USER ACTIVITY RECOGNITION IN AUTOMATED CONTROL OF SMART ENVIRONMENT

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Abstract

The main approach to the activity pattern recognition problem is based on the data obtained from many simple sensors having binary output (e.g. motion sensor, door opening sensor, etc.). We propose a method using Bluetooth beacons RSSI and heart rate sensor data as an input dataset. Basing on the dataset analysis we implemented a simple activity pattern recognition model and evaluated accuracy metrics. The results of experiments show that the method may be successfully used for solving the activity pattern recognition problem. Disadvantages of the simple model and ways to improve it are discussed.

1. INTRODUCTION

There are several approaches to analyze user activity in context of smart environment. The easiest and prevailing approach nowadays is manual set up triggers on particular sensors data, e.g., “turn on the light when motion detected by the sensor”. Although this approach is rather simple, it has a set of disadvantages. It requires to set up the system manually by entering all desired triggers. It is not adaptive. Therefore, triggers should be updated manually when user behavior changes. And, the last but not least, it requires many sensors with simple output (such as motion or door opening ones).

Another set of approaches is based on machine learning. One of the first researches related to using machine learning for user activity recognition was performed in MIT research [3], where many simple two state sensors were used as a data source. The sensors were located on different objects that user interacts with (e.g. faucets, doors, oven). The sensors were activated when user interacted with some part of an environment (e.g. opened a door). The disadvantages of this approach are the large number of sensors and the lack of knowledge about user state. Authors had less data sources to choose from than available nowadays. Another relevant research is CASAS project [5]. It utilizes a significant amount of motion sensors located uniformly across an environment. The result is an approximate knowledge about user state (user movements in space). Researches prove that it is a reasonable idea to use data related to user motion in space. However, motion sensors provide only binary data (motion detected / no motion). Such kind of information is barely worth investments into significant number of sensors.

In this work we discuss a possibility to use raw Bluetooth-beacons RSSI data for recognizing user activity in smart environment. This problem is actual in the context of automated control of smart environment. User activity patterns are usually correlated with a desired environment state at the moment when a particular pattern occurs.

The correlation between raw RSSI data and environment state itself was proved earlier [2].

MIT approach has significant disadvantage in the context of automated control problem. It uses environment changes to recognize user activity, but when solving the automated control problem we should control the environment state itself, without direct user interaction. So, some kind of data describing user activity directly, without environment, is required. Actually, in most cases the data describing a user movement in space is appropriate. Such kind of data was collected and researched in CASAS project [5]. Motion sensors spaced one meter apart were used. Later P. Rashidi in his research [6] presented an approach to user activity recognition based on CASAS data.

Although motion sensors describe user movements in space they have only two states. Thus, such sensors provide very limited information about user movement. For example one cannot differentiate if a user is sitting on a sofa or dressing up close to it. It is preferable to have more information about the user movement and current state.

This kind of information can be obtained by using GPS-navigation idea in local scale. GPS technology measures a satellites signal strength to calculate the position. Local beacons with static position can be used with the same motivation. Then local beacons signal strength can be used to get an information about user position and movement. Nowadays Bluetooth and Wi-Fi modules are widely used in many different devices. These devices can be used as beacons if they have a static position. Also, special beacons can be used, e.g. ones based on iBeacon technology. Such beacons are relatively simple and cheap devices. Five iBeacon-based beacons and two Bluetooth-devices with static position were used for this work.

Unfortunately, the precision obtained by such an approach is barely enough for purposes of user activity recognition (as it was mentioned, for example, in [7]). The main purpose of similar researches was to translate raw beacons RSSI data into Cartesian coordinates. In the context of automated control of smart environment such translation is not required. Moreover, it is the translation that is the main source of precision loss. Without the translation, we were able to obtain data with precision enough even to differ if user is sitting or standing at the same position.

