Presence Detection, Identification and Tracking in Smart Homes Utilizing Bluetooth Enabled Smartphones

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***Abstract*—Advances in ubiquitous computing over the last decade have allowed us to inch closer to the realization of true smart homes. Many sensors are already embedded in our living environments which can monitor several environmental parameters such as temperature, humidity, brightness and appliance-level power consumption. However, in order to achieve the primary goal of the smart home, we should be able to detect, identify, and localize the entities inside it. Therefore, the user detection, identification and localization problems represent a crucial facet of the challenges introduced by the smart home problem. Our approach towards solving these challenges entailed the usage of Bluetooth technology for user identification and tracking, alongside a Wireless Local Area Network setup to collate the sensor data at a centralized server such as a home gateway which subsequently processed and stored the entries. Moreover, we have studied the efficacy of various pattern recognition algorithms for real time processing and decision modeling on the received data. We have hence demonstrated our solution represents a non-intrusive, inexpensive and energy-conserving methodology to solve an essential part of the smart home problem by integrating already existent devices and infrastructure in an innocuous manner to obtain good results with minimum overhead.**

***Index Terms*—Smart Homes, Ubiquitous Computing, Bluetooth Positioning, Bluetooth Tracking, Support Vector Machines, Multilayer Perceptrons.**

I. Introduction

As succinctly stated by Mark Weiser in his seminal 1991 paper, "The Computer for the 21st Century" [10],

> *"The most profound technologies are those that disappear. They weave themselves into the fabric of everyday life until they are indistinguishable from it."*

This vision is increasingly becoming a reality in the era of the Internet of Things (IoT) where more and more sensors are becoming embedded in our ambient environments to achieve the main goal of making our daily lives "smarter". One manifestation of this vision is the concept of the smart home where different kinds of sensors are deployed at home in order to achieve different goals such as assisting elderly people as seen in the Ambient Assisted Living (AAL) research. Another goal which represents the crux of our smart home research is that of energy conservation where we create systems which are able to learn the users' behavior at home and make the smart home more energy-aware. Our concept for the home of tomorrow constitutes a home which is able to track and learn its inhabitants daily routine unobtrusively, and armed with this knowledge seek to make life at home as comfortable and personalized as possible. All this while also simultaneously optimizing power utilization to lessen environmental impact and conserve natural resources. For any smart home set-up to achieve these goals, the tasks of knowing who is where when is of paramount importance. Thus the overall problem can be seen to consist of three constituent sub-problems:

- Presence detection: In this step, the system should be able to detect presence but need not determine the identity of the detected entity or her/his exact position.
- Presence identification:In this step, the identity of the detected entity is to be determined.
- Presence localization: In this step, we determine the exact position of the detected entity inside the monitored space.

Presence detection is the fundamental problem. As clarified in Figure 1, both presence identification and presence localization are subsets of this problem, and the satisfaction of either automatically implies presence detection capability. Particularly to be noted, for the presence localization sub-problem the degree of resolution required plays a key role in the design of the system. Our requirements for the design plan of our solution demanded both person identification and localization up to a resolution of the room level, which we consequently went about designing for.

The remainder of this paper is structured as follows. In Section II, we discuss the different type of sensors which can be used for presence detection in smart home. We describe the advan-

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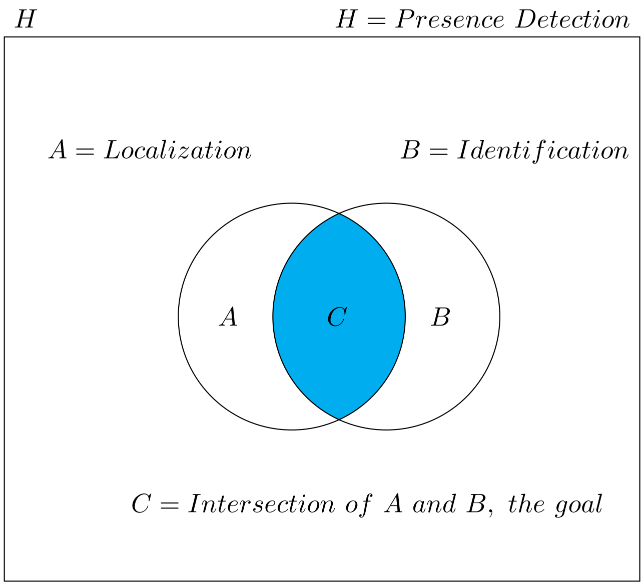


