Improving Activity Monitoring Through a Hierarchical Approach

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Abstract: Performance of sensor-based telemonitoring and home support systems depends, among other characteristics, on the reliability of the adopted sensors. Although binary sensors are quite used in the literature and also in commercial solutions to identify user's activities, they are prone to noise and errors. In this paper, we present a hierarchical approach, based on machine learning techniques, aimed at reducing error from the sensors. The proposed approach is aimed at improving the classification accuracy in detecting if a user is at home, away, alone or with some visits. It has been integrated in a sensor-based telemonitoring and home support system. Results show an overall improvement of 15% in accuracy with respect to a rule-based approach. The system is part of the BackHome project and is currently running in 2-healthy-users' home in Barcelona and in 3-end-users' home in Belfast.

1 INTRODUCTION

Activity monitoring is an increasingly important research area due to the fact that it can be applied to many real-life, human-centric problems, such as eldercare and healthcare. Recent studies have shown that physical activities in daily life are an important predictor of risk of hospital readmission and mortality in patients with chronic diseases (Yohannes et al., 2002) (Pitta et al., 2005).

Monitoring users' activities allows therapists, caregivers, and relatives to become aware of user context by acquiring heterogeneous data coming from sensors and other sources. Moreover, activity monitoring provides elaborated and smart knowledge to clinicians, therapists, carers, families, and the patients themselves by inferring user habits and behaviour. Various methods of subjective and objective physical activity assessment tools have been developed. Subjective methods, such as diaries, questionnaires and surveys, are inexpensive tools. However, these methods often depend on individual observation and subjective interpretation, which make the assessment results inconsistent (Meijer et al., 1991). On the other hand, objective techniques use remote monitoring techniques relying on sensors, such as home-automation, wearable and/or environmental ones (Warren, 2000).

A lot of telemonitoring systems have been proposed in the literature (Carneiro et al., 2008) (Corchado et al., 2010) (Mitchell et al., 2011) and are currently adopted in real environments (Scanaill et al., 2006), enabling the healthcare provider to get feedback on monitored people and their health status parameters.

Sensor-based telemonitoring systems rely on a conjunction of sensors, each one devoted to monitor a specific status, a specific activity or activities related to a specific location. Sensor technology can range from vital signal devices –such as blood pressure monitors, heart rate monitors and devices which can measure body temperature– to sensors which can detect presence in a room or detect a door being opened (Nugent et al., 2008). Once all of the data have been recorded it is then necessary for data processing to take place to identify if the person requires a form of assistance since an unusual activity has been recognized. Of course, this requires a certain degree of intelligence which should take into consideration the current state of the environment, the performed activity and/or some physiological data (Cook and Das, 2007). Due to issues regarding personal privacy, technical installations, and costs of technology the most adopted sensors are anonymous binary sensors (Nugent et al., 2008). Binary sensors do not have the ability to directly identify people and can only present two possible values as outputs ("0" and "1"). Typical examples of binary sensors deployed within smart environments include pressure mats, door sensors, and movement detectors. A number of studies reporting

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the use of binary and related sensors have been undertaken for the purposes of activity recognition (Tapia et al., 2004). Nevertheless, sensor data can be considered to be highly dynamic and prone to noise and errors (Ranganathan et al., 2004).

The increasing social demand for intelligent telemonitoring systems makes necessary to put more emphasis in activity recognition methods that deal with environments prone to errors (Jafari et al., 2005). In this paper, we make a step forward in this direction by introducing a novelty and effective discriminative method based on machine learning. The goal is to discover the very initial but crucial information regarding the user location and recognition whether s/he is alone or with visits under complex, noisy and unstable environments. The method has been evaluated at two healthy user homes in Barcelona where it is currently running. Moreover, the system has been installed and it is working in 3-end-users' home in Belfast. Evaluation is performed by using a novelty technique to gain further user objectivity based on the information collected from an activity tracking mobile application.

