classification
embedded systems
iBeacon

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HUMAN ACTIVITY DETECTION BASED ON THE IBEACON TECHNOLOGY

Paper presents a new method of patient activity monitoring, by using modern ADL (Activities of Daily Living) techniques. Proposed method utilizes energy efficient Bluetooth iBeacon BLE (Bluetooth Low Energy) modules, developed by Apple. Main advantage of this technology is the ability to detect neighboring devices, which belong to the same device family. Proposed method is based on observing changes of received signal strength indicator (RSSI) in the time domain. The RSSI analysis is performed in order to asses a human activity. Such observation may be particularly useful for monitoring consciousness of elder people, where reaction time of emergency rescuers and appropriate rescue operations may save the human lives.

1. INTRODUCTION

In the common understanding the Internet means computers connected in a network. This was true at the beginning of this century, but today the Internet is not just a network of personal computers. It connects also the devices that we use every day. It is likely that soon almost every device we use will be connected within one network. In XXI century we witness digital revolution. Important branch of this revolution is the Internet of Things. This term relates to a concept created by Kevin Ashton. It describes an ”ecosystem” in which devices equipped with sensors are able to communicate with computers [2]. The scale of the Internet of Things usage is wide: from apparel accessories, through smart home appliances and building automation, to water management and defense systems. Among all the IoT applications it’s impact on health care should be emphasized. In the age of increasing amount of processed data, this ”ecosystem” gives new opportunities in the area of data collection and processing. The direct benefits of using the Internet of Things can be found at the three levels of maturity proposed by Kirk Borne [3]. The first one is ”Data to Discovery”, where based on incoming sensor data a phenomena that have not been noticed so far can be discovered. New disease patterns that can be found in detailed data that comes from telemedicine devices may serve as an example.

The next maturity level has been named ”Data to Decisions”. Based on the analysis of collected data, knowledge is discovered, which allows the system to take a specified action, e.g., emergency notification. The last level of maturity is ”Data to Dollars”. Where, on the basis of the two previously mentioned functionalities, a new quality is created.

In the case of medical devices, recent research has demonstrated the usefulness of creating user profiles based on daily activity (activities of daily living - ADLs). There are six basic ADLs:

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eating, bathing, dressing, toileting, transferring and maintaining continence [10]. Estimates of the number and characteristics of people with ADL problems are equally important because of the growing number of private long-term insurance policies and proposed public long-term insurance programs that rely on ADL to determine whether a person qualifies for benefits. There are currently many solutions that monitor human activity by using different sensors.

2. RELATED WORKS

Several methods of patient activity monitoring have been proposed in the related literature. A simple solution focused on the recognition of user activities was presented by A. Harasimowicz [4]. According to this approach, a measurement was based on accelerometer embedded in a mobile device. Similar to our case the device was carried in a specific location of the users's clothing, e.g., pocket. In that solution three types of classifiers has been tested on different size of the samples. Authors conducted a study on the impact of a sample length, which was considered in the classification, on the recognition effectiveness.

Other authors also presented their own idea of registering human activity by using a mobile phone. In a specified time the device may take an action if a motion disorder is detected [7]. This system was designed for home or outdoor usage as a mobile healthcare assisting device. Strong point of this solution is the detection of abnormal motion in real time. Method presented in that paper is especially useful in case of Parkinsonian patients, where an auditory feedback can warn the patient about particularly dangerous situations such as the freezing of gait.

More complex solution has been presented by Jie Yin [13]. In this article two-phase approach for detecting abnormal activities has been presented. The authors have based their research on wireless sensors attached to a human body. Main purpose of this method was to minimize the issue of high false positive rate, particularly when the abnormal events are rare. Reducing the false positive rate problem has been solved by employing the support vector machine (SVM) and kernel nonlinear regression (KNLR).

