of the circuit board and the orientation of the axes on the board and on the person.

to detect distress situations when applied to elderly people, by automatically recognizing distress keywords [17]. A total of seven activities were recognized. These activities covered a large part of the 35 activities included in [11] because they were more general (we acquired the activity "eating" and not "preparing a breakfast," "preparing a diner," etc., for instance). We only considered activities occurring solely at home. These activities covered the ADL scale part concerning life at home.

III. Health Smart Home for ADL Recognition

ADL, as defined by the medical community, are "the things we normally do in daily living, including any daily activity we perform for self-care (such as feeding ourselves, bathing, dressing, grooming), work, homemaking, and leisure." To work on the classification of these activities, the home has to be equipped with several sensors. In this section, we will introduce the flat and its equipment, and also the notion of ADL and our selected activities with an objective in the future ADLs scale.

A. Grenoble Health Smart Home

1) Presentation of the Flat: In 1999, researchers of the Techniques de l'Ingénierie Médicale et de la Complexité–Informatique, Mathématiques et Applications de Grenoble (TIMC-IMAG) Laboratory of Grenoble installed, inside the Grenoble Medical School, a real 47 m^2 flat, with all the rooms and the comfort required. This flat included a bedroom, a living room, a hall, a kitchen (with cupboards, fridge, etc.), a bathroom with a shower, and a cabinet.

During the AILISA project, it was equipped only with infrared presence sensors. It was since equipped with several sensors to monitor people at home.

1) Infrared presence sensors, for the location of the person inside the flat. These sensors detect all movements in their area they cover and send a signal each time a movement is detected. They were previously used and validated in [8] and [18] for hospital suites and in-home use, respectively. They were placed to monitor important location in the flat such as the bed, the kitchen table, etc.
2) Door contacts for the detection of the fridge use, the cupboard, and chest of drawers.
3) Microphones, to process every sound inside the flat and classify them into sounds of daily living (within eight different classes) or speech (two classes). The development of this system and various algorithms is explained in [17] and its validation is presented in [19].
4) A wearable kinematic sensor, equipped with a triaxis accelerometer and a triaxis magnetometer. The algorithm of this homemade sensor was developed to detect and classify postural transitions using adapted wavelets and also to detect walking episodes using frequency parameters. This system is presented with its validation in [20].
5) Wide-angle web cams used only to timestamp the various ADL for supervised machine-learning algorithms.

All the sensors, their location, and the organization of the flat are presented in Fig. 1. There are a small number of sensors inside the flat to reduce costs by using only the most informative sensors for the classification of the selected ADL.

2) The Technical Room: The four computers and electronic devices (wireless receiver, controller area network (CAN) bus, etc.) of the Habitat Intelligent pour la Santé (HIS) are located in the technical room of the Health Smart Home. The four computers receive and store information from the HIS in real time.

1) The first is devoted to sound and speech analysis. It contains the National Instrument acquisition board and analyses signals from the seven microphones in the flat.
2) The second is dedicated to the capture of three web cams and also receives data from the flat's CAN bus.

3) The third receives data from the two other web cams and from the systems that collect temperature and hygrometry parameters in the bathroom.
4) The fourth collects data from kitchen and bedroom door contacts.

Connections are made via serial or universal serial bus (USB) port, except for microphones that require a National Instrument acquisition board for analog-to-digital signal conversion (a version of the software that uses only the computer's sound card is also available).

B. Activities of Daily Living

Katz and Akporn defined a scale for ADL [21]. This scale is used by geriatrics to evaluate the dependence level of elderly people. There are numerous variations of this scale (defining the final score differently, but always considering the same activities). One of them defines the following activities:

1) bathing (sponge bath, tub bath, or shower), receives either no assistance or assistance in bathing only one part of the body;
2) dressing, finds clothes and dresses without any assistance except for tying shoes;
3) toilet use, goes to the toilet, uses toilet, dresses, and returns without any assistance (may use cane or walker for support and may use bedpan/urinal at night);
4) transferring moves in and out of bed and chair without assistance (may use cane or walker);
5) continence, full control of bowel and bladder;
6) feeding, feeds without assistance (except for help with cutting meat or buttering bread).

Depending on the answer yes or no to each of these questions, geriatricians compute the ADL score of the elderly person. This scale is internationally recognized as one of the references.

Other scales were also defined. Lawton and Brody [22] defined the instrumental ADL. These activities are those that require interaction with objects and people, such as using the phone, shopping, ability to handle finance or personal medication, etc. It gives another score on the dependency of elderly people.

In France, geriatricians use the AGGIR grid, defining ten discriminatory variables: coherence, orientation, toilet use, dressing, feeding, bowel movement, transfers (sitting, standing, and lying), moving inside the flat, moving outside the flat, and communication (on the phone, for example). This scale, close to the ADL scale is used to determine whether elderly people will need to be institutionalized, or have access to financial and material assistance to face dependency. It defines six levels according to the ability to perform the ten activities alone, partly independently, or with mandatory help.

The goal of this research project was to automatically classify sensor data to recognize a temporal frame as part of one of the ADL. The temporal frame width for our study was chosen as equal to 3 min. This duration was the minimum length for a given set of activities. We defined seven different activities, from the previous ADL and AGGIR scales, which we tried to learn and recognize, which are as follows.