The rest of the paper, is organized as follows. Section 2 illustrates the implemented sensor-based telemonitoring and home support system. In Section 3, we present the adopted approach aimed at improving habit recognition whereas in Section 4, we summarize our preliminary results that show the improvement in adopting the proposed solution. In Section 5, we recall relevant work related to the partial detection of some of the activities that concern us and with settings similar to those presented in this work. Section 6 ends the paper with conclusions and future work.

2 THE SENSOR-BASED TELEMONITORING AND HOME SUPPORT SYSTEM

To monitor users' activities, we develop a sensor-based telemonitoring and home support system (SB-TMHSS) able to monitor the evolution of the user's daily life activity. The implemented system is able to monitor indoor activities by relying on a set of home automation sensors and outdoor activities by using Moves[1]. Information gathered by the SB-TMHSS is also used to provide context-awareness by relying on ambient intelligence (Casals et al., 2014). Monitoring users' activities through the SB-TMHSS gives us also the possibility to automatically assess quality of life of people (Vargiu et al., 2014). In this Section, we briefly describe the SB-TMHSS, the interested reader may refer to (Miralles et al., 2014) for further details.

The high-level architecture of the SB-TMHSS is depicted in Figure 1. As shown, its main components are: home; healthcare center; middleware; and intelligent monitoring system.

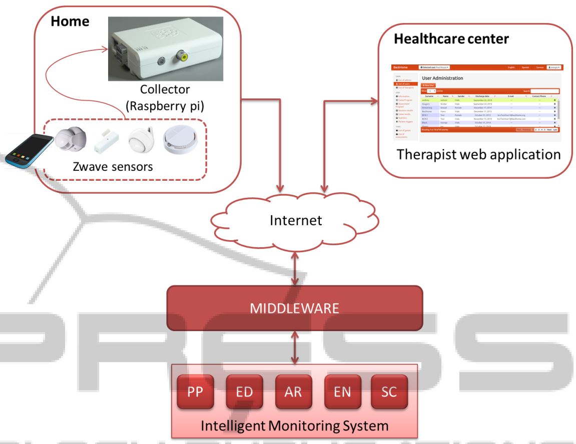

Figure 1: Main components of the SB-TMHSS.

At home, a set of sensors are installed. In particular, we use presence sensors (i.e., Everspring SP103), to identify the room where the user is located (one sensor for each monitored room); a door sensor (i.e., Vision ZD 2012), to detect when the user enters or exits the premises; electrical power meters and switches, to control leisure activities (e.g., television and pc); and pressure mats (i.e., bed and seat sensors) to measure the time spent in bed (wheelchair). The system is also composed of a network of environmental sensors that measures and monitors environmental variables like temperature, but also potentially dangerous events like gas leak, fire, CO escape and presence of intruders. All the adopted sensors are wireless z-wave[2]. They send the retrieved data to a collector (based on Raspberry pi[3]). The Raspberry pi collects all the retrieved data and securely redirects them to the cloud where they will be stored, processed, mined, and analyzed. The proposed solution relies on z-wave technology for its efficiency, portability, interoperability, and commercial availability. In fact, on the contrary of other wireless solutions (e.g., ZigBee), z-wave sensors are able to communicate with any z-wave device. Moreover, we adopt a solution based on Raspberry pi because it is easy-to-use, cheap, and scalable. We are also using the user's smartphone as a sensor by relying on Moves, an app for smartphones able to recognize physical activities

[1]http://www.moves-app.com/

[2]http://www.z-wave.com/

[3]http://www.raspberrypi.org/

and movements by transportation. Among the activity trackers currently on the market, we select Moves because it does not need user intervention being always active in background. The user interacts with the overall system through a suitable interface aware of end-user needs and preferences.

The middleware, which acts as a SaaS, is composed by a secure communication and authentication module; API module to enable the collector transmitting all the data from sensors to make them available to the intelligent monitoring system; and further utilities such as load balancing and concurrency.

In order to cope with the data necessities of the actors of the system (i.e., therapists, caregivers, relatives, and end-users themselves), an Intelligent Monitoring system has been designed. It is aimed to continuously analyzing and mining the data through 4-dimensions: detection of emergencies, activity recognition, event notifications, and summary extraction. In order to cope with these objectives, the Intelligent Monitoring system is composed of the following modules: PP, the pre-processing module to encode the data for the analysis; ED, the emergency detection module to notify, for instance, in case of smoke and gas leakage; AR, the activity recognition module to identify the location, position, activity- and sleeping-status of the user; EN, the event notification module to inform when a new event has been detected; and SC, the summary computation module to perform summaries from the data.

