ORIGINAL RESEARCH

Sleeping recognition to assist elderly people at home

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Received: January 29, 2016 **Accepted:** March 20, 2016 **Online Published:** May 17, 2016
DOI: 10.5430/air.v5n2p64 **URL:** http://dx.doi.org/10.5430/air.v5n2p64

ABSTRACT

In elderly care, activities of daily living are used to assess cognitive and physical capabilities of people. In fact, cognitive and physical decline may start with problems in doing daily living activities. Elderly people may not be able to complete an activity by themselves or the activity takes more time than usual. Moreover, forgetting to do some daily activity may indicate diseases that affect memory. Sleep disorders represent a very common problem for elderly people and may influence the overall quality of life. In this paper, we focus on sleeping and propose a study aimed at recognize this kind of activity. The goal is twofold; on the one hand, to monitor elderly people at their home to give assistance in case of needs; on the other hand, to give a support to therapists, caregivers, and familiars to become aware of the health status of the monitored elderly people and to receive alarms and alerts in case anomalies are detected. Experiments, performed with volunteers at their homes, show that the proposed approach is able to recognize sleeping activities with high accuracy.

Key Words: Telemonitoring, Home healthcare, Context-awareness, Machine learning, eHealth

1. INTRODUCTION

Europe is faced with an ageing population, currently 24 per cent of the population is over 60. Furthermore, the population ageing is growing at a rate of 3.26% per year.[1] This phenomenon occurs due to two main factors: on the one hand, advances in medicine are helping millions of people live longer and, on the other hand, women have fewer than 2.1 children on average, the level required for full replacement of the population in the long run. The foregoing observations highlight long-term care as a major problem, as well as, cognitive impairments and problems associated with ageing. Moreover, these problems will increase during the foreseeable future.

Elderly people may be affected by a decline in functioning that usually involves the reduction and discontinuity in daily routines and a worsening in the quality of life. Among other factors, quality of life of people may be influenced by sleep quality.[2] Sleep disorders represent a very common problem, especially in the Western industrialized countries.[3] Epidemiological studies show that the prevalence of sleep disturbances lies between 20% and 30% and increases with age (1$\pm$3). Chronic sleep disorders may involve a risk of somatic/psychic diseases.

Various methods, both subjective and objective, have been proposed to activity recognition and assessment. 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.[4] Recently, objective solutions have been proposed to unobtrusively monitor activities of elderly people.[5] Tele-assistance systems that rely on a conjunction of sensors – each one devoted to moni-

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tor a specific status or activity – are normally used.[6]

In this paper, we present a study aimed at recognizing sleeping activity of elderly people that live alone at their home. In particular, we focused in recognizing the time in which the user goes to sleep and the time in which the user wakes up. First, a rule-based approach has been implemented. Subsequently, to improve results a supervised classifier has been adopted. All the approaches have been tested using data coming from a tele-assistance system composed of a set of sensors, an intelligent monitoring system, and a healthcare center. Experiments have been performed with 3 volunteers at their home. Results coming from the classifier have been compared with those coming from the rule-based approach. On average, the classifier performs better than the rule-based approach.

2. Related work

In the literature, several work has been proposed in the field of activity recognition at home.[7,8] Ye *et al.* pointed out difficulties and drawbacks in being able to discriminate activities of daily life (ADL) relying only on data gathered by binary sensors.[9] In their study, they performed automatic recognition by using a set of rules defined from the context and taking into account the duration of the activities. Data were gathered monitoring activities at home during 14 days. In Ref.,[10] an approach, based on switch and motion sensors, has been presented to track people inside home. Tests were performed with 3 simultaneous users and high performances were reported. A more complex template learning model based on Support Vector Machine (SVM) was adopted in Ref.[11] to automatically recognize among 11 ADLs. The proposed approach relied on different sliding window strategies (*e.g.*, weighting sensor events, dynamic window lengths, or two levels of window lengths). Six months of data from 3 user´s homes were used to monitor and recognize activities such as "entering" or "leaving home". Moreover, in Ref.,[12] a more exhaustive work that uses Naïve Bayes, Hidden Markov Models (HMM) and Conditional Random Fields, was presented. Seven smart environments were used, 11 different data sets were obtained, and ADLs were attempted to be recognized. A hybrid approach aimed at recognizing ADLs from home environments using a network of binary sensors was proposed in Ref.[13] It was based on SVM classifiers to estimate the emission probabilities of an HMM.