1) *Sleeping:* A bed was available in the bedroom for the individual to sleep as long as necessary.
2) *Preparing and having a breakfast:* The fully equipped kitchen also contained material and foods necessary for breakfast. Everything was available for the individual to choose and prepare in his own way; he would then clean up the kitchen and do the dishes.
3) *Dressing and undressing:* Clothes were available for this activity.
4) *Resting:* This activity was the broadest one. The individual could do whatever he wants and enjoys doing during his leisure time at home. He could read a book or a magazine, listen to the radio, or watch the TV, etc.
5) *Hygiene activities:* During this activity, the individual was inside the bathroom and performed normal hygiene activities. It was difficult to ask the individuals to take a shower for a first experiment, thus, we only asked them to wash their hands and teeth. To respect privacy, neither the bathroom nor the toilets were recorded on video. We asked the individuals to close the door completely or partially when in the toilets or in the bathroom, respectively, so as to differentiate the activities.
6) *Bowel movement:* For this activity, the subject was in the toilets.
7) *Communication:* This last activity consisted of answering a phone call and having conversations. In our protocol, the subject was called five times on the phone and has to answer with given previously created, phone conversations, which were randomly selected.

IV. SVMs for the Classification of the ADL

A. Introduction to SVMs

Numerous methods are available to classify real data. In our case, the Bayesian classification or neural networks methods were not adapted because of the less number of available samples. This is why we decided to test the SVM method that seemed to be better adapted to our problem and that could be used for training with small sets of data.

Considering two classes of points, labeled -1 and 1 and that we have a set of N vectors $\mathbf{x}_i \in X \subset \mathbb{R}^d, i \in [1; N]$ (d is the dimension of our input space) with their associated class $y_i \in \{-1; 1\}$, supervised learning is the problem of inferring a function f so that

$$f : X \subset \mathbb{R}^d \to \{-1; 1\}$$

from a set of observations, which will correctly classify the maximum number of vectors x_i and more important, which will correctly describe the phenomenon responsible for the separation between the two classes, so that a new and unknown point will be classified into the right class (capacity of generalization of the classifier).

This problem can be solved with multiple existing algorithms. A simple method, based on the perceptron [23], builds a linear separation starting with a random initialization followed by the test of the different points in the training database, to adjust the separation, until it correctly classifies a maximum number of points from that database. Vapnik *et al.* designed another algorithm, based on linear separation, but which tries to maximize the margin between the separation and the nearest points of the training database in each class [24]. This margin will give the maximum of "safety" for the generalization of the algorithm and its application to new points. SVM have been widely used to solve classification problems since their invention (speaker identification [25], face recognition [26], gene extraction [27], etc.). This method was shown to perform as well as other algorithms and often better [28].

SVMs are equivalent to the construction of a hyperplane of equation $\mathbf{w}^T\mathbf{x} + w_0 = 0$ (where w and w_0 are the equation parameters of the hyperplane to compute). From this hyperplane, we build the function f given by

$$\begin{cases} \mathbf{w}^T\mathbf{x_i} + w_0 > 0 \Rightarrow f = 1 \\ \mathbf{w}^T\mathbf{x_i} + w_0 < 0 \Rightarrow f = -1 \end{cases} \tag{1}$$

where f represents the output of the algorithm for a new point x_i, output that allows to classify x_i as belonging to one of the two classes. To build the hyperplane, we have to solve the following equation that maximizes the distance between the closest points of each classes and the separation:

$$\arg\max_{w,w_0} \min_{i=1\ldots N} \{\|x - x_i\| : x \in \mathbb{R}^d, \mathbf{w}^T\mathbf{x} + w_0 = 0\}.$$

This is done by solving the linear problem

$$\text{Min} \quad \frac{1}{2}\|\mathbf{w}\|^2 \tag{2}$$

$$\text{s.t.} \quad f(\mathbf{w}^T\mathbf{x_i} + w_0) \geq 1, \qquad i = 1..N. \tag{3}$$

The solution of this problem is the saddle point of the Lagrangian

$$L_p = \frac{1}{2}\|\mathbf{w}\|^2 - \sum_{k=1}^{N} \alpha_k (f(\mathbf{w}^T\mathbf{x_i} + w_0) - 1). \tag{4}$$

In this equation, the coefficients α_k are the Lagrange multipliers. Considering (4), (1) can be written as follows:

$$\begin{cases} \sum_{\alpha_k > 0} f(\alpha_k \langle \mathbf{x}, \mathbf{x_k} \rangle + w_0) > 0 \Rightarrow f = 1 \\ \sum_{\alpha_k > 0} f(\alpha_k \langle \mathbf{x}, \mathbf{x_k} \rangle + w_0) < 0 \Rightarrow f = -1. \end{cases} \tag{5}$$

$\mathbf{x_k}$ are the support vectors, the one chosen in each class to define the separation and $\langle ., . \rangle$ is the inner product for two vectors. This last equation allows classifying a new vector $\mathbf{x}$ unknown in the training database.

This case describes only the classification for a binary problem that can be linearly separated. The next sections will explain how to deal with nonlinear separation and multiclass separation, as in our problem that includes seven classes.