The healthcare center receives notifications, summaries, statistics, and general information belonging to the users through a web application.

3 THE HIERARCHICAL APPROACH

The SB-TMHSS described in the previous section is aimed at recognizing activities and habits of a user who lives alone. One of the requirements of the implemented SB-TMHSS was to be cheap and no-intrusive. In other words, we use the minimum number of sensors depending on the user's home configuration, avoiding camera or wearable sensors. In particular, we decided to not use a camera for privacy reason and in accordance with the requirements coming from the end-user of the proposed system. Moreover, the sensors are wireless and rely on wi-fi connection to send data to the collector. Let us note that we decided to do not adopt a wired solution because is more expansive and intrusive. These requirements imply that we have to take into account with errors and noise coming from this configuration and to find a solution to avoid them. In fact, sensors are not 100% reliable: sometimes they loose events or detect them several times. When sensors remain with a low battery charge they get worse. Moreover, also the Raspberry pi may loose some data or the connection with Internet and/or with the sensors. Also the Internet connection may stop working or loose data. Finally, without using a camera or wearable sensors we are not able to directly recognize if the user is alone or if s/he has some visits. Although, as said, a wireless solution is not 100% reliable, .

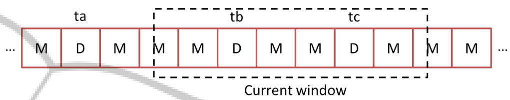

Figure 2: An example of the sliding window approach, where M means "motion event" and D means "door event".

In order to solve this kind of limitations with the final goal of improving the overall performance of the SB-TMHSS, we propose an approach based on machine learning techniques. In this initial solution, we only consider motion and door sensors. The intelligent monitoring system continuously and concurrently listens for new data in a given window, according to a sliding window approach (Datar et al., 2002). For each window, data are pre-processed by the PP and analyzed. As an example, let us consider the Figure 2 where once the current window recognizes a door event at time tb, it looks for the previous one in the window or before (in the example ta). Then, the period from that door events (i.e, $tb - ta$) is classified by the hierarchical classifier. Seemly, when the event tc has been recognized, the period from tb and tc is classified. Finally, the period from tc to the end of the window is classified. In case of no door events have been recognized, the period from ta to the end of the window is classified.

The hierarchical classifier, depicted in Figure 3, is composed of two levels. The upper is aimed at recognizing if the user is at home or not, whereas the lower is aimed at recognizing if the user is really alone or if s/he received some visits.

The goal of the classifier at the upper level is to improve performance of the door sensor. In fact, it may happen that the sensor registers a status change (from closed to open) even if the door has not been opened. This implies that the SB-TMHSS may register that the user is away and, in the meanwhile, activities are detected at user's home. On the contrary, the SB-TMHSS may register that the user is at home and, in the meanwhile, activities are not detected at user's home. To solve, or at least reduce, this problem, we built a supervised classifier able to recognize

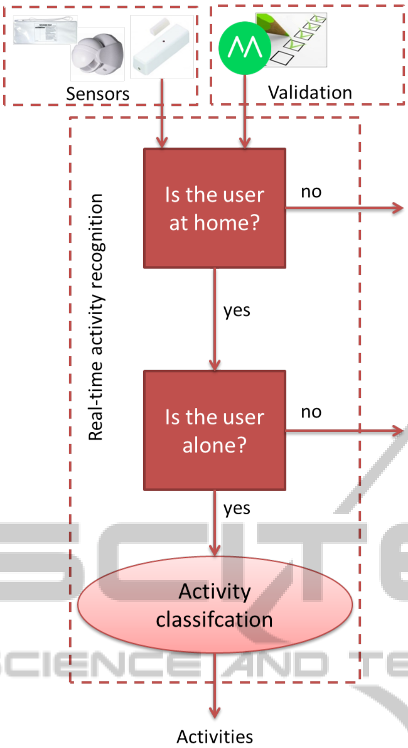

Figure 3: The hierarchical approach in the activity recognition module.

