Sensor-Based Activity Recognition Inside Smart Building Energy and Comfort Management Systems

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***Abstract*—The challenge of Smart Building Energy and Comfort Management (BECM) systems is to schedule home appliances according to users' comfort requirements, while contributing to an efficient and sustainable use of the available energy sources, supplied by either the electricity grid or Renewable Energy Sources (RES). To this aim, BECM systems have to monitor users' habits and learn their preferences, so that their actions can be predicted and appliances can be scheduled accordingly.**

This paper stems from the observation that actions are usually performed in sequences that repeat according to a pattern. Therefore, activities can be recognized and predicted as soon as a pattern of actions is detected. The framework proposed in this paper aims to predict activities by analyzing the sequences of actions detected by sensors deployed in a Smart Building. Furthermore, a correlation between subsequent activities is found so that sequences of activities can be predicted. Simulation results show that activities can be predicted with an accuracy of 74.78%.

***Index Terms*—Activity recognition; activity prediction; action recognition; Smart Building**

I. Introduction

Building Energy and Comfort Management (BECM) systems make use of distributed smart objects and sensor networks to monitor and control buildings, with the aim to ease appliance management while ensuring efficient use of them from the energetic point of view [1]. To develop such kind of systems, context-awareness is crucial. Indeed, context-awareness can take advantage of artificial intelligence mechanisms to predict user activities based on sequences of actions [2][3]. Consequently, the sequence of appliances that are going to be turned on can be schedule appropriately. This provides a twofold advantage: on the one hand it enhances users' comfort, unburden them from having to turning on/off appliances themselves. On the other hand, it improves energy efficiency by implementing demand response approaches.

Several studies addressed the challenge of predicting users' actions by analyzing data gathered from sensors placed in the surrounding environment and/or on personal smart devices [4][5]. However, most of the approaches in the literature only consider correlations between sensors' activation and action recognition, without taking into account that actions are typically part of sequences. These sequences of actions are usually carried out by users according to a definite pattern that remains almost unchanged depending on the activity they are performing. Therefore, patterns of actions can be associated to a specific activity. This makes it possible to predict an activity after few actions have been observed by sensors.

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In this paper, a framework for activity recognition based on patterns of sensors' activations is proposed. The framework offers two important contributions: 1) activities can be predicted by analyzing actions that are detected by sensors; 2) sequences of activities can be predicted based on correlation among subsequent activities. As a results, activities can be predicted well ahead of when they will be actually performed, and appliances can be scheduled appropriately taking this information into account.

The remainder of the paper is structured as follows. Section II discusses the main related works in this area. Section III defined the problem under study and the terminology used in the paper. Section IV describes the model of the proposed system. In Section V the reference use case is presented. Section VI presents the performance of the proposed approach. Finally, Section VII draws final conclusions and future works.

II. Past Works

Smart technologies can be used in all kinds of different buildings (i.e., residential, office, and retail sectors) to improve the comfort and the safety of people in their home, concerning various topic, from healthcare and providing living assistance, to environmental monitoring and ensuring energy saving. Systems implementing solutions for these problems must be able to discover and predict users habits and course of actions.

The monitoring of activities of people in their home can be done by analyzing data that can be gathered with different technologies. In many cases, cameras and wearable sensors are used to understand what someone is doing [6]. These solutions present some problems because people are often not incline to accept those devices [7]. Some studies are based on the data that are provided by phone accelerometer and gyroscope to understand repetitive body motions (walking, running, sitting) [4]. This solution is not very practical in home scenarios, where residents don't always take their phone with them. To monitor what activities people are performing in their house, non intrusive sensors are often preferred: typical devices that are installed in the environment are motion sensors, door sensors or temperature and pressure sensors [8][9]. The data collected from sensors are analyzed using data mining and machine learning techniques to build activity models that are used for the basis of behavioral activity recognition. Feature extraction from the sequence of sensor events is a key step to better modelling and then recognizing human activity. In [5] four methods used to extract features for online recognition on streamed data are presented. With their approach they can recognize activities while new sensor events are recorded.

About the modelling and classification methods, researchers have investigated the recognition of resident activities using a variety of mechanisms such as naive Bayes classifiers, Markov models, and dynamic Bayes networks. A comparison of classification approaches for activity recognition is provided in [10] and [11]. In [12], 4 algorithms that can identify the activities while they are being performed are proposed. In this work, activities are recognized even if they are done in an interleaved and concurrent manner. The models used in the proposed algorithms are: a Nave Bayes classifier, a Hidden Markov Model (HMM) with a time window, a frequency-based HMM with a sliding window and a frequency-based HMM with a shifting window. In [13] authors focus on the activity discovering problem, proposing an approach to build a model under the form of HMM, from a training database of observed events emitted by binary sensors, without the knowledge of actions really performed during the learning period.