B. Kernel Trick

The previous section describes the case in which the two classes can be linearly separated. This case is rare. If the SVM were not able to solve other problems, their interest and use would be limited. Moreover, we can notice that (5) presents the resolution of the problem and the classification of a new point and 1), the way to find the support vector. For these two equations and also in all the description of SVM, the $\mathbf{x}$ vector always appears in an inner product.

In 1964, Aizerman *et al.* described a family of functions that acts as an inner product [29]. Such functions K give the equivalence: $K(\mathbf{x_i}, \mathbf{x_j}) = \langle \mathbf{x_i}, \mathbf{x_j} \rangle$. K functions will map the input space into a high-dimensional space (even infinite), named feature space. In this space, the nonseparable case will be transformed in a separable case. This function is chosen as a *a priori*. The problem of determining the best kernel for a given application is always an open issue. The resolution of the problem is then obtained by replacing the dot products in (4) and (5) by the kernel function $K(\cdot, \cdot)$.

The construction of such functions is described by the Mercer conditions [30]. This theorem describes these functions as symmetric continuous and positive semidefinite. Taking this condition into account, a kernel function adapted to a problem can be built. There are also generic kernels. We used two of them to compare the results in our case.

1) Polynomial kernel: $K(\mathbf{x_i}, \mathbf{x_j}) = (\mathbf{x_i}^T\mathbf{x_j} + 1)^p$.
2) Gaussian kernel (also called radial basis function): $K(\mathbf{x_i}, \mathbf{x_j}) = \exp(-\|\mathbf{x_i} - \mathbf{x_j}\|^2 / 2\sigma^2)$.

C. Multiclass SVM

The two previous sections describe the methods for classifying data with SVM in separable and nonseparable cases, both in the case of binary problems. Our problem contained seven classes. The extension of the SVM to multiclass problem was done by using two different families of solutions. The first one was to consider the N-class problem as a set of two-class problems. The simplest manner to address this problem, called "one-versus-all," was to train N binary classifiers that learned to distinguish one class from all the others [31]. The decision for a new point was taken using majority vote. This method presented two drawbacks. The first one is that there was a zone of the space for which the class could not be determined. The area of this zone depend on the number of classes and it decreased when N rose. SVM could be distorted with unbalanced training sets. The other drawback was that with this method, each classifier was trained with the whole dataset. If this training set was unbalanced, the N classifiers could also be distorted. The second possible scheme, named 'one-versus-one" and first introduced in [32], was to build classifiers, using all the pairwise combinations of the N classes. In this case, we would build binary classifiers to differentiate classes C_i and C_j, $0 < i \leq N$ and $0 < j < i$. With this method, as illustrated by Fig. 2, there was always a part of the space that remained undetermined, but it was maximally reduced. Moreover, in case of an unbalanced training set, fewer classifiers were distorted. Finally, the constructions of the set of classifiers were not more complicated and time consuming than for "one-versus-all." Indeed, even if more classifiers were built, the resolution of one of the linear problems was much smaller (and faster) in the second case because each classifier considered only a subset

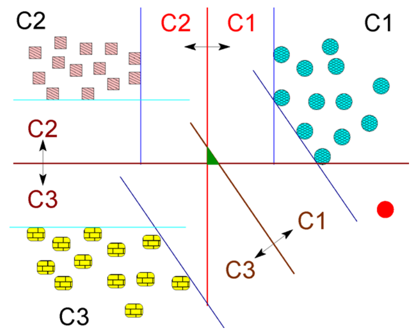


Fig. 2 "One-versus-one" classification of three linearly separable classes with SVMs.

of the training dataset. A majority vote was made to determine the class of a new point (the isolated point on the figure for instance). Mathematically speaking, the decision was given by: $C = \max_{k=1\dots N} \mathrm{Card}(\{y_{i,j}\} \cap \{k\})$, where $y_{i,j}$ was the decision given, for this new point, by the SVM trained to distinguish classes i and j. In case of equality, the chosen class was the one with the maximal margin from the final subset.

Both previous methods use a set of binary classifiers for a final decision in a multiclass problem. The various equations presented in the Section IV-A were used. The other method, introduced in [33], consisted of resolving a single optimization problem, thus creating a real multiclass separation as a multivariate linear regression model (a set of hyperplanes of cardinality equal to the number of classes). This drawback of this method was that the determination of separations, by resolution of the linear problem, was complicated and time consuming, as compared to other methods. A comparison of the three methods is given in [34] and demonstrates, in their applications, similar results between multiclass implementation and "one-versus-one" methods.

Given these facts, we selected the "one-versus-one" method for our application. In this method, we selected the various classes in the database and we trained binary classifiers to distinguish them (pairwise combinations selection). We first implemented the SVM algorithm under MATLAB, then we tested it and compared the results with those of another existing implementation [35].

D. Features Extraction

The classification of the activities could not be performed on the raw data that was too different from one person to another and for a given individual from the execution of an activity to another execution. Indeed, when an activity was performed, depending on the stage of the activity, the values of the different sensors could be different. We had to find parameters that varied only for two different activities, but neither for two executions of the same activity nor for the execution of an activity by two different people.

To determine these features, we performed a preliminary small experimentation, we computed a large number of parameters, and then, we extracted the most significant for the different activities using principal component analysis (PCA). The results of this *a priori* feature selection on a small number of activity performance are given in the Table I.