Another approach, presented in [12] implements the fuzzy logic. In that paper a fuzzy Bandler and Kohout's sub-triangle product (BK subproduct) was used. Main purpose of this method was not only to detect and recognize human motion, but also to detect ongoing human action early, i.e., an action is detected as soon as it begins, but before it finishes. The novelty of that approach lies in the construction of a frame-by-frame membership function for each kind of possible movement.

In another paper a system for detecting vehicle collisions and rollovers was presented [5]. Data is acquired from gyroscope and 3-axis accelerometer which is integrated into MPU-6050 motion sensor. By using these sensors, the system is able to detect collisions and rollovers in road traffic but it can also be used for detection of human motion disorders. The previously mentioned solutions use dedicated external sensors that can reduce the object's mobility. The solution proposed in [9] uses a small and inexpensive sensor built into a smartphone.

3. PROPOSED METHOD

This section describes an algorithm, which detects human motion and potential lost of consciousness. The objective of the algorithm is to enable human activity detection by using the Bluetooth BLE device. The purpose of this method is to detect human movement via received signal strength indicator (RSSI) analysis.

RSSI is a common name for the signal strength in a wireless network environment. It is a measure of the power level that RF client device is receiving from an master device. In other words RSSI is a term used to measure the relative quality of a received signal to client device, but has no absolute value. In computer systems, where data transmission is performed wirelessly often signal strength is described in dBm. dBm and RSSI are different units of measurement that both represent the same thing. The difference is that RSSI is a relative index, while dBm is an absolute number representing power levels in mW (miliwatts). RSSI is often expressed in decibels (db), or as percentage values between 1-100. At maximum Broadcasting Power (+4 dBm) the RSSI ranges from -26 (a few inches) to -100 (40-50 m distance) [11].

Finding distance from RSSI is very complex problem and it depends on lots of factors, even test environment and antenna orientation etc. [6].

Chipcon [1] specifies the following formula to compute the RSSI:

$$RSSI = -(10n \log_{10} r + A), \tag{1}$$

where n is signal propagation constant, also named propagation exponent, r is the distance from sender and A is the received signal strength at 1 meter distance.

By connecting two modules in a master-slave configuration, it is possible to measure signal level information that changes proportionally to the distance between the modules as shown in Figure 2.

When one device is stationary (a master or a central device), and another one is held by a patient under observation (a slave or a satellite device), it becomes possible to distinguish and classify human activity on the basis of the RSSI data. It is also worth to mention that these devices are inexpensive and power efficient. As a satellite device also a smartphone can be used, and it will have a minimal impact on its battery life. From a medical point of view it is particularly important to detect a state of immobility. Such a condition may indicate unconsciousness. In the proposed method the signal level is measured at a fixed intervals and registered for further processing. Three types of human activity were included in the study: sitting, walking and unconscious (motionless). Reference RSSI samples were registered for each of the above activity categories. The standard deviation of RSSI level has been calculated with the sliding window approach in order to asses deviation of signal level in time. Sliding window approach was shown in Figure 1. This method allows for continuous calculation of standard deviation from the current sample and a given number of previous samples. The optimal number of analyzed samples has been determined experimentally, what is described in the latter part of this paper. Same procedure is applied to the input data in real time.

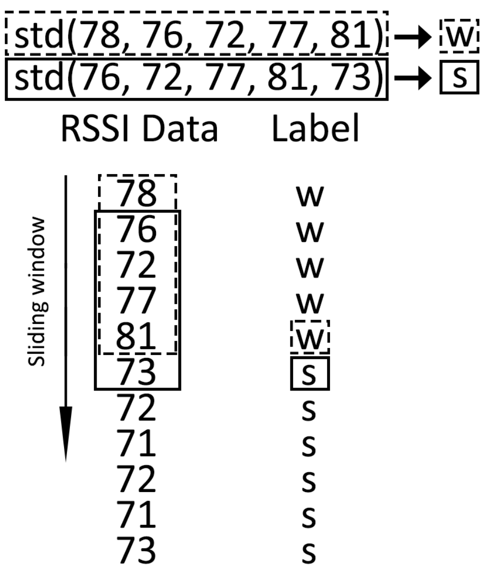

Fig. 1. Sliding window approach to the problem of signal volatility measurement

Previously calculated standard deviations of labeled reference data are feed into the kNN classifier as a training samples. Standard deviations of input samples are classified in real time using the kNN classifier. Details of the implemented kNN classification algorithm can be found in [8]. The final decision is taken on the basis of the classifier decision in a decision window, i.e. for current sample and a given number of previous decisions in the process of a majority voting, which is described in the experimental section of this paper.