III. Problem Statement

The reference scenario considered in this paper is that of an Energy and Comfort Management System (ECMS) that leverages distributed Smart Home sensor networks to elaborate user profiles to monitor and control buildings. More specifically, sensors are used to make observations, identify users' actions and learn which sequences of actions can be associated to specific activities. Therefore, the ECMS can predict users' activities based on their previous monitored actions, and make appropriate management decisions accordingly.

As an explanatory example, suppose that, according to their profile, a user usually wakes up, then have a coffee watching TV, and later take a shower while having the bathroom heater on. Furthermore, suppose that the *wake up* activity is detected when the *turn the bedroom light* action is identified (i.e. the light sensor inside the user bedroom detects some light) after the *sleep* activity occurred. Since the ECMS knows that the following activities are *have a coffee*, *watch TV* and *take a shower*, it can increase the user's comfort by: turning on the coffee machine as soon as the user wakes up, turning on the TV right after the coffee is made, and at the same time turning on the water heater and the bathroom heater so that the water and room are warm when the user goes to the bathroom.

Fig. 1 expresses the relationship between sensors, observations, actions and activities. An observation corresponds to a change in the state of a sensor. As depicted in the picture, the same sensor can correspond to more than one observation. This is the case, for example, of a smart meter monitoring a washing machine: according to the measured power consumption, the related observation corresponds to turning on different wash cycles. Let $\mathcal{O} = \{o_i\}$ be the set of observations that can be detected by sensors inside a house. An observation is then defined as the tuple $o_i = \{s_i^{ID}, s_i^{STATE}\}$, where s_i^{ID} is

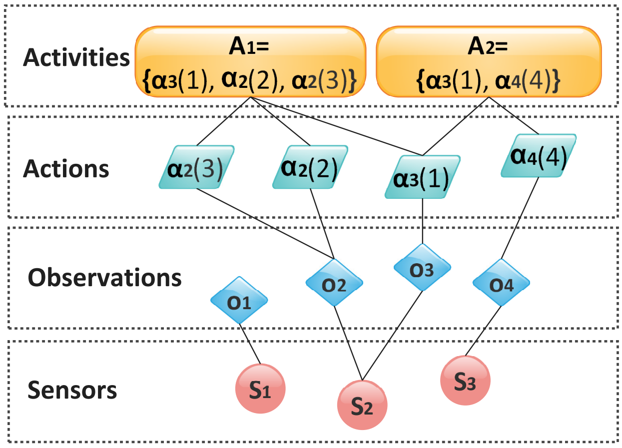

Fig. 1. Example of activities and relevant subdivision into actions and observations, in connection with related sensors

the ID of the sensor used for observation o_i and s_i^{STATE} is the corresponding state (e.g. *ON*, *delicate cycle*). An action is then defined as an observation enriched with information describing the context in which it was experienced. According to this vision, activities are composed by several actions that are performed in sequence. More specifically, as illustrated by Fig. 1, an activity $\mathcal{A}_j$ is modelled as a sequence of actions ordered by their starting time, i.e. $\mathcal{A}_j = \langle \alpha_i(t_k^S) \rangle$, where an action is defined as the tuple $\alpha_i(t_k^S) = \{o_i, t_k^S, t_k^E\}$, with t_k^S and t_k^E respectively starting time and ending time of observation o_i for action $\alpha_i(t_k^S)$.

IV. System Model

Observations o_i are the basic information needed to understand what users are doing, and as seen previously they are strongly connected to sensors activation. The proposed system is then based on recognizing activities performed in smart environments from sequences of collected sensor readings. The choice of sensor types to use leads to different models that can be used for solving activity recognition problems. Choosing only non intrusive binary sensors is a better option for experiments in real life, so that there is no need for people to remember to always wear wearable sensors or to be monitored with cameras.

From raw data, feature vectors that can be analyze to perform classification of activities are constructed. Every activity is strongly connected to a specific group of sensors that change their states during a definite time span. In order to extract the required features, a sensor-based windowing implementation is considered. The result is that every sensor is treated like a feature and is associated to a particular activity based on its distribution probability to be in a sequence that is labeled with the name of that activity. This is done by implementing a Naive Bayes Classifier (NBC). This type of classifier is based over the Bayes' theorem of indipendece between features, so that the model is constructed to find, for each class C,