Fig. 1: Presence Detection, Identification, and Localization

tages and disadvantages of each type of sensors. In Section III, we introduce several related projects that dealt with the topic of presence detection in smart homes. We introduce the hardware components as well as the testbed of our system in Section IV. In Section V, we evaluate the accuracy of our system using different decision algorithms. The algorithms studied for this purpose include simple thresholding, K-Means clustering, Support Vector Machines and Multilayer Perceptrons, with results obtained after implementing the above using the Weka data mining platform [6] also presented. Finally in Section VI, we conclude the paper and introduce potential ideas for future work.

II. Sensors for Presence Detection

Presence detection system can be realized with different type of sensors. Each type has its pros and cons. The following list presents a set of these sensors. Compelling arguments for/against each type of sensors are provided:

1) Binary Sensors - These sensors have only two states i.e presence is either detected or not. Examples of them include contact sensors, breakbeams, Passive Infrared sensors (PIRs). Of these, PIRs are the most popular, being cheap, passive and easy to program. They can also be used in an array configuration to estimate position and number of people in the room [11]. However, they face issues in detecting stationary people as their functioning hinges on movement, and Presence identification, while possible, requires a huge amount of data processing [4].
2) Pressure sensors - These include piezo-electric materials and strain gauges. They are a good way to achieve localization, but the number of those required to achieve presence detection over a whole room would prove to be prohibitive. Also, they lack person identification capabilities as well.
3) Chemosensors - Including sensors like CO2 sensors, humidity sensors etc. Chemosensors are not suitable for our case because they are too slow in detecting presence in the environment.
4) Cameras - In this category, we have CMOS image sensors, CCD image sensors, specialized motion- or edge-detecting imagers, microbolometer arrays and PVDF (Polyvinylidene Fluoride) arrays (the last two being thermal imagers). While these do provide person identification and localization and were viable options for implementation, it too suffers from problems of detecting stationary people after extended periods. Also, the overwhelming ethical qualms one associates with taping a person's complete life at home necessitated the search for more viable alternatives.
5) Ranging sensors - This category contains ultrasonic range-finders, scanning range sensors like radars, lidars, sonars etc. come under this category. While they work well for detecting stationary people, person identification remains an issue.
6) Inertial sensors - These include accelerometers, gyroscopes, magnetometers etc. While viable, they would have to be combined with another type of detector to get rid of accumulated errors and, thus, serve better as secondary detectors to enhance resolution rather than standalone implementations.
7) Vibration sensors - This includes seismic sensors, piezoelectric sensors, electrostatic microphones, laser microphones etc. The accuracy of the implementation after the amount of signal processing required to extract results stymied its use. Also, it too lacks person identification capabilities.
8) RFID sensors - The best fit for the problem, provides person identification and localization with a resolution capability of room level and even better. The primary issue with its use is convenience. RFID tags will have to be continuously carried on person all the time during one's movement at home, and dedicated RFID reader hardware will have to permeate the house.
9) Bluetooth and WLAN - Both ubiquitous technologies, both unobtrusive, both low power and both easily available on a device that people tend to carry around everywhere with them, even at home - their mobile phone. Out of all possibilities studied, it was concluded use of one of these seemed the most viable option to satisfy the project goals and hence went about designing and implementing a system based on it. Bluetooth was chosen over WiFi primarily because of lower power drain on the mobile devices, and also since Bluetooth signals are weaker than WiFi, better room level localization was achievable.