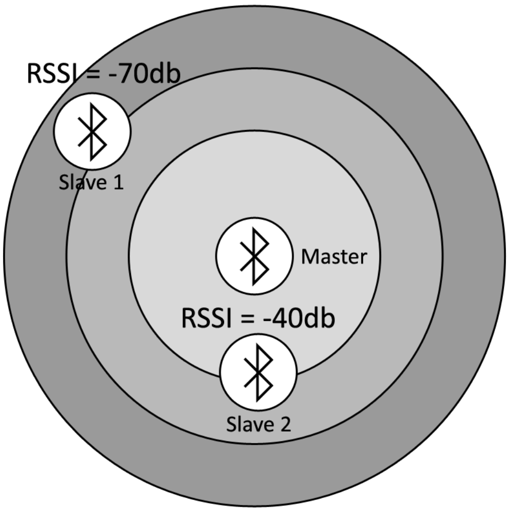

Fig. 2. Different level of signal strength depending on the distance from the master device.

4. EXPERIMENT

Data has been collected in a real life environment. Slave device was placed in the patient's pocket. Maximum distance between master and slave device was about 10 meters. Experiment has been conducted in place about 60 m^2. During the measurement patient may walk in whole flat (not only in one room, where master device was placed). In this way obstacles, such as furniture, walls, other persons, have influenced to the collected RSSI values. While experiment has been performed 2 other person participated in the study. In case of device disconection, pooling mechanism was implemented. If the device fails after the specified time, the emergency services may be called. For each of the three types of human activity included in the study (sitting, walking and unconscious) 300 samples were registered. The next step was to read from the master device all transient situations between these types of activity. Portions of the reference data for above mentioned activities together with the data for transients between activities were used to construct test data. In further part of the paper we will call these data a scenario. These scenarios are combination of two activities interleaving each other, ending with loosing of a consciousness. Data from the scenarios is used to test the kNN classifier by means of calculating overall accuracy of a classifier and FAR and FRR of a class that represents loosing of consciousness. 40 of such scenarios, each containing 300 samples, has been tested. The training data set has been composed of 870 samples for each scenario. One of analyzed scenario was shown in Figure 3. Due to the fact that the algorithm use signal volatility instead of value, the standard deviation is used. The data thus prepared are not as noisy as it was during the RSSI analysis. The analyzed data in the form of standard deviation was shown in Figure 4.