The sensor-based system used in this paper differs from those cited above because it uses only motion-luminance-temperature sensors and doors sensors. It is worth noting that using only uses these two types of sensors put limits to the machine learning model. Thus, instead of using generative models as many authors, we used discriminative models.

3. Method

To perform the study we rely on eKauri, a tele-assistance system that uses a set of sensors to monitor people indoors.[5] Activities and habits of the monitored users are recognized by relying on data gathered by the adopted binary users considering a set of relevant automatically-extracted features. Those features are then used to recognize ADL, such as sleeping. Figure 1 shows an example of information provided to therapists and caregivers.

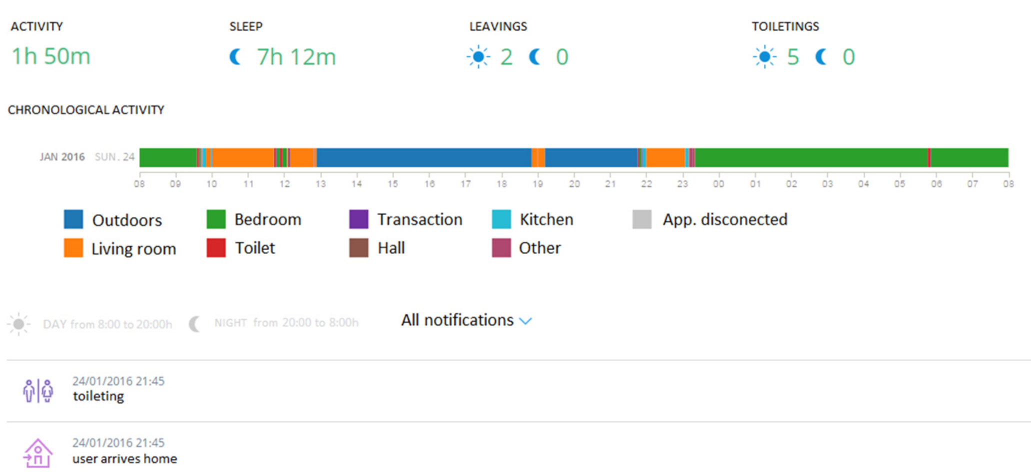

Figure 1. The healthcare center gives information to therapists and caregivers on activities performed by the users

Due to the limitations of the adopted sensors, we defined the sleeping activity as the period which begins when the user goes to sleep and ends when the user wakes up in the morning. Sleep recognition is aimed at reporting the following information: (i) the time when the user went to sleep and woke up; hereinafter we will refer to them as "go to sleep time" and "wake up time", respectively; (ii) the number of sleeping activity hours; and (iii) the number of rest hours, which are sleeping activity hours minus the time that the user spent going to the toilet or performing other activities during the night. Let us also note that, through the healthcare center, therapists may define rules personalized for each user. In so doing, also rule regarding the sleeping activity may be defined (*e.g.*, send an alarm if the user sleep more than 10 hours).

A rule-based approach was designed as a first approach. The adopted rules were: the user is in the bedroom; the activity is performed at night (*i.e.*, the period between 8 pm to 8 am); the user is inactive; and the activity duration is more than half an hour. Unfortunately, experimenting that approach some issues arose: night periods where the user moved in the bed were wrongly classified; the approach assumed all users wake up before 8 am, which is a strong assumption; and the approach cannot distinguish if the user is in the bedroom watching TV or reading a book, thus classifying all those actions as sleeping. In order to overcome those limitations, a supervised binary classifier has been adopted to classify the periods between two bedroom motions in two classes, awake and sleep. Let us note that awake corresponds to the period in which the user goes to another room; performs activities in the bedroom; or stays in the bedroom with the light switched on. Otherwise, the activity is sleep.

4. EXPERIMENTS AND RESULTS

In order to collect a real-world dataset we contacted with Centre Vida Independent (CVI), a center aimed at improving quality life of people that need assistance, both elderly and disabled, making their home life easier.