In this work we propose a method to collect more data using less sensors, namely to use Bluetooth beacons instead of motion sensors and analyze RSSI values. In our previous work [2] we considered the using RSSI values to solve automated control problem directly. In this article we apply this method to recognize activity patterns. As activity patterns are directly related to user location, the new approach gives better results as it involves only user state analysis (without an environment state).

2. MODEL DESCRIPTION

The activity recognition problem is a problem of classification where classes are considered as activity patterns. A set of features may vary, but it always should describe an individual behavior inside an environment (directly or indirectly).

There are two general approaches to activity recognition problem: one defines a finite set of activity patterns and marks a dataset according to the patterns set, the second — extracts a set of activity patterns directly from the dataset (using clustering or another similar approach). We start from the first one.

Consider the following set of activity patterns:

- breakfast;
- cooking breakfast;
- cooking dinner;
- dinner;
- entered home;
- leaving home;
- preparing to sleep;
- shower;
- using toilet;
- washing hands;
- watching TV.

We implemented an iOS application to collect dataset and mark it with these activity patterns. The features are Bluetooth beacons RSSI values and heart rate value. They are also collected by the iOS application.

As a result, we have a raw data to analyze in the following format:

- timestamp
- data source UUID
- value
- human readable description

Example (for a beacon):

- 1466771448.85298
- EBEFD083-70A2-47C8-9837-E7B5634DF524
- -79
- HallBeacon

Activity patterns are marked by the same way:

- 517783557.614923
- 7c5d5f96-4667-4d35-9bf1-4cf604e2bc35
- 1
- Watching TV

The value encodes activity start (1) and activity end (0).

The user marks activity patterns manually using the application.

Our task is to construct a model able to classify an activity pattern using the feature set described above as an input data. The usual approach to this problem widely used in other researches ([3][5][8])

is to train a classifier for each activity pattern. In earlier researches the best performance in related problems was provided by SVM. We also start experiments with it.

3. DATA COLLECTION AND EXPERIMENTS

The data collection process was described in detail in our previous work [2]. Only the most important aspects will be described below.

We implemented an iOS application that collects necessary data: Bluetooth beacons RSSI, heart rate sensor data from Apple Watch – and provides a user interface to mark activity patterns. The result is a CSV document with separate row for each event in the following format:

timestamp, UUID, value, description

Possible event types are:

- new data from heart rate sensor;
- new measured RSSI value for a particular beacon;
- activity pattern begin/end.

The user lived in one bedroom apartment. Seven Bluetooth beacons were located uniformly across the apartment (see Figure 1 for the apartment scheme and beacons location). The data were collected for two weeks.

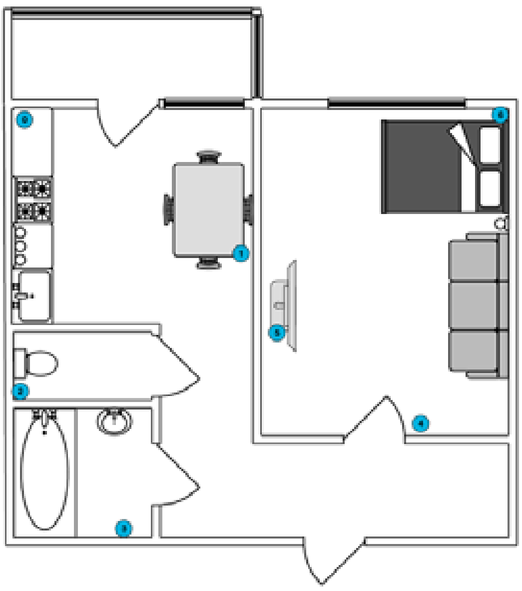

Figure 1. Bluetooth beacons location

4. DATA ANALYSIS

Raw dataset consists of separate records for each event (such as new data from sensor or changes in current activity pattern). To proceed with analysis the dataset should be converted into feature vectors and target values for each particular activity pattern (1 if pattern occurred, –1 if feature vector is not related to the considered pattern).