III. Related Work

There have been several previous attempts to use Bluetooth for presence detection and identification in smart homes, each employing a variety of different decision models for the purpose to reach the highest possible accuracy. In their work "An indoor Bluetooth based positioning system concept - Implementation and Experimental Evaluation "[12], S. Feldmann et al. have employed triangulation based on the Received Signal Strength Indicator (RSSI) values empirically fitted to distance measurements to achieve localization within a 46 m^2 room split into 1 m^2 squares. Cheung et al. [8] employed a Peak RSSI value model to determine localization with Room Level Resolution (2-3 m) based on the probabilities of presence of fixed Bluetooth signal beacons. In their paper "Beacon Placement for Indoor Localization using Bluetooth" [3], Chawathe et al. divided the testbed into cells, each with certain Bluetooth beacons visible, the combination of which uniquely identifies the cell. Another interesting concept has been tested by Fischer et al. in their work "Bluetooth Indoor Localization System" [5]. In this work, time differences in the signals received from different Bluetooth beacons was used to calculate position. Machine learning has been also employed for the purpose of user localization. This can be seen in [1], where the authors have employed neural networks in conjunction with RSSI values to predict user position. Unsupervised machine learning has also been used for the purpose of implementing user localization based on Bluetooth. In their work "Indoor Localization Using Multiple Wireless Technologies" [7], the authors have designed a localization system based on Bluetooth and Wi-Fi technologies in which the localization is performed using the K-Nearest Neighbor and Bayesian Probabilistic Model algorithms. Linear regression is exploited to facilitate the under-trained location system.

IV. Equipment and testbed

To set up the Bluetooth Personal Area Network (PAN), for the beacons 3 powered USB hubs were used in combination with 3 Bluetooth USB sticks as shown in Figure 2a. It was decided against using Bluetooth headsets like in [8], as while the hub-based implementation does cost marginally more, it has the advantage of requiring much less maintenance as there is no requirement to charge each Bluetooth beacon every couple of days, thus creating periods where the whole network has to be taken off-line. The only setup required is that initially, each USB stick has to be connected to a PC and made discoverable. After this was done, each beacon was then ready and setup in a different room.

The mobile phone used in this experiment was a Motorola MB525 with Bluetooth v2.1 and Wi-Fi 802.11 b/g/n as shown in Figure 2b. It was programmed to periodically (every 30 seconds) run a Bluetooth discovery search and extract RSSI values for the 3 known beacons. These 3 values and a time stamp were then transmitted to the home gateway over the WLAN. The home gateway then proceeded to perform localization and identification of the users in the testbed. The measurements have been conducted in three rooms in the building of our institute as clarified in Figure 3.

V. Decision Models

For the purpose of user identification and localization, the home gateway was programmed to use the received RSSI values with decision algorithms which are responsible for determining the location of the user based on the collected RSSI values. We decided to test a set of decisions algorithm so that we examine the different accuracies which can be achieved by our system depending on the used decision algorithm. These algorithms, the logic behind their usage, the optimizations performed in each case to extract the best results and the results themselves are presented in the following sections.

A. Peak RSSI Decision Model

This algorithm has the advantage of being simple to realize while achieving good results. In this model, the three RSSI values returned were simply collected and the maximum among them was taken without any preprocessing. Figure 4 clarifies the concept of this algorithm. The logic behind this is that the RSSI obtained is correlated with the signal strength, which is itself inversely correlated with distance from the receiver. Thus, the closer the user is to a beacon, the higher the RSSI value of that beacon the handset registers. So the user was subsequently localized to the room containing the beacon corresponding to the maximum value.

This simple algorithm yielded quite good results (out of 350 samples, it only misclassified 3) as shown in Figure 5a in which the x-axis represents the room in which the system predicted the user to be, while the y-axis represents the room in which the user was. The high accuracy achieved by this model is largely due to the setup of the testbed (very isolated rooms, lots of intervening walls). Regardless, it served as very encouraging proof of working for the design employed, and does provide a very simple implementation for situations where processing power is at a premium.

B. Supervised Learning - Multilayer Perceptron

Supervised learning techniques have always performed very well when it comes to a scenario in which a training dataset is available. In this scenario, a training dataset of 300 labeled readings was created and served as the training set for a neural network created using the Weka data mining platform [6]. A test set comprised of 50 readings was used to test the neural network. The neural network thus trained achieved perfect results as shown in the confusion matrix in Figure 5b. It is clear from the figure that the neural network was able to classify the whole test set correctly.

C. Supervised Learning - SMO

Another supervised learning technique which proved to achieve very good results in classification tasks is Support Vector Machines (SVMs). The same dataset previously created was used to train a Support Vector Machine, again implemented using Weka. Normalization of the attributes was turned off as absolute magnitude of deviation of received RSSI values from mean was important in this case. The SVM correctly classified all 50 test cases as shown in Figure 5c.