The system was installed in 10 homes of 10 volunteers CVI users (mean age 72.4 $\pm$ 6.4 years, 1 man and 9 women). Unfortunately, one of these users left the project because her home was flooded some days after the installation was done. The data collected from this user was not used so henceforth only the other 9 users will be taken into account.

4.1 Data preparation

We installed a presence-luminance-temperature sensor in each room of each home, and a door-sensor in each entrance door. The monitored period lasted for five months, from May 15th, 2015 to October 20th, 2015. Due to the fact that eKauri is not able to distinguish among different users, in case of visits, we filtered days in which users were not alone. We also disregarded days in which they were away for vacations. After this filtering activity, only data from 3 users remained, making a total of 14 days.

To label the activities, we asked monitored users to daily answer to a questionnaire composed of 20 questions (12 optional). Moreover, they daily received a phone-call by a caregiver who manually verified the data. Unfortunately, they did not answer the questionnaire every day as requested. Thus, to finally label the activities, three experts labelled the data and their labelling was compared. If two of them coincided this time was chosen as definitive, in case the three answers of the experts differed they explained why they chose their answer and reached an agreement. This information has been used as baseline (ground truth) to evaluate the performance of the system.

In order to build the classifier, a set of identifying characteristics were defined to characterize the activity to predict. As mentioned previously, sensors send data about motion, temperature (in Celsius degrees), and luminance (as a percentage). Experimentally, we noted that temperature does not significantly vary when the user enters a room or when sleeping, so this information was not used to calculate the features to distinguish if the user is performing her/his sleeping activity or not. Using motions as a reference and slicing the time in fixed periods, the following features were considered:

(1) The time that motion took place.
(2) Number of motions in bedroom [2, 5, 10, 15] minutes before the motion.
(3) Number of motions in bedroom [2, 5, 10, 15] minutes after the motion.
(4) Number of motions in all the rooms [2, 5, 10, 15] minutes before the motion.
(5) Number of motions in all the rooms [2, 5, 10, 15] minutes after the motion.
(6) Average of luminance in bedroom [2, 5, 10, 15] minutes before the motion.
(7) Average of luminance in bedroom [2, 5, 10, 15] minutes after the motion.
(8) Average of luminance in all the rooms [2, 5, 10, 15] minutes before the motion.
(9) Average of luminance in all the rooms [2, 5, 10, 15] minutes after the motion.

To reduce the number of features to use with the classifier and taking into account that the quantity of hours that the user spent performing sleeping activity is calculated on-line, we considered only those features which did not contain information after the motion (*i.e.*, 1, 2, 4, 6 and 8). In order to validate not only the classifier but also the overall system and compare the classifier results with the ruled-based results, the reduced-dataset has been split so that all the rows from the same night go to the same set. As the dataset only contains 14 nights in total, it has been split so that the train set will contain 8 nights and a test set 6 nights. Moreover, both sets have nights from each user. The fact that the split was made by nights and not by samples and each night has a different number of samples means that the number of samples in both sets are almost the same, as shown in Table 1.

Table 1. Number of samples from each class in each set

Class	Train	Test	Total
Awake	371	393	764
Sleep	122	109	231
Total	493	502	995

4.2 Evaluation

Three different machine learning techniques have been adopted to build a classifier (Support Vector Machine, SVM; k-Nearest Neighbor, KNN; and Random Forest, RF). A Grid-Search 10-fold cross-validation method has been used over the training set to choose the best parametrization. Table 2 shows the results of the best parametrization for each one. All the classifiers have obtained a great accuracy, the best performance has been obtained relying on the SVM, Radial Basis Function (RBF) kernel, with C = 1.0, γ = 1.0, where C is the regularization parameter, which is used to weigh the misclassifications, and γ is a RBF kernel parameter, which is used to define the influence of the training examples.

Table 2. Classification results during the training

Classifier	Parameter(s)	Accuracy
SVM	kernel = rbf, C = 1 , γ = 0.055	0.947 ± 0.072
SVM	kernel = rbf, C = 1.0, γ = 1.0	0.953 ± 0.038
KNN	weights = uniform, k = 13	0.941 ± 0.048
KNN	weights = distance, k = 9	0.945 ± 0.066
RF	n_estimators = 7, n_features = 4	0.939 ± 0.073
RF	n_estimators = 10, n_features = 1	0.941 ± 0.050

The classifier that performed better during the training has been used with the test dataset and, on average, it obtained a F1 of 0.91 and an accuracy of 0.964. Table 3 shows the performance split by classes. The confusion matrix showed on Table 4 obtains a Mathews coefficient of 0.89, only 18 samples were misclassified in sleep class when they were in fact awake.