The feature vectors have the following format:

99, –48, –65, –81, –83, 0, –83, 0

where the first value is a heart rate value and other values are RSSI of beacons (0 corresponds to the beacons that are too far away to measure RSSI).

Consider a subset of data obtained for "Watching TV" pattern (the beginning of observation):

92,-58,-78,0,0,0,0,0,-1

92,-62,-70,0,0,0,0,0,-1

92,-62,-70,0,0,0,0,0,-1

92,-57,-70,0,0,0,0,0,-1

92,-56,-70,0,0,0,0,0,-1

92,-56,-70,0,0,0,0,0,-1

92,-60,-75,0,0,0,0,0,1

92,-60,-75,0,0,0,0,0,1

92,-60,-75,0,0,0,0,0,1

92,-60,-75,0,0,0,0,0,1

Columns 2 and 3 correspond to the beacons #4 and #5 on the Figure 1. Notice that the signal from these beacons become weaker while user is approaching to the sofa.

"Watching TV" pattern in the process of activity:

78,-64,-75,0,0,-83,0,0,1

78,-64,-75,0,0,-83,0,0,1

78,-64,-75,0,0,-83,0,0,1

78,-64,-75,0,0,-83,0,0,1

78,-65,-75,0,0,-82,0,0,1

78,-65,-75,0,0,-82,0,0,1

78,-65,-75,0,0,-82,0,0,1

78,-65,-75,0,0,-82,0,0,1

Notice that the heart rate becomes lower while user is sitting. Another beacon appeared (column 6, beacon #6 on the Figure 1).

"Watching TV" pattern in the end of activity:

78,-62,-74,0,0,-83,0,0,1

78,-69,-74,0,0,-83,0,0,1

78,-69,-74,0,0,-83,0,0,1

78,-60,-76,0,0,-85,0,0,1

78,-60,-76,0,0,-85,0,0,1

78,-60,-76,0,0,-85,0,0,1

78,-60,-76,0,0,-85,0,0,1

78,-65,-77,0,0,0,0,0,1

78,-65,-77,0,0,0,0,0,1

78,-65,-77,0,0,0,0,0,1

78,-54,-77,0,0,0,0,0,1

78,-65,-88,0,0,0,0,0,1

78,-65,-88,0,0,0,0,0,1

78,-65,-88,0,0,0,0,0,1

78,-65,-88,0,0,0,0,0,1

78,-62,-88,0,0,0,0,0,-1

78,-62,-88,0,0,-82,0,0,-1

78,-62,-88,0,0,-82,0,0,-1

78,-62,-88,0,0,-82,0,0,-1

78,-62,-88,0,0,-82,0,0,-1

78,-56,-59,0,0,-82,0,0,-1

78,-56,-59,0,0,-82,0,0,-1

78,-56,-59,0,0,-82,0,0,-1

78,-56,-59,0,0,-82,0,0,-1

78,-56,-59,0,-80,-82,0,0,-1

78,-56,-61,0,-80,-82,0,0,-1

78,-56,-61,0,-80,0,0,0,-1

78,-56,-61,0,-80,0,0,0,-1

78,-56,-61,0,-80,0,0,0,-1

Signal from the beacons #4 and #5 becomes stronger, another beacon appears while user is approaching to the corridor (column 5).

With a little delay, heart rate value is updated:

78,-64,-72,0,-82,0,0,0,-1

78,-64,-72,0,-78,0,0,0,-1

117,-63,-71,0,-78,0,0,0,-1

117,-64,-71,0,-78,0,0,0,-1

The user is moving fast so the heart rate increases.

"Watching TV" pattern is not the most trivial because user is moving around this room a lot and "Watching TV" requires heart rate analysis to recognize that user not just near the sofa, but is sitting on it. It is also a frequently appearing pattern so there is a lot of data to analyze. Other patterns considered have the same or lower recognition complexity.