TABLE I
SUMMARY OF THE VARIOUS MODALITIES WITH SELECTED FEATURE AND THE ACTIVITY FOR WHICH IT IS INFORMATIVE

Modality	Features selected	Information sample
Actimeter	Percentage of time spent in various postures (standing, sitting, lying) and percentage of time spent walking	Sleeping (lying), resting (lying and sitting) and having a meal (walking and sitting down)
Microphones	Number of events per class (speech, door locking, door shutting, dish sounds, walking sounds, phone ringing, object falling, glass breaking, and shouting) and number of events per microphone	Communication (phone ringing and speech), cooking (dishes sounds), resting (TV or radio sounds in the living room)
IPR	Percentage of time in each room (mobility) and number of events for each detector (agitation)	Sleeping and dressing/undressing (in the bedroom, immobile for the first, moving for the second), cooking (in the kitchen), hygiene (in the bathroom), bowel movements (in the toilet), resting and communication (in the living room)
Door contacts	Percentage of time "open" and predominant position (open or close) in the time frame	Cooking (use of the cupboards and fridge), dressing/undressing (use of the chest of drawers)
Environmental	Differential measure for the last 15 minutes for temperature and hygrometry	Hygiene (use of the shower)

E. Data Classification

We described the selection of features for each sensor. Table I summarizes the different sensors and their selected features, and also enumerates the information given by the different sensors for each activity. The final vector, created for the classification of ADL currently occurring, was the concatenation of all these previous features. We had a set of 42 parameters (α_{i_j} with $i = 1 \dots 5$ are the different modalities and j is an index for the features inside each modality) used to create one vector $X = [\alpha_{1_1}, \alpha_{1_2}, \alpha_{1_3}, \dots, \alpha_{5_1}, \alpha_{5_2}]'$. This new vector was used in the SVMs algorithm previously described.

F. Data Normalization

The selected features were heterogeneous. This could lead to problems when creating the classifiers, if one of the dimensions varied more than another. The first step before training and validation was to normalize the set of data. To do this, we determined the mean and standard deviation of the dataset in this dimension for each dimension of the feature vectors. With this set of means and standard deviations, we created a new training dataset that was zero-mean and had a unit standard deviation in every dimension. This was done to remove distortion dues to the data heterogeneity. New and tested vectors were normalized using the set of coefficients determined with the current training dataset.

G. Indexation and Training

Our goal was to investigate a supervised algorithm for the classification of the ADL. To achieve this, we had to build a training database. We made a first experimentation involving 13 individuals used for learning and testing using a leave-one-out cross-validation method. Five video cameras gave us an (almost) complete view of the flat. These were used to index the activities performed by the individuals. For each individual, we created an XML file that contained all the information on the experimental session, which are as follows:

1) the identifier of the individual;
2) the information on the different sensors, the location of each file containing the raw data (one file per sensor);
3) the information used to synchronize the kinematic sensors with the others (unlike all the other sensors acquired simultaneously on the different computers synchronized by network time protocol, the wearable sensor is the only one that is synchronized later, so a synchronization movement is needed at the beginning of the experimentation).

With all this information created from the experimental session, we were able to build the training database and test it with the “leave-one-out” algorithm.

H. Validation

This first experimentation allowed the conception of a training database for the different ADL. From this dataset, we wanted validation results as accurate as possible. However, the number of frames in the database was very low. For this reason, the most adapted validation protocol was “leave-one-out”. Indeed, this protocol allowed to perform the same number of tests than the number of items in the database. It consisted in keeping a vector from the database of K elements, learning from the $K-1$ vectors, and testing on the Kth vector. K tests were performed in this protocol, removing a different vector every time. K was the maximum possible number of tests for a cross validation and was also better adapted to our small dataset.

Another possibility would have been to learn from 12 individuals and test on one individual. However, the first drawback was that when one of the individuals was removed, a large percentage of frames were also removed (almost 8%). On very small database, this distorted the different classifiers. Moreover, the distortions were different in each case because the number of frames removed in each loop was greatly different.

The “leave-one-out” protocol was implemented under MATLAB.

TABLE II
DISTRIBUTION OF ELEMENTS IN THE TRAINING DATABASE (NUMBER OF FRAMES AND PERCENTAGES) AND RESULTS FOR THE POLYNOMIAL AND GAUSSIAN KERNELS

Class	Frames	Percentage	Polynomial	Gaussian
Sleeping	49	21.1%	77.6%	93.9%
Resting	73	31.4%	76.7%	78.1%
Dressing/undressing	16	6.9%	56.2%	75%
Eating	45	19.4%	84.4%	97.8%
Toilet use	16	6.9%	68.7%	93.75%
Hygiene	14	6%	50%	64.3%
Communication	19	8.1%	89.5%	89.3%
Total	232	100%	75.9%	86.2%

V. EXPERIMENTATION AND RESULTS

A. Experimental Protocol, Population, and Collected Data

We described the implementation of a solution to monitor the ADL of a person living alone at home. We determined a set of seven activities that we wanted to classify automatically. We had to build an experimental protocol to produce a first training database to build the classifier and to learn the models for each activity.