if the door sensor is working well or erroneous events have been detected. First, we revise the data gathered by the SB-TMHSS searching for anomalies, i.e.: (1) the user is away and at home some events are detected and (2) the user is at home and no events are detected. Then, we validated those data by relying on Moves, installed and running on the user smartphone. In fact, Moves, among other functionality, is able to localize the user. Hence, using Moves as an "oracle" we build a dataset in which each entry is labeled depending on the fact that the door sensor was right (label "1") or wrong (label "0").

The goal of the classifier at the lower level is to identify whether the user is alone or not. The input data of this classifier are those that has been filtered by the upper level, being recognized as positives. To build this classifier, we rely on the novelty detection approach (Markou and Singh, 2003) used when data has few positive cases (i.e., anomalies) compared with the negatives (i.e., regular cases); in case of skewed data. Let us recall here that novelty detection is the identification of new or unknown data that a machine learning system has not been trained with and was not previously aware of. In particular, we rely on the approach presented in (Schölkopf et al., 2001) that tries to estimate a function f that is positive on the dataset and negative on the complement. The functional form of f is given by a kernel expansion in terms of a potentially small subset of the training data; it is regularized by controlling the length of the weight vector in an associated feature space. The expansion coefficients are found by solving a quadratic programming problem, which we do by carrying out sequential optimization over pairs of input patterns.

4 PRELIMINARY EXPERIMENTAL RESULTS

The SB-TMHSS presented in this paper is part of BackHome[4], an European R&D project that aims to provide telemonitoring and home support using Brain Computer Interfaces (BCI) and other assistive technologies to improve autonomy and quality of life of disabled people (Vargiu et al., 2012). The system is currently running in five homes, two in Barcelona and three in Belfast. In Barcelona installations have been made at healthy-users' home, whereas in Belfast at BackHome end-user's home (Edlinger et al., 2015).

To train and test the proposed approach, we consider a window of 4 months for training and evaluation (training dataset) and a window of 1 month for the test (testing dataset). Experiments have been performed at each level of the hierarchy. First, we performed experiments to identify the best supervised classifier to be used at the upper level of the hierarchy. Subsequently, we applied the novelty detection algorithm on the data filtered by the classifier at the upper level, to validate the classifier at the lower one. Finally, we measure the performance of the overall approach.

4.1 Is the User at Home?

First of all we build the training dataset with door events (gathered by the door sensor) in a window of 4 months. Those data have been then validated by relying on the information coming from Moves. The entries are manually labeled in two classes *Correct data* and *User not at home* according to the following criteria:

- *Correct data*: 0 if the data gathered from the door sensor differs from the data gathered from Moves; 1 otherwise.
- *User not at home*: 0 if the user is at home; 1 otherwise.

[4] http://www.backhome-fp7.eu/backhome/index.php

Table 1: Results for the high-level classifier during the training (T) and evaluation (E) phase.

Classifier	**Parameter(s)**	**Accuracy (T)**	**Accuracy (E)**
LR	$C = 0.005$	0.945 ± 0.09	0.885
SVM	$\gamma = 0.01, C = 1.0$	0.945 ± 0.09	0.885
SVM	$\gamma = 1.0, C = 0.452$	0.853 ± 0.12	0.943
SVM	$\gamma = 0.05, C = 0.452$	0.930 ± 0.11	0.885
SVM	$\gamma = 0.01, C = 0.257$	0.945 ± 0.09	0.885
RF	$n\_estimators = 5$	0.943 ± 0.09	0.942
RF	$max\_features = 12$	0.930 ± 0.09	0.942
AB	$n\_estimators = 15$	0.918 ± 0.10	0.823

First, we define and implement a rule-based system to verify if an approach based on rules may help in improving the overall performance. The results coming from the rule-based system have been then compared with those manually validated using Moves. Unfortunately, results show a very few improvement with an accuracy of 77%. Thus, we decide to implement a supervised classifier.