As a result of preliminary data analysis, we came to conclusion that the data considered definitely correlates to user activity and can be used in activity pattern recognition problem.

5. IMPLEMENTATION

Consider the activity pattern recognition problem in terms of particular choice of input data and corresponding hardware. The dataset consists of beacons RSSI at particular timeframes, heart rate value at every timeframe and manually marked activity patterns occurred while collecting the data.

Taking into account results achieved in related works, radial basis function was chosen as a kernel for SVM. In was the best performer in similar problems. Moreover, our task is to recognize a subspace in RSSI values coordinate space. SVM with RBF kernel was designed to perform this task the best way using an optimal hyperplane principle.

Both classification and data preprocessing were performed using Python programming language as it has many utilities and libraries available that are able to speed up the research process.

Dataset was preprocessed and a classifier was trained for each activity pattern. Cross-validation approach was used with different train and test set distributions (1:2, 1:1, 2:1).

The dataset consists of 164770 samples that were collected for two weeks.

6. RESULTS AND DISCUSSION

Two metrics were used to evaluate the classification quality: accuracy and AUC (area under ROC curve). Accuracy in this case means the time interval when a pattern was recognized right.

Accuracy values for each activity pattern are given in the Table 1.

Table 1. Accuracy evaluated for different activity patterns

Activity pattern	Accuracy (for different test and train sets distribution)		
Breakfast	0.965	0.965	0.965
Cooking breakfast	0.947	0.947	0.947
Cooking dinner	0.962	0.962	0.962
Dinner	0.979	0.979	0.979
Entered home	0.981	0.981	0.981
Leaving home	0.973	0.973	0.973
Preparing to sleep	0.977	0.974	0.969
Shower	0.990	0.990	0.990
Toilet	0.881	0.913	0.892
Washing hands	0.923	0.923	0.923
Watching TV	0.871	0.821	0.887

High accuracy is not determinative without AUC. In this case a particular pattern does not occur as significant portion of time. AUC values for each activity pattern with different train and test set distribution are presented in the Table 2.

Table 2. AUC evaluated for different activity patterns

Activity pattern	AUC (area under ROC curve)		
Breakfast	0.348	0.548	0.561
Cooking breakfast	0.695	0.589	0.601
Cooking dinner	0.703	0.606	0.594
Dinner	0.682	0.518	0.418
Entered home	0.529	0.534	0.552
Leaving home	0.636	0.602	0.590
Preparing to sleep	0.887	0.869	0.870
Shower	0.881	0.949	0.876
Toilet	0.789	0.833	0.812
Washing hands	0.818	0.785	0.768
Watching TV	0.683	0.643	0.622

AUC values are much better than for random guess (which is 0.5). For particular patterns AUC is greater than 0.8. Taking into account the fact that no data filtering was implemented, such result means that the data type considered (beacons RSSI and heart rate) can be used to solve an activity pattern recognition problem even without any additional data sources.

7. CONCLUSIONS AND FUTURE WORK

By analyzing the results we noticed the following:

- data filtering is important for RSSI data (signal can be lost for a couple of timeframes and then appear again);
- manual activity patterns marking is not necessary for the production system (it is still required for research to measure results), clusterization approach can be used to extract activity patterns set.

A dataset containing beacons RSSI values, heart rate data and activity patterns marks was collected and analyzed.

A basic solution of activity pattern recognition problem based on the data sources considered was implemented. The accuracy is from 82% to 99% for different activity patterns. AUC is up to 0.95. The metrics values mean that the data type considered can be used to solve an activity pattern recognition problem without any additional data sources.

The main result is a fact that Bluetooth beacons and an optical heart rate sensor can be used to provide all necessary data to solve an activity pattern recognition problem, at least for particular finite set of activity patterns.

This information can be used to implement further, more complex and accurate solutions.

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