This experimental protocol was quite simple. The individual was equipped with an wearable sensor and asked to enter the flat and behave as if he were in his own home. Before this, the experimenter had organized a detailed visit of the flat to make sure that the individual would not search for things and would feel at home. Then, the individual was asked to perform each of the previously defined ADL at least one time. He had neither order nor time constraint to perform these activities. He was asked to perform them as he would normally do. All the required conditions were present to complete the seven activities correctly.

As previously described, the individual closed the door completely if he was in the toilet and partially if he was in the bathroom to differentiate between hygiene and toilet use.

This experimentation was performed by 13 healthy and young subjects (six women and seven men). The average age was 30.4 ± 5.9 years (24–43, min–max), height 1.76 ± 0.08 m (1.62–1.92, min–max), and weight 69 ± 7.42 kg (57–80, min–max). The mean execution time of the experiment was 51 min 40 s (23 min 11 s–1 h 35 min 44 s, min–max). Table II gives the details of the training database.

Table II shows that the training database was not well-balanced. Indeed, it resulted from the experimental protocol, since the subject had no time constraint to perform the activities. The sleeping activity was longer to perform, whereas hygiene and toilet activities were very short (one frame). The number of frames for the sleeping activity was more than three times higher than the number of frames for hygiene. Since the individuals had no orders on the time to spend for each activity, some of them lied down and stayed in this position only few minutes before performing another activity. Moreover, due to the really low number of frames, if an individual spent more than 2 min, but less than 3 min for an activity, the window was considered as a full-time three-minutes frame.

TABLE III
CONFUSION MATRIX IN THE CASE OF A GAUSSIAN KERNEL WITH THE OPTIMIZED VALUE OF σ

		Classification Results						
		Sleeping	Resting	Dress/undress	Eating	Toilet use	Hygiene	Communication
Activity	Sleeping	**93.9%**	6.1%	0%	0%	0%	0%	0%
	Resting	13.8%	**78.1%**	1.3%	1.3%	4.2%	1.3%	0%
	Dressing/undressing	6.25%	12.5%	**75%**	0%	0%	0%	6.25%
	Eating	0%	0%	2.2%	**97.8%**	0%	0%	0%
	Toilet use	0%	0%	0%	6.25%	**93.75%**	0%	0%
	Hygiene	7.1%	0%	0%	7.1%	21.5%	**64.3%**	0%
	Communication	0%	5.3%	5.3%	5.9%	0%	0%	**89.5%**

B. Classification Results

We tested the classification of the activities using a polynomial kernel (with degree 1 and 2) and with a Gaussian kernel. As previously mentioned, the validation was performed using the "leave-one-out" method. For the Gaussian kernel, the best value for the parameter of the kernel was chosen by minimizing the global error rate. The results for both kernels are compared in Table II. The complete results for the Gaussian kernel with the optimal value are given in Table III.

This last table shows relatively similar results for both kernels. We can see that the classes are divided into two groups. The first one includes dress/undress and hygiene. These two classes had less good results than the others. This was due to the fact that they were less represented in the training database. Due to this, when the support vectors were removed from the database to be tested, the construction of the model was corrupted and this mistake would then have more importance than in the case of better-represented classes. We obtained 75.9% of well-classified temporal frames for the polynomial kernel and 86.2% for the Gaussian one.

The confusion matrix confirmed this. For example, the errors for dress/undress were dispatched in the classes sleep and rest, the most represented in the database and so the best described. The smallest classes were not correctly described in the training database. When an important support vector (that participated in the correct description of the class) was removed, the small number of items remaining in the training database for the class was not sufficient for a good description and this lead to a distortion in the classifier.

This matrix also showed us that the classes hygiene and toilets were close and the probability to misclassify them was higher than for other activities. This could be explained by the fact that the toilet activity normally included a hygiene activity (washing hands). They both included detections in the bathroom in the standing position. We could also notice that the errors in resting activity were mostly present in the sleeping class (that could be identical for the actimeter, the sounds, and that if the person did not move, there was no detection in either case, only the presence in the bedroom or in the living room was indicated). But, we could also notice that there were some misclassified frames in all the other activities, except for communication. This could be explained by the fact that this class was larger than the other ones. It was then logical that misclassifications would be equally shared in all the other classes. The sleep activity, when misclassified, was recognized as rest. This could be explained by the fact that the changes of posture could be missed. In that case, the other sensors could induce an error (location, no detection of sounds, etc.). Eating activity was well recognized in more that 97% of the time. Finally, for the communication activity, misclassification were found in dressing (i.e., in the same location than communication), eating (explained by the validation of the sound modality [19], during which we found that the misclassifications, for the sound modality, were mostly in the speech class, close to the dish sound class), and resting, also in the same location than communication. If the phone ringing or speech was missed by the sound and speech classification system, this led to a misclassification due to the location.

Finally, the global percentage of well-classified frames was 86%, and the better classified classes were those that were the more represented in the training database, with the higher number of items.