Once the classifier has predicted the class of each period a simple sequential track allows us to obtain the "go to sleep time" and the "wake up time" and to compute the number of sleeping activity hours and the number of rest hours. The "go to sleep time" is the time when the first sleep period started, and the "wake up time" is the time when the last sleep period finished. The number of sleeping activity hours is computed as the difference between them. Finally, the duration of the awake periods between "go to sleep time" and "wake up time" are added together and then subtracted from the number of sleeping activity hours, in order to compute the number of rest hours.

Table 3. Results using test set split by class

	Precision	Recall	F1	Support
Awake	0.96	1.00	0.98	393
Sleep	1.00	0.83	0.91	109
Total	0.97	0.96	0.96	502

In order to compare the classifier results with the results obtained by the ruled-based approach, the nights from the test set has been evaluated comparing the sleeping activity hours according to the ground truth and those coming from the results. Figure 2 shows the comparisons between the baseline and the results obtained with ruled-based (on the top) and SVM (on the bottom). All the plots have as temporal axis (axis x) and each coordinate in axis y represents nights in the dataset, each subfigure shows, in red, the sleep activity hours according to the ground truth and, in blue, the sleep activity hours obtained by the system. As both sleep activity hours of the same night are plotted in the same y coordinate, if the ground truth and the results coincide the color turns purple. If the "go to sleep time" and/or "wake up time" do not coincide, there is a text next to the corresponding side with the difference between the time coming from the ground truth and that coming from the results. In the middle of each bar there is the total time which results differ from the baseline.

Table 4. Confusion matrix using test set

Real	Predicted	
	Awake	Sleep
Awake	393	0
Sleep	18	91

Figure 3 shows the comparison between the two adopted approaches (rule-based and machine learning). It can be viewed that the accuracy of each system increasing the error allowed. The error is measured as the difference between the results and the ground truth, in increments of 6 minutes. As shown, machine learning results achieves an accuracy of 50% with an error of 0 minutes, which means 50% of the results coincide with ground truth and the 100% of accuracy is reached with an error of 18 minutes. Regarding ruled-based results, an accuracy of 50% is reached with an error of 24 minutes and an accuracy of 100% is obtained with an error of 2 hours and 18 minutes, with two hours of difference respect machine learning results.