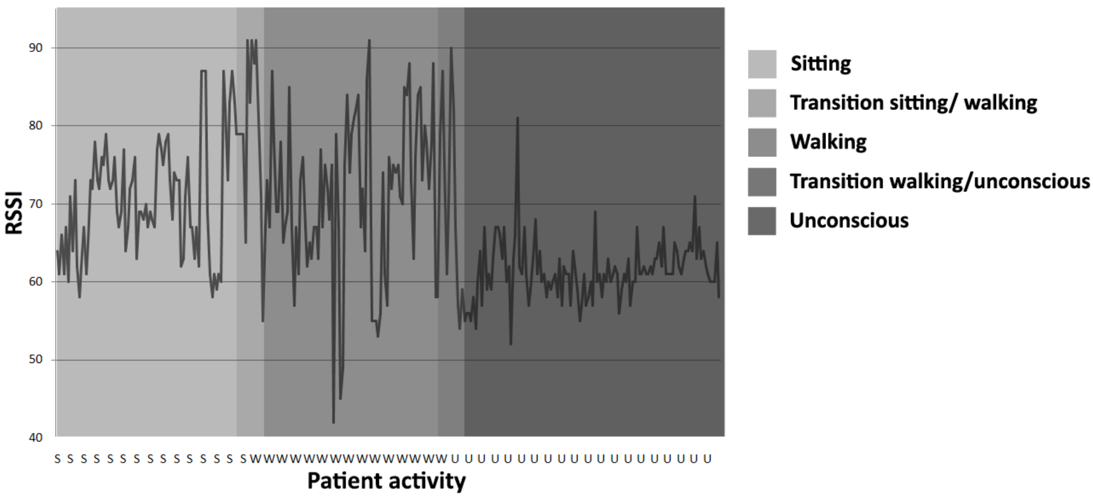

Fig. 3. An example of the scenario being analyzed

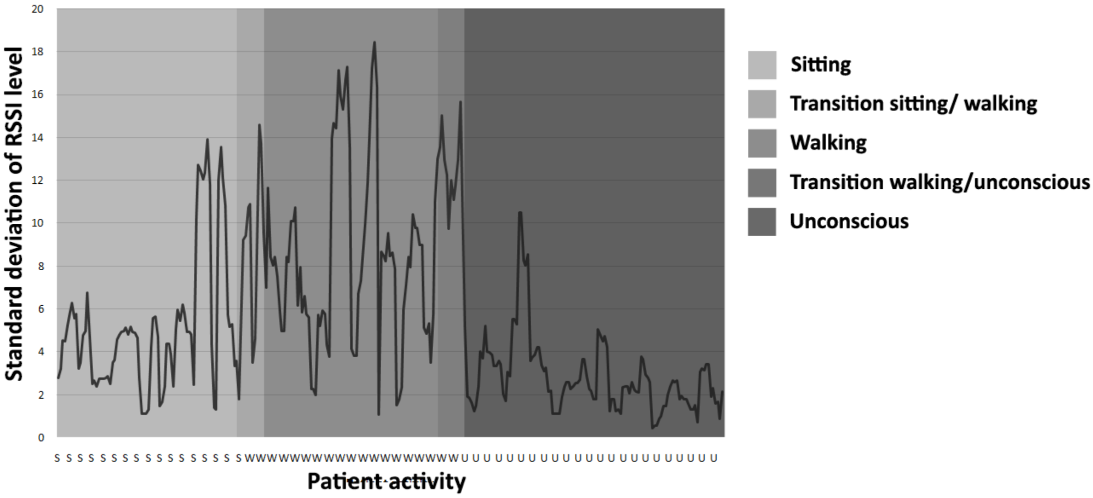

Fig. 4. An example of the scenario being analyzed

Research has identified the need for real-time human motion detection using the smallest number of samples [6], [10], [12]. Mechanism of majority voting was presented on Figure 5. Previously mentioned voting is important because window size determined history of measurements. Window for mechanism of majority voting was was defined in formula 2-3. Voting decision was defined in formula 4.

$$X = \{x_i\}_{i=1}^{N} \quad , \quad x_i \in \{s, u, w\} \tag{2}$$

$$\begin{gathered} A_1 = \{x_i : x_i = w\}\,, \\ A_2 = \{x_i : x_i = u\}\,, \\ A_3 = \{x_i : x_i = s\}\,, \\ N = \#A_1 + \#A_2 + \#A_3 \quad , \quad A_1, A_2, A_3 \subset X, \end{gathered} \tag{3}$$

$$A = max\,\{\#A_1, \#A_2, \#A_3\}\,, \tag{4}$$

where:
A_1 - subset of samples x_i which object state is "Walking",
A_2 - subset of samples x_i which object state is "Unconscious",
A_3 - subset of samples x_i which object state is "Sitting",
X - set of all samples,
N - Number of all samples,
A - Algorithm decision.
If number of elements in each subset is equal, then A_2 will be selected. Based on research, only 18 previous measurements are enough to make the summarized overall accuracy for all classes around 91%.