VI. DISCUSSION AND CONCLUSION

This study presents the classification of the ADL in a Health Smart Home based on SVMs. We installed, in a real and usable flat, sensors that were useful for our application. We used location (presence infrared) sensors, microphones for sound and speech recognition, an wearable sensor constituted of accelerometers and magnetometers, which indicated walking periods and postural transfers, door contact on appliances (fridge, cupboard, and dresser), and finally, temperature and hygrometry sensors. After a presentation of the various sensors and their installation into the flat, we presented the selection of features for each sensor. These features were chosen because they were representative of an activity and allowed a correct differentiation of two different activities. These features were then put together to create a feature vector significantly representative of an activity. The "one-versus-one" algorithm determined the model for the seven ADL monitored. An experiment on 13 young individuals was performed to build the training database and then the "leave-one-out" cross-validation method allowed to test these hypotheses.

This cross-validation test gave interesting preliminary results with a good classification rate of 75% for a polynomial kernel and 86% for a Gaussian kernel with an adapted parameter. The classification rates were different for each class and higher for the most represented classes in the database. This was expected because the most representative classes in the database were the best described in the model and the most robust when removing an element for testing purpose. The results were close to the best published ones, with 88% of correct classification in [10], but with many less sensors (without tagging every object). Our method was closer to [14], but with more activities (seven instead of two).

In this study, we proposed a model for the monitoring of elderly people living independently at home. However, this first experimentation was made on young individuals. Future studies will be made on elderly people and, on longer terms, to obtain a larger database that should allow cross validation with multiple folds and stratification. We think that, due to the selected variables, the model should not change from one population to another. But only the future experimentations will confirm or invalidate this hypothesis. These experimentations will also be more informative on the importance of each sensor in the classification. Moreover, in the generalization of the method, the data to be classified will not be timestamped and well-separated, as in this validation. It is mandatory to create an additional class, which will represent the transition between two activities. Indeed, when the algorithm classifies a temporal frame, it will be possible for this frame to contain 1 min 30 s of cooking activity and 1 min 30 s of resting activity. This kind of frame should be classified in this new class.

Moreover, the experiments were only performed in the experimental Health Smart Home of Grenoble. We could question the "instruction effect" (the fact that our way to present the experimentation had an influence on the way the individual performed it). We tried to avoid this by presenting differently the activities and the order of execution. Still, an unanswered question is what is the influence of the location of the experiment on the construction of models? The future measurement surveys on elderly people should be performed at their home. We will have to set up more flats like the one used in our study and organize better-structured measurement protocols to deal with a greater number of flats, to confirm our initial results, and evaluate the generalization capacity of the algorithm to other/larger populations.

In this paper, we aimed at demonstrating that constructing models of activities, independents of the person and without *a priori* knowledge (so that we do not have to take into account any seasonality problem, for example) was possible. These models will have to face changes of population in future experimentations, to determine the influence of the target population on the selected features.

A review is presented in [36] on the different techniques to incorporate *a priori* knowledge in the SVM. This knowledge can allow to represent an invariance (rotation, scaling, ...) on the data that is not enough described by the training samples. This can also be used to assign different weights to some of the dimensions or classes to give more or less importance to some results. Another way to improve the classification results, when necessary, could be to specialize our models with such methods. This would result in a reduction of the generalization capacity of the algorithm in our case. Indeed, for example, we could associate a moment of the day (morning, afternoon...) or a room (kitchen, ...) to a subset of activities. We could, for instance, consider that the three lunches of the day are taken in the kitchen and in the three different time slots 6 AM–9 AM, 11 AM–2 PM, and 7 PM–9 PM. However, doing so, we would consider a "normal" behavior that needs to be defined. This behavior will be obviously restricted to a targeted part of the population. Moreover, one of the aim of this paper is to tend to the detection of behavior modification to early anticipate the apparition of specific long diseases. Adding generic models to the learnt behavior of the subject could damage this detection by reducing the specific part (the one concerning the subject or population) in the global model.

A future interrogation lies in determining if the improvements brought by the insertion of these *a priori* knowledge (in term of sensitivity and specificity) compensate for the lower generalization capacity of the algorithm that is created. The answer will come with considering the results on larger and different populations and, moreover, by analyzing the real benefit from the medical point of view. It will be then mandatory to determine the acceptable error rate versus the amount of predefined conditions on the population.

Acknowledgment

The authors would like to thank the volunteer from TIMC Laboratory, who accepted to perform this experimentation and kindly gave their time. They would also like to thank C. Villemazet and RBI for the development of the AILISA software [presence infrared sensors (PIR)], and H. Glasson, who worked very hard on the AuditHIS application.

References

[1] K. Nakajima, H. Matsui, T. Motoya, and K. Sasaki, "Television-operating-state telemonitoring system in caring for elderly people living alone," presented at the Int. Conf. Int. Soc. Gerontechnol., Pisa, Tuscany, Italy, Jun. 4–7, 2008.

[2] M. Chan, D. Esteve, C. Escriba, and E. Campo, "A review of smart homes—present state and future challenges," *Comput. Methods Progr. Biomed.*, vol. 91, no. 1, pp. 55–81, Jul. 2008.

[3] S. Intille, "Designing a home of the future," *IEEE Pervasive Comput.*, vol. 1, no. 2, pp. 76–82, Apr.–Jun. 2002.

[4] S. Intille, "A new research challenge: Persuasive technology to motivate healthy aging," *IEEE Trans. Inf. Technol. Biomed.*, vol. 8, no. 3, pp. 235–237, Sep. 2004.