TABLE I
DATA EXTRACTED FROM ARUBA DATASET

DATE	TIME	SENSOR ID	SENSOR VALUE	ACTIVITY
04/11/2010	09:56:22.785482	M018	ON	
04/11/2010	09:56:23.801652	M017	ON	
04/11/2010	09:56:26.467399	M019	ON	
04/11/2010	09:56:27.334395	M018	OFF	Meal Preparation end
04/11/2010	09:56:34.362031	M018	ON	
04/11/2010	09:56:37.729204	M020	ON	
04/11/2010	09:56:38.776094	M018	OFF	
04/11/2010	09:56:40.172391	M020	OFF	
04/11/2010	09:56:41.831135	M014	ON	Eating begin
04/11/2010	09:56:56.043362	M014	OFF	
04/11/2010	09:57:15.209217	M014	ON	
04/11/2010	09:56:16.412611	M014	OFF	

the probability p that, given those features, the class being observed is C_k:

$$p(C_k|x_1...x_n) \tag{1}$$

where $\mathbf{x} = x_1, ..., x_n$ is the vector of the features. For each activity there is then a model vector, that is representive about the probability that a group of sensors is connected to every activity. When an event associated to a sensor is counted for a certain number of times during the observed sequence, it is possible to understand which activity is statistically more probable. After the probabilistic model is obtained, the system has to recognize the activities performed by evaluating which is the most likely to be happening. This is done by calculating the cosine similarity between activity vectors model and the one occurring in a particular moment.

V. REFERENCE USE CASE

The algorithm for modelling the activities and then discovering what the resident is doing is implemented and tested using the Aruba real-word dataset from the CASAS smart environmnet project of the Washington State University [14]. The data were collected from one smart apartment provided with motion sensors, contact sensors in the doors or cabinets and temperature sensors. There is only one resident living in the home. The events decoded by these sensors are significant for recording elementary actions that people are performing, for example door sensors are easily associated with opening and closing medical cabinet, food storage or the entrance door, while with motion sensors it is possible to monitor the presence of the resident in one room and the proximity with a specific object or furnitures [15]. The aggregation of these elementary actions define one activity of interest.

The gathered data are presented with information about date and time of every sensor event registered, the id of the activated sensor with its value and the beginning or end of each activity that is monitored. The dataset has the structure presented in Table I. In the dataset, 11 different activities performed by the resident are noted. Table II shows the details of the number of times each activity appears in the data. Sensors detect even the activities that are not registered, that corrispond to ”Other activity” with no label in the dataset. Since they are classified with difficulty, this events have been ignored in the proposed framework.

TABLE II
ACTIVITIES AND STATISTICS OF ARUBA DATASET

Activity	Number of events
Meal Preparation (MP)	1606
Relax (Rel)	2910
Eating (Eat)	257
Work	171
Sleeping (Sleep)	401
Wash Dishes (WD)	65
Bed to Toilet (BTT)	157
Enter Home (EH)	431
Leave Home (LH)	431
Housekeeping (HK)	33
Resperate (Resp)	6

With a window that takes into account all the sensor events for one activity from its beginning till its end, a probabilistic model of each performed activity has been made. Considering the length, in terms of occurred sensor event, for every instance of one activity at a time, it is possible to obtain a feature vector that contains every sensor in the environment with its frequency of activation, activity for activity. These instance vectors are the ones presented to the classifier for the training phase of the algorithm to calculate the modeled vector that better rappresents each one of the activity. Most part of the monitored activities have a long representation in terms of sequence of activated sensors. Only three of them generally are concluded in less than 15 sensor events, and they are the activities of ”Enter Home”, ”Leaving Home” and ”Bed to Toilet Transition”. The others are more variable and can last longer. Because of this variability, it is difficult to find a common size to consider for the window of activations sequence. The size of this window is essential, because for the activity recognition problem the algorithm evaluates the sensors events that occur within this window. Based on that, the most probable activity being performed is found by searching for the minumin distance between the modeled feature vector and the new instances that are happening at the moment and that has to be classified.

TABLE III
TRANSITION PROBABILITY OF ACTIVITIES

	BTT	Eat	EH	HK	LH	MP	Rel	Resp	Sleep	WD	Work
Bed to Toilet	0.017	0	0	0	0	0	0	0	0.41	0	0
Eating	0	0.14	0	0.030	0.12	0.02	0.034	0	0.007	0.61	0.068
Enter Home	0	0.015	0	0.061	0.26	0.095	0.041	0	0.035	0	0.136
Housekeeping	0	0	0	0	0.042	0.0036	0.006	0.33	0	0	0.025
Leave Home	0	0	1	0	0	0	0	0	0	0	0
Meal Preparation	0	0.75	0	0.121	0.009	0.374	0.237	0.33	0	0	0.11
Relax	0	0.09	0	0.58	0.403	0.344	0.644	0.333	0.523	0.356	0.348
Resperate	0	0	0	0	0	0	0.001	0	0	0	0
Sleeping	0.98	0	0	0	0.0035	0.14	0.003	0	0.042	0	0
Wash Dishes	0	0.005	0	0.091	0.017	0.003	0.0197	0	0	0.017	0.042
Work	0	0.01	0	0.121	0.059	0.003	0.015	0	0.014	0.017	0.27

VI. PERFORMANCE EVALUATION

To evaluate the algorithm, an assessment of the classification accuracy that shows the percentage of correctly classified sequences of events for each class is used. The accuracy is obtained by observing the number of times a label of an activity is recognized as true, compared to all the times the same label is detected incorrectly, i.e. even if another activity was performed. Accordingly, the accuracy is expressed by:

$$Accuracy = T_l/(T_l + F_l) \tag{2}$$

where T_l are the labels of the activity that the resident is truly doing while F_l are the mistaken labels.