The proposed method uses two windows: one for calculating the standard deviation of RSSI data (Fig. 1) and another one for majority voting of classifier decisions (Fig. 5). Size of the two windows has been independently experimentally optimized for maximal overall accuracy. Impact of the window size for calculating standard deviation on the overall accuracy of is presented in Figures 6 and 7). The dependency between the size of majority voting window and the classification accuracy is illustrated in Figures 8 and 9. Based of the above mentioned results, the window size of 5 was used for the calculations of standard deviation and 18 for the majority voting.

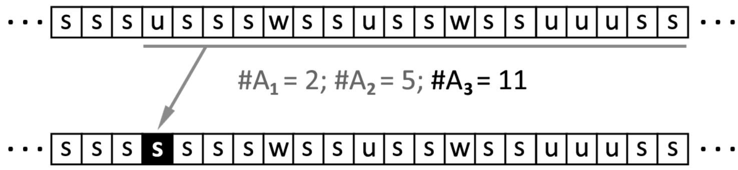

Fig. 5. Mechanism of majority voting

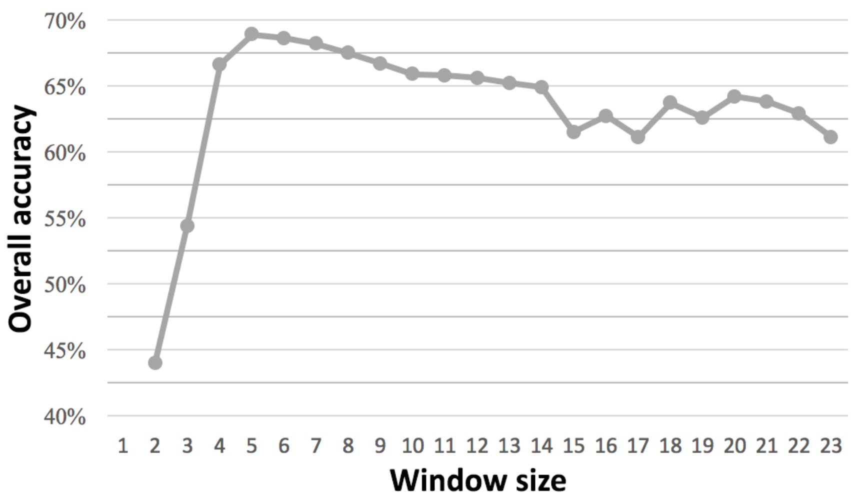

Fig. 6. Standard deviation window size optimalization.

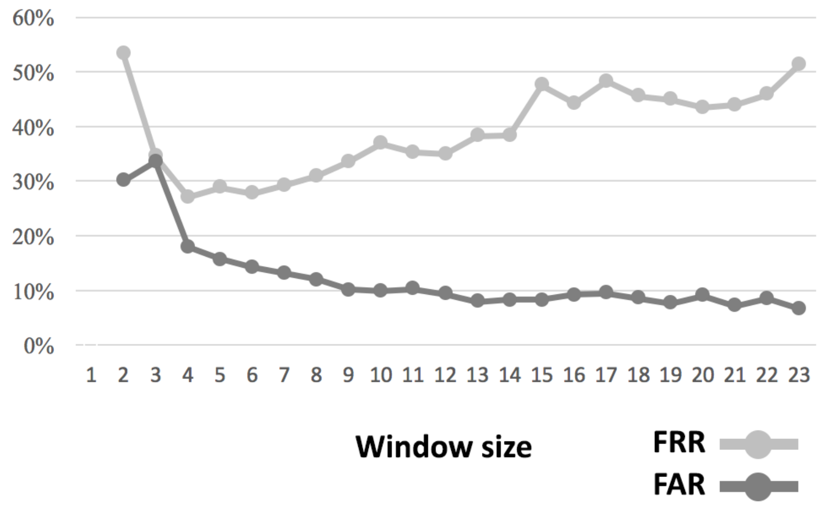

Fig. 7. Standard deviation (majority voting) window size optimalization.