[5] G. Abowd, E. Mynatt, and T. Rodden, "The human experience [of ubiquitous computing]," *IEEE Pervasive Comput.*, vol. 1, no. 1, pp. 48–57, Jan.–Mar. 2002.

[6] D. Moore and I. Essa, "Recognizing multitasked activities from video using stochastic context-free grammar," in *Proc. Amer. Assoc. Artif. Intell. Conf. (AAAI)*, Alberta, Canada, Jul. 2002, pp. 770–776.

[7] Q. T. Tran and E. D. Mynatt, "What was i cooking? towards deja vu displays of everyday memory," Georgia Instit. Technol., Atlanta, GA, Tech. Rep. GIT-GVU-TR-03-33, 2003.

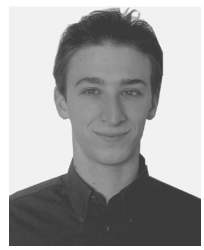
[8] G. Le Bellego, N. Noury, G. Virone, M. Mousseau, and J. Demongeot, "A model for the measurement of patient activity in a hospital suite," *IEEE Trans. Inf. Technol. Biomed.*, vol. 10, no. 1, pp. 92–99, Jan. 2006.

[9] S. Bonhomme, E. Campo, D. Esteve, and J. Guennec. (2008, Mar.). Prosafe-extended, a telemedicine platform to contribute to medical diagnosis. *J. Telemed. Telecare* [Online]. *14(3)*, pp. 116–119. Available: http://dx.doi.org/10.1258/jtt.2008.003003

[10] M. Philipose, K. P. Fishkin, M. Perkowitz, D. J. Patterson, D. Fox, H. Kautz, and D. Hahnel, "Inferring activities from interactions with objects," *IEEE Pervasing Comput.*, vol. 3, no. 4, pp. 50–57, Oct. 2004.

[11] E. Tapia, S. Intille, and K. Larson, "Activity recognition in the home using simple and ubiquitous sensors," in *Proc. Int. Conf. Pervasive Comput.*, Lecture Notes in Computer Sciences, 2004, vol. 3001, pp. 158–175.