The data labeled as 1 for the class *Correct data* have been used to extract the following features:

- number of motion events divided by their duration, calculate after a door event (from $t = i$ door event to $t = i+1$ door event) [Feature 1];
- number of motion events divided by their duration, calculated before a door event (from $t = i-1$ door event to $t = i$ door event) [Feature 2];
- number of motion events happened during minute before a door event ($t = i$) [Feature 3];
- number of motion events happened during the 2 minutes before a door event ($t = i$) [Feature 4];
- number of motion events happened during the 5 minutes before a door event ($t = i$) [Feature 5];
- number of motion events happened during minute after a door event ($t = i+1$) [Feature 6];
- number of motion events happened during the 2 minutes after a door event ($t = i+1$) [Feature 7];
- number of motion events happened during the 5 minutes after a door event ($t = i+1$) [Feature 8].

The dataset is then used to train four well-representative and successful families of supervised classifiers (Fernández-Delgado et al., 2014): a Logistic Regression (LR) classifier, a Support Vector Machine (SVM), a Random-Forest (RF) and an AdaBoost (AB).

The dataset has been divided in a training and in an evaluation set and a 10-fold cross-validation method has been used. The classifiers have been then tested with an independent dataset. Table 1 shows results during the training phase and evaluation phase. As shown, the best performance has been obtained by relying on the SVM (with $\gamma = 1.0$ and $C = 0.452$), see Figure 4, which shows different combination of the parameters kernel coefficient (γ) and penalty parameter of the error term (C).

The best classifier has been then used with the testing dataset and, on average, it obtained a F_1 of 0.97 and an accuracy of 0.968. Finally, it showed an improvement of 20% with respect to the rule-based approach.

4.2 Is the User Alone?

The data filtered by the classifier at the upper level, belonging to the monitored window of 4 months, are the training dataset of the classifier at the lower level. The corresponding dataset is composed by 57 normal instances (i.e., the user was alone) and 8 anomalies (i.e., the user received visits).

First of all, also in this case, we defined and implemented a rule-based classifier to verify if a rule-based approach could solve this problem. The adopted rules together with the number of anomalies detected by each one are the following:

- Number of movement events every 60 seconds greater than 6: 23 anomalies detected;
- Number of movement events every 60 seconds greater than 10: 1 anomaly detected;
- Simultaneous movement events: 20 anomalies detected;
- Simultaneous movement events in less 2 seconds: 23 anomalies detected;
- Maximum number of movement events in 60 seconds greater than 6 or simultaneous moves in less 2 seconds: 28 anomalies detected;
- Maximum number of movement events in 60 seconds greater than 6 or simultaneous moves: 21 anomalies detected.

Since the rule-based approach is not able to correctly recognized anomalies, we use, also in this case, an SVM classifier (one-class SVM with RBF, non linear). The following features have been considered:

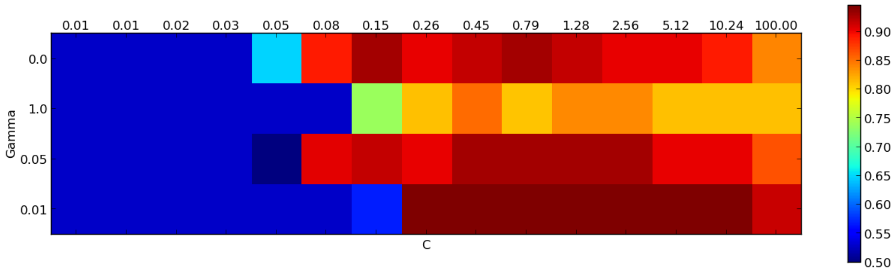

Figure 4: Cross-validation results of the different setting of parameters in the SVM classifier.

- maximum number of motion events in intervals of 60 seconds [Feature 1];
- maximum number of motion events in intervals of 120 seconds [Feature 2];
- maximum number of motion events in intervals of 180 seconds [Feature 3];
- number of motion events happened in a range of 5 seconds [Feature 4];
- number of motion events happened in a range of 2 seconds [Feature 5];
- number of motion events happened simultaneously [Feature 6];
- minimum number of seconds between two consecutive motion events [Feature 7];
- average of seconds between two consecutive motion events [Feature 8].