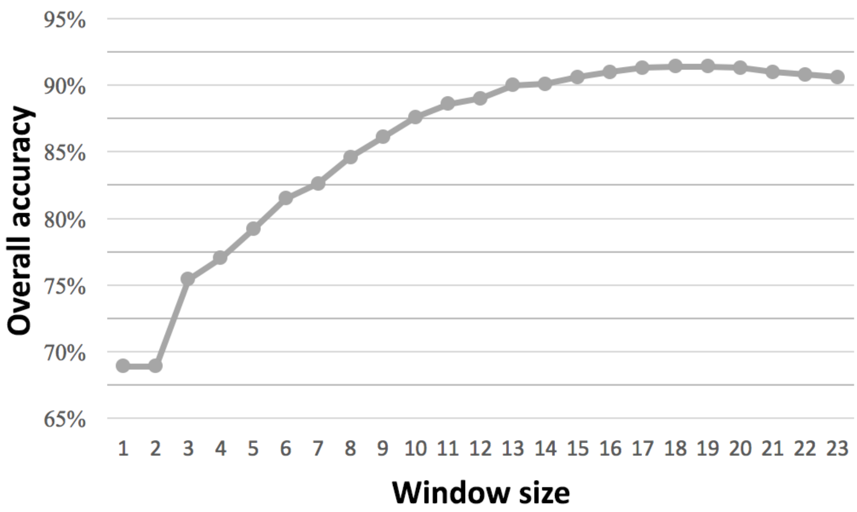

Fig. 8. Classifier decision window size optimalization.

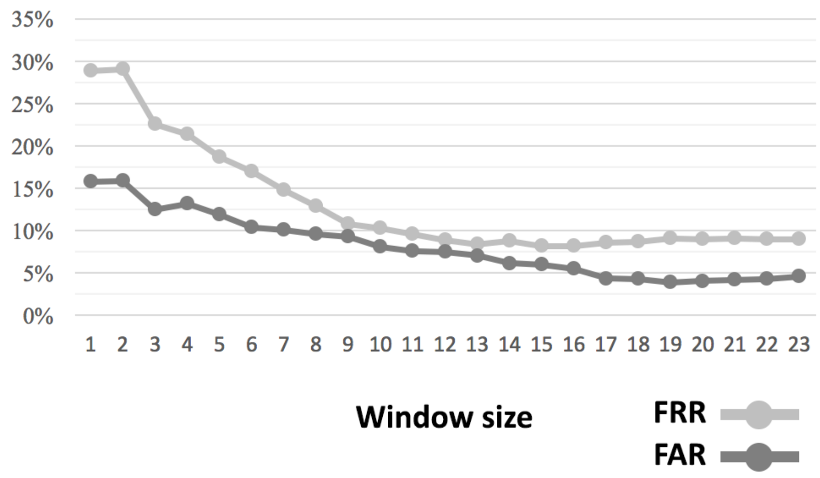

Fig. 9. Classifier decision (majority voting) window size optimalization.

5. CONCLUSION

The research results presented in this paper shows that the energy efficient Bluetooth iBeacon modules can be used not only in the area of marketing, but also in healthcare. By using the proposed method it is not only possible to detect that observed person is not moving (lost consciousness), but also to name some other physical activities. The described method is not only precise, but also inexpensive. Only the central module has to be a dedicated device. Remote device, which person keeps with him/her, may be a regular smartphone. Low power consumption and ability to enter sleep mode, makes it possible to run battery powered device for 12 months, and makes no noticeable impact on battery run time of smartphone.

It is possible to further improve the accuracy of immobile detection by activating additional sensors built into phones such as accelerometer, magnetometer and gyroscope.

When the algorithm detects lack of motion of the observed object, it is then possible to increase the confidence of the detection by using other sensors that are available in the phone. This approach saves battery power. This problem is especially important in mobile devices.

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