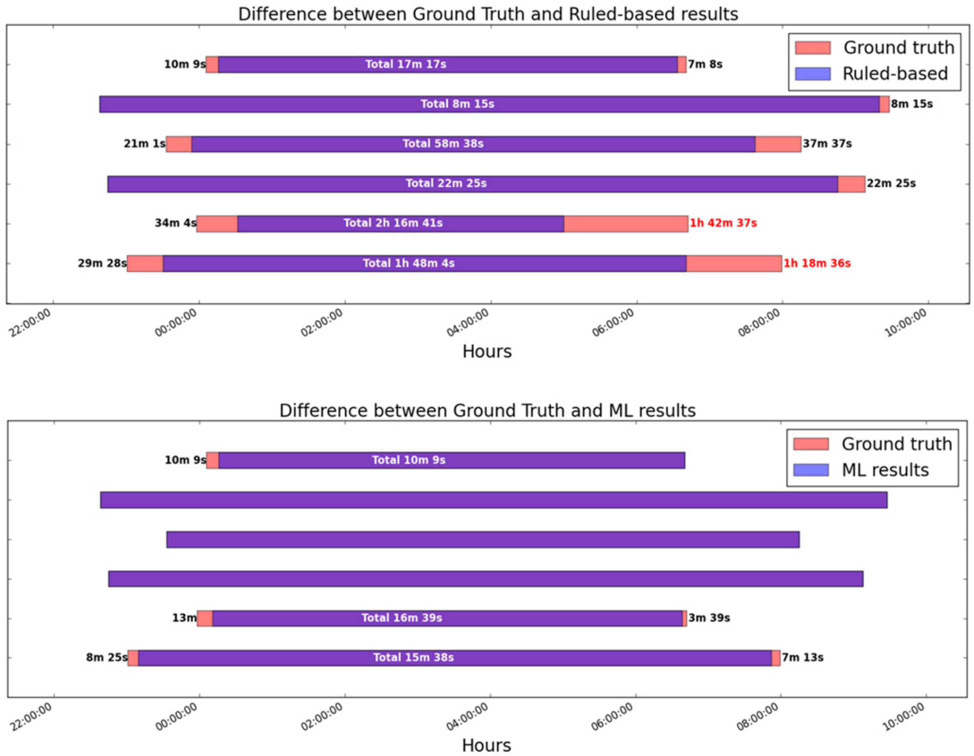

Figure 2. Comparison between the rule-based approach and the machine-learning (SVM) one

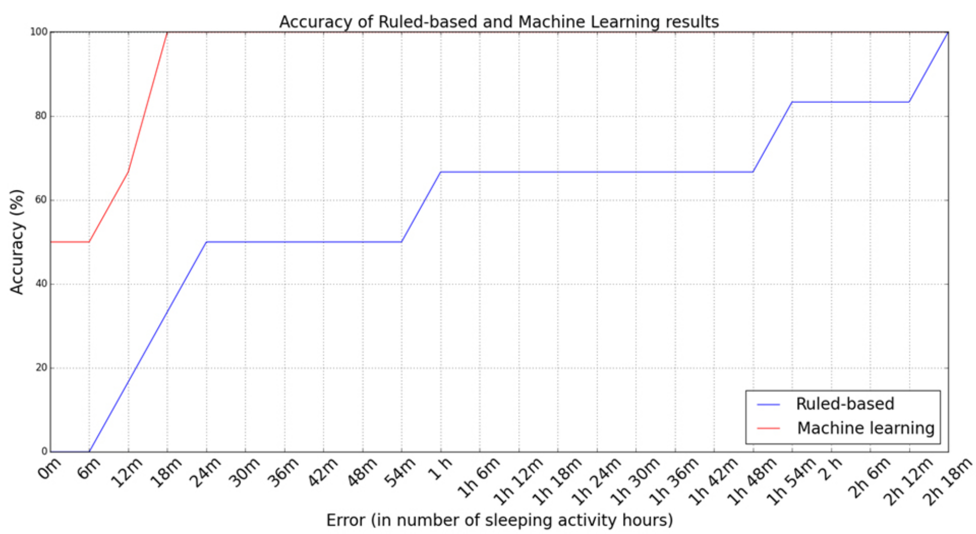

Figure 3. Accuracy comparison between the rule-based approach and the machine-learning (SVM) one

5. Discussion

The goal of eKauri is twofold: helping and supporting elderly people that live alone at home; and constantly providing a feedback to therapists/caregivers about the evolution of the status of each monitored user.

Results presented in this paper show that the proposed classifier, tested with the data from eKauri, is able to recognize when the user is performing her/his sleeping activity. In particular, the proposed approach reaches an F1 of 96%. Moreover, the adopted classifier is able to easily detect the "go to sleep time", the "wake up time", the number of sleeping activity hours and the number of rest hours.

It is worth noting that data used in this work come from a real-world scenario, with real end-users, performing their normal lives. Thus, data reflect the complexities of the real-world. At the same time, using real data leads two main downsides. On the one hand, the number of days which the users answered the questionnaire was limited, compared to the number of days which the monitored period lasted. On the other hand, the information given by the users, through the questionnaire answers, was not as accurate as the information which could be obtained in a lab. Despite these inconveniences, we strongly believe that it is important to train the models with real-world data. Let us also note that in Ref.[14] we studied the learning curve of the best classifier in order to see if it is possible to obtain better performance by increasing the training set. Results show that the score will not improve by adding more samples in the training set.

As for the future work, we envisage three main directions that may be gone through. First, we are currently setting-up a system to accurately obtain the ground truth from the end-users. Moreover, we will investigate the possibility of adding press mats and electrical switches in order to make the results more accurate, and use generative models. Finally, we are also interested in studying whether we can generalize the proposed approach to adopt it for all the users of the system, or if we have to use a personalized approach for each different user.

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