The classifier has been trained by considering the normal instances and then evaluated introducing the anomalies. Figure 5 shows the results obtained considering two features at time. In particular, for each pair of features the frontier, the training observations and the observations in case of normal instances (regular) or anomalies (abnormal) have been shown. Table 2 shows the overall results .

Results during the evaluation phase show that the system is able to correctly recognize all the anomalies. According to the obtained results, we select the classifier with the regularization parameter $(\nu) = 0.01$ and $\gamma = 0.1$.

Similarly to the classifier at the upper level, the system has been tested with the data coming from the 1-month window of monitored events. Results showed an average accuracy of 0.94.

4.3 Overall Results

Finally, we tested the performance of the overall hierarchical approach. Once both classifiers have been trained, we tested the performance of the overall approach with the testing dataset corresponding to a window of 1 month. We compared the overall results with those obtained by using the rule-based approach in both levels of the hierarchy. Results are shown in Table 3 and point out that the proposed approach outperforms the rule-based one with a significant improvement.

Table 2: Results for the classifier at the lower level. The table reports the classification error calculated as the ratio between the number of detected anomalies and the number of instances in the dataset.

Parameter(s)	**Error (T)**
$\nu = 0.01, \gamma = 0.1$	0.0701
$\nu = 0.01, \gamma = 0.5$	0.0877
$\nu = 0.01, \gamma = 1$	0.1578
$\nu = 0.05, \gamma = 0.1$	0.0877
$\nu = 0.05, \gamma = 0.5$	0.0877
$\nu = 0.05, \gamma = 1$	0.1403
$\nu = 0.1, \gamma = 0.1$	0.1052
$\nu = 0.1, \gamma = 0.5$	0.1052
$\nu = 0.1, \gamma = 1$	0.1403
$\nu = 0.5, \gamma = 0.1$	0.4912
$\nu = 0.5, \gamma = 0.5$	0.5087
$\nu = 0.5, \gamma = 1$	0.4912

Table 3: Results of the overall hierarchical approach with respect to the rule-based one.

Metric	**Rule-based**	**Hierarchical**	**Improv.**
Accuracy	0.80	0.95	15%
Precision	0.68	0.94	26%
Recall	0.71	0.91	20%
F_1	0.69	0.92	23%

To highlight the performance of the proposed approach, let us consider the Figure 6 that shows a comparison between the real data, labeled during the validation phase (on the left), and the data classified by relying to the approach proposed in this paper (on the right).