[12] X. Hong, C. Nugent, M. Mulvenna, S. McClean, and B. Scotney, "Evidential fusion of sensor data for activity recognition in smart homes," *Pervasive Mobile Comput.*, vol. 5, pp. 1–17, 2008.
[13] C. Nugent, X. Hong, J. Hallberg, D. Finlay, and K. Synnes, "Assessing the impact of individual sensor reliability within smart living environments," in *Proc. IEEE Int. Conf. Autom. Sci. Eng. (CASE)*, 2008, pp. 685–690.
[14] B. Krose, T. van Kasteren, C. Gibson, and T. van den Dool, "Care: Context awareness in residences for elderly," presented at the Int. Conf. Int. Soc. Gerontechnol., Pisa, Tuscany, Italy, Jun. 4–7, 2008.
[15] S. Tsukamoto, H. Hoshino, and T. Tamura, "Study on indoor activity monitoring by using electric field sensor," presented at the Int. Conf. Int. Soc. Gerontechnol., Pisa, Tuscany, Italy, Jun. 4–7, 2008.
[16] M. Berenguer, M. Giordani, F. Giraud-By, and N. Noury, "Automatic detection of activities of daily living from detecting and classifying electrical events on the residential power line," in *Proc. 10th IEEE Int. Conf. e-Health Netw., Appl. Serv. HealthCom*, 2008, pp. 29–32.
[17] M. Vacher, A. Fleury, F. Portet, J.-F. Serignat, and N. Noury. "Complete Sound and Speech Recognition System for Health Smart Homes: Application to the Recognition of Activities of Daily Living," in *Recent Advances in Biomedical Engineering*, In-Tech, Vienna, Austria, to be published. ISBN: 978-953-7619-X-X, 26p.
[18] N. Noury, C. Villemazet, A. Fleury, P. Barralon, P. Rumeau, N. Vuillerme, and R. Baghai, "Ambient multi-perceptive system with electronic mails for a residential health monitoring system," in *Proc. 28th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBS)*, Aug. 28–Sep. 1, 2006, pp. 3612–3615.
[19] A. Fleury, N. Noury, M. Vacher, H. Glasson, and J.-F. Serignat, "Sound and speech detection and classification in a health smart home," in *Proc. 30th IEEE EMBS Annu. Int. Conf.*, Vancouver, BC, Aug. 20–24, 2008, pp. 4644–4647.
[20] A. Fleury, N. Noury, and M. Vacher, "A wavelet-based pattern recognition algorithm to classify postural transition in humans," in *Proc. 17th Eur. Signal Process. Conf. (EUSIPCO)*, Glasgow, Scotland, Aug. 24–28, 2009, pp. 2047–2051.
[21] S. Katz and C. Akpom, "A measure of primary sociobiological functions," *Int. J. Health Serv.*, vol. 6, no. 3, pp. 493–508, 1976.
[22] M. Lawton and E. Brody, "Assessment of older people: Self-maintaining and instrumental activities of daily living," *Gerontologist*, vol. 9, pp. 179–186, 1969.
[23] F. Rosenblatt, "The perceptron: A probabilistic model for information storage and organization in the brain," *Psychol. Rev.*, vol. 65, no. 6, pp. 386–408, 1958.
[24] B. E. Boser, I. M. Guyon, and V. N. Vapnik, "A training algorithm for optimal margin classifiers," in *Proc. 5th Annu. Workshop Comput. Learning Theory*, Pittsburgh, PA: ACM, 1992, pp. 144–152.
[25] A. Stolcke, S. Kajarekar, and L. Ferrer, "Nonparametric feature normalization for svm-based speaker verification," in *Proc. ICASSP 2008*, pp. 1577–1580.
[26] B. Heisele, P. Ho, and T. Poggio, "Face recognition with support vector machines: Global versus component-based approach," in *Proc. Int. Conf. Comput. Vis. (ICCV)*, Vancouver, Canada, 2001, vol. 2, pp. 688–694.
[27] T. M. Huang and V. Kecman, "Gene extraction for cancer diagnosis by support vector machines—an improvement," *Artif. Intell. Med.*, vol. 35, pp. 185–194, 2005.
[28] C. J. C. Burges, "A tutorial on support vector machines for pattern recognition," *Data Mining Knowl. Discov.*, vol. 2, no. 2, pp. 121–167, 1998.
[29] M. Aizerman, E. Braverman, and L. Rozonoer, "Theoretical foundations of the potential function method in pattern recognition learning," *Autom. Remote Control*, vol. 25, pp. 821–837, 1964.
[30] J. Mercer, "Functions of positive and negative type and their connection with the theory of integral equations," *Philos. Trans. R. Soc. Lond. Ser. A*, vol. 209, pp. 415–446, 1909.
[31] L. Bottou, C. Cortes, J. S. Denker, H. Drucker, I. Guyon, L. D. Jackel, Y. LeCun, U. A. Muller, E. Sackinger, P. Simard, and V. Vapnik, "Comparison of classifier methods: A case study in handwritten digit recognition," in *Proc. 12th Int. Pattern Recogn. (IAPR) Vol. 2—Conf. B: Comput. Vis. & Image Process. Conf.*, Oct. 9–13, 1994, vol. 2, pp. 77–82.
[32] S. Knerr, L. Personnaz, and G. Dreyfus, "Single-layer learning revisited: A stepwise procedure for building and training a neural network," in *Neurocomputing: Algorithms, Architectures and Applications*. Berlin, Germany: Springer-Verlag, 1990.
[33] Y. Guermeur, "Combining discriminant models with new multi-class svms," *Pattern Anal. Appl.*, vol. 5, no. 2, pp. 168–179, 2002.
[34] C.-W. Hsu and C.-J. Lin, "A comparison of methods for multiclass support vector machines," *IEEE Trans. Neural Netw.*, vol. 13, no. 2, pp. 415–425, Mar. 2002.
[35] S. Canu, Y. Grandvalet, V. Guigue, and A. Rakotomamonjy, "Svm and kernel methods matlab toolbox," Percept. Syst. et Inf., INSA de Rouen, Rouen, France, 2005.
[36] F. Lauer and G. Bloch, "Incorporating prior knowledge in support vector machines for classification: A review," *Neurocomputing*, vol. 71, pp. 1578–1594, 2008.



Anthony Fleury (S'05–M'08) received the Engineer degree in computer science and the M.Sc. degree in signal processing, in Grenoble, in 2005 and the Ph.D. degree in signal processing from the University Joseph Fourier, Grenoble, in 2008, where he was involved in the automatic recognition of activities of daily living in health smart homes from sensor fusion.

He is currently an Assistant Professor with the Department of Computer Sciences and Automation, Ecole des Mines de Douai, Douai, France. His research interests include the modeling of human behaviors and activities, machine learning, and pattern recognition with applications in biomedical engineering.

Michel Vacher received the Ph.D. degree in acoustical science from the Institut National des Sciences Appliquées de Lyon, Lyon, France, in 1982.

Since 1986, he has been a Research Scientist with the Centre National de la Recherche Scientifique, La Tronche Cedex, France. He was with the Laboratoire de Thermodynamique et Physicochimie Métallurgiques Laboratory, where he was engaged in high-resolution electron microscopy image simulation and analysis. Since 2000, he has been with the Laboratory of Informatics of Grenoble, Grenoble, France (ex CLIPS Laboratory), where he has been engaged in developing new research direction for smart house applications. His current research interests include sound classification and keyword/speech recognition in smart environments. He has authored or coauthored some 30 papers on various aspects of these topics.

Norbert Noury (M'04–SM'06) received the M.Sc. degree in electronics from Grenoble Polytechnic Institute, Grenoble, France, in 1985 and the Ph.D. degree in applied physics from Grenoble University, Grenoble, in 1992.

From 1985 to 1993, he was with various industrial companies. In 1993, he was with the Grenoble University, where he was involved in a new research activity on Health Smart Homes in 2000. He is currently a Full Professor with the University of Lyon, Lyon, France. He has guided 16 Ph.D. students. He has authored or coauthored around 150 scientific papers (including 30 journal papers, 80 communications in International Conferences, and 14 book chapters) and holds eight patents. He is a recognized expert at the European Commission. His research interests include "smart sensors" for ambient assisted living environments and for ubiquitous health monitoring systems.