The test is performed considering three weeks of data from the dataset and taking a window of 10 sensor events as the sequence that as to be classified. The choice of the window is done by taking into account that there are three activities indicated in the section above that are shorter than the others. The feature vector containing this 10 events is then compared with the different models of the activities by evaluating the cosine similarity expressed by the equation below:

$$Similarity = \bar{a}\bar{b}/(|\bar{a}| \cdot |\bar{b}|) \tag{3}$$

where $\bar{a}$ and $\bar{b}$ represent respectively the vector in exam that as to be classified and the representative vector of each activity. The activity that gives the higher similarity is the one chosen as the more probable class where the feature vector belongs to. Simulations results achieve an average accuracy of 74.78%. The results are presented in the confusion matrix in Fig. 2. The problem of choosing a small window is evident in the achieved results because when longer activities are being performed the algorithm frequently confuses possible activities that are similar. It is evident that almost half of times there are errors discerning activity 5, correspondig to ”Meal Preparation”, from activity 9, that is ”Wash Dishes”. This is due to the fact that both activities are performed in the kitchen and involving the same sensors. Better performance could have been obtained considering for example that when an action is starting it is more likely that it is still performed after a short amount of time, instead of jumping to a different activity.

To better recognize those activities, it could be possible to take into account not only the detected actions, but also considering the activity that was performed before. It is possible to estimate the user habits and so make the algorithm more efficient in detecting the real activity performed. For this purpose, from the trainig phase we gathered the transition probability from one activity to the others, obtaining the results presented in Table III. The table shows the probabilities that the activity in a column follows the activity in a row.

VII. CONCLUSIONS AND FUTURE WORKS

This paper proposes a framework for action recognition and prediction of activities, based on data gathered from sensors deployed inside a Smart Building. Simulation results show that not only is it possible to predict activities according to patterns of actions with a good degree of reliability, but it is also possible to predict activities according to previous activities.

Future works will be focused on improving the performance of the proposed framework by considering variable windows of observations of sequences of actions. The research will further proceed searhing patterns of activities that will improve the prediction of the activities that will be performed later.

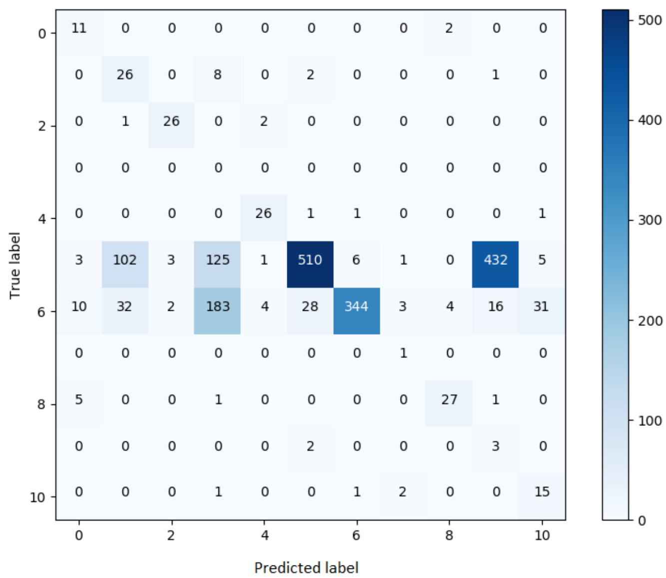

Fig. 2. Confusion matrix between true and predicted label

Furthermore, other features, such as the time (e.g. the period of the day) and the presence of multiple residents, will be introduced in the model.

ACKNOWLEDGMENT

This work was partially supported by MIUR, within the Smart Cities framework (Project CagliariPort2020, ID: SCN 00281), by "Fondazione di Sardegna" within the research project "SUM2GRIDS – Solutions by mUltidisciplinary approach for intelligent Monitoring and Management of power distribution GRIDS – Convenzione triennale tra la Fondazione di Sardegna e gli Atenei Sardi, Regione Sardegna – L.R. 7/2007 annualità 2017–DGR 28/21 del 17.05.2015, and within the project Design and Implementation of a Novel Hybrid Energy Storage System for Microgrids, which is funded by the Sardinian Regional Government (Regional Law no. 7, August 7, 2007) under the Grant Agreement no. 68 (Annuity 2015).

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