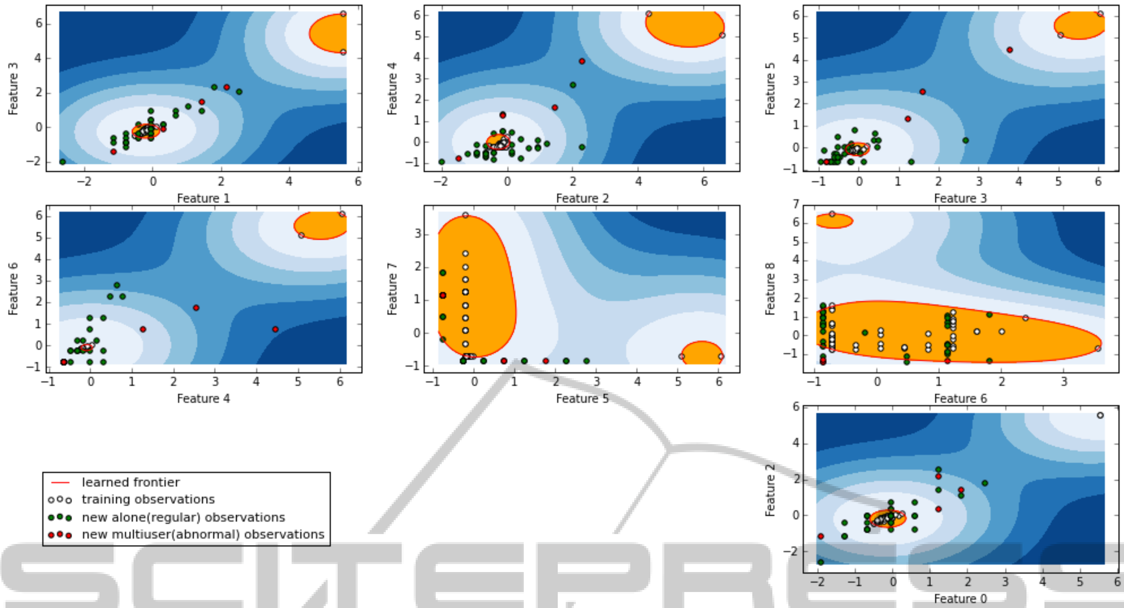

Figure 5: Feature analysis of select novelty outlier method.

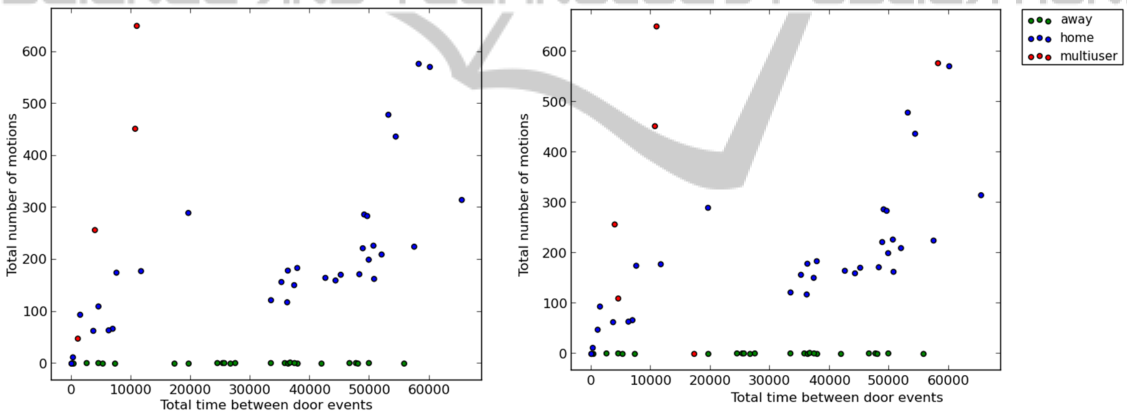

Figure 6: Comparison between real labeled data and data classified by the hierarchical approach.

Thanks to the proposed approach, the system is able to recognize if the user is at home, away and/or if s/he had some visits. An example of results in recognizing if the user is at home or away and if s/he received some visits is given in Figure 7.

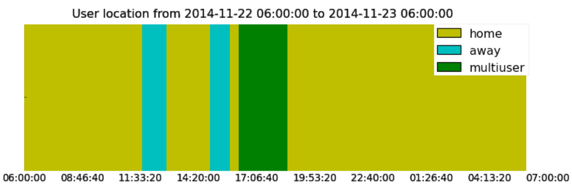

Figure 7: Example of results in recognizing if the user is at home or away or if s/he received some visits.

5 RELATED WORK

There is a large literature on recognition of activities at home (Van Kasteren et al., 2008) (Ye et al., 2012). At the same time, we find a great variability in the settings of the experiments either in the number of sensors and their type, individuals involved or the duration thereof. Also noteworthy is the large amount of recognition techniques (supervised, either generative or discriminative; and unsupervised). This diversity makes it extremely difficult to compare performances and draw conclusive findings from those studies. Despite this high variability, it is noteworthy to mention that we have not found extensive studies that analyze altogether the detection of visits, presence or absence of users at home using wireless binary sensors. Even so; we report a number of different papers with different approaches related to the partial detection of some of the activities that concern us and with settings similar to those in our work.

A former study (Tapia et al., 2004) already points out some of the difficulties in discriminating daily life activities based only on binary sensors activities. The automatic recognition system was based on rules defined from the context and the duration of the activities to identify. The data of the study were obtained from 14 days of monitoring activities at home. Although promising accuracies were achieved for some activities, detection tasks such as ”leaving home” were nothing less than satisfactory with 0.2 of accuracy. This was because the activities were represented by rules directly defined on the firings outputted by single sensors (i.e. door switches); so they did not contemplate that could be activated for other reasons and in varying times, which made reduce their discriminating power.

A more exhaustive work regarding the use of switch and motion sensors for tracking people inside home is found in (Wilson and Atkeson, 2005). Tests were done with up to three simultaneous users. High performances were reported by the trained tracking models. However it is interesting to note that this type of sensors experimented occasional lag between “entering” a room and triggering a sensor; making to decrease the performance of the tracking models.

In (Krishnan and Cook, 2014) a more complex template learning model (SVM) was used to automatically recognize among 11 different home activities. The proposed technique was integrated in different window sliding strategies (e.g. weighting sensor events, dynamic window lengths, or two levels of window lengths). They used 6 months of data from 3 different homes in which activities such as “entering” or “leaving home” were monitored. From the best experimental settings the authors claimed accuracy for “entering” home about 0.80 of f1-score but around 0.4 for “leaving” home tasks.

In a more extensive work (Cook, 2010) they use Naïve Bayes (NB), Hidden Markov (HMM) models and Conditional Random Fields (CRF) for the activity recognition problem. In this study, 7 smart environments were used and 11 different data sets were obtained. Several activities were attempted to be recognized. Among others, we highlight “entering” and “leaving home” as relevant for our approach. Although they did not report specific accuracies for these activities, authors claimed an overall recognition performance on the combined dataset of 0.74 for the NB classifier, 0.75 for the HMM model, and 0.72 for the CRF using 3-fold cross validation over the set of annotated activities.

In (Ordónez et al., 2013), authors proposed a hybrid approach to recognize ADLs from home environments using a network of binary sensors. Among the different activities recognized “leaving” was one of them. The hybrid system proposed was composed by using an SVM to estimate the emission probabilities of an HMM. The results showed how the combination of discriminative and generative models is more accurate than either of the models on their own. Among the different schemes evaluated, the SVM/HMM hybrid approach obtains a significant 0.7 of f1-score a notable better performance than the rest of approaches.

Detecting “multiple” people in single room by using binary sensors was already studied in an early work (Wilson and Atkeson, 2004). In that work, authors proposed a method based in Expectation Maximization Montecarlo algorithm. In a more recent article (Nait Aicha et al., 2013), high accuracy (0.85) were reported on detecting visits at home using binary sensors. In that approach, they used an HMM algorithm over the room events although not all rooms of the home were monitored.

6 CONCLUSIONS AND FUTURE WORK

Community based living, often alone with intermittent care, creates possible scenarios of risks for all individuals. When cognitive changes are likely to have taken place it is crucial to understand what the risks may be and monitor these. To monitor users at home, we develop a sensor-based system which is able to gather data and report on the stability and evolution of the user’s daily life activity. Unfortunately, performance of sensor-based telemonitoring and home support systems depends, among other issues, on the reliability of the adopted sensors. It is particularly true in the case of a wireless and binary sensors are adopted. To solve this problem, we presented a hierarchical approach, based on machine learning techniques, aimed at improving the recognition of the presence of the user at home and, being interested in monitoring people that live alone, if the user is alone or received some visits. The system has been developed under the umbrella of the BackHome project and is currently running in 2-healthy-users’ home and in 3-end-users’ home. Results clearly show an high discriminative performance improvement of 15% with respect to a rule-based solution. Let us also stress the fact that the proposed approach can be used as a pre-processing phase in every activity recognition system, being completely independent from that.

As for the future work, we are currently setting-up new experiments aimed at comparing the hierarchical approach with a multi-class classifier and with an ensemble (not hierarchical) of classifiers. Moreover, we are improving the approach in order to be totally automatic, by using data from Moves as feature instead of to validate the initial dataset. We are also interested in studying if we can generalize the proposed approach to adopt it for all the user of the system, or if we have to use a personalized approach for each different user (or a small group of them).

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