(a) The Bluetooth Beacon

(b) The Bluetooth-enabled Handset

Fig. 2: Snapshots of the Test Equipment

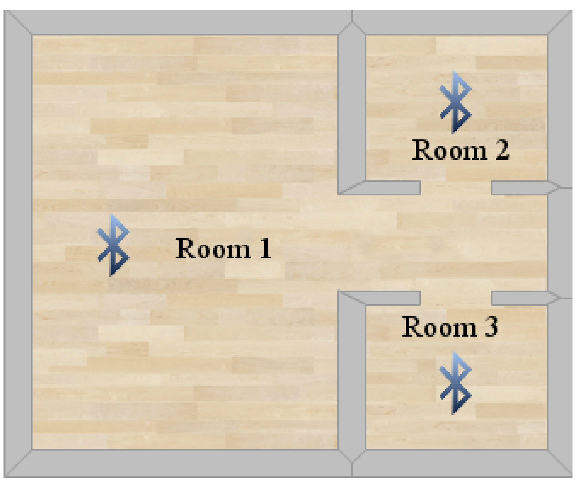


Fig. 3: Floor Plan of the Testbed

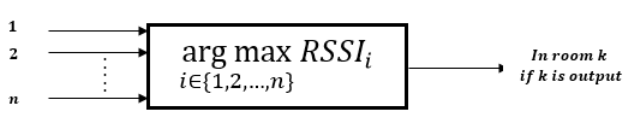


Fig. 4: Peak RSSI Algorithm

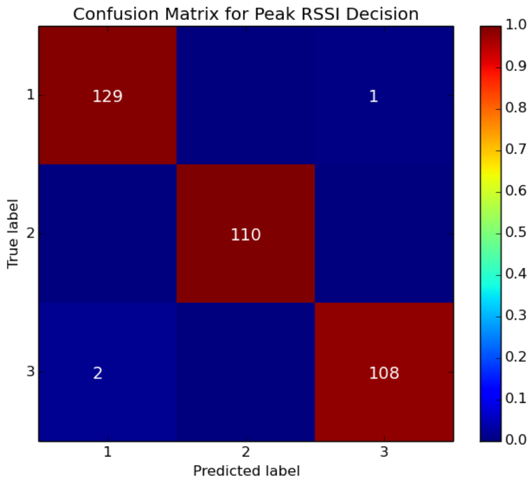
D. Unsupervised Learning - SimpleKMeans

Unsupervised learning represents another possibility to achieve the goal behind our system. In this scenario, we decided to use a simple yet efficient unsupervised learning algorithm, namely k-means clustering. Number of clusters was known and set to three. Normalization was also turned off due to similar reasons as in the case of the SVM. While employing euclidean distance as the distance metric, the classifier clustered 4 out of 50 test set samples wrong. Performance was improved when using Manhattan distance as the distance metric as only 1 test sample was classified incorrectly as shown in Figure 5d. This is likely because for points on the boundary between clusters where distances in two or more are similar, Manhattan distance tends to accentuate biases and work similar to the first method of extracting peak RSSI value.

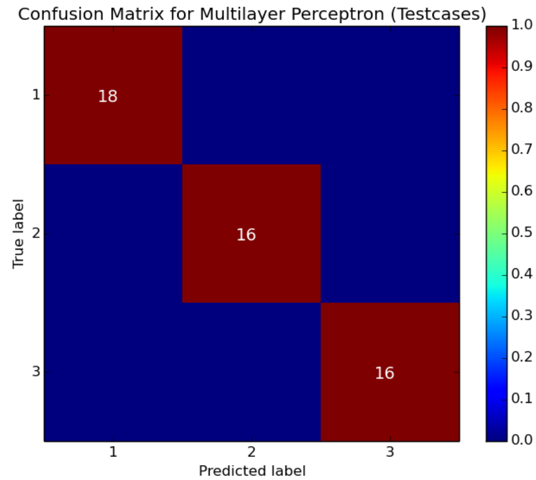
By looking at the previous four sections, we can see that all the algorithms have achieved a very good accuracy. Supervised machine learning techniques have achieved the prefect results by classifying all test instances correctly. Furthermore, the peak RSSI algorithm as well as the k-means algorithm have shown a very good performance. This proves our system to be a promising solution for the problem of presence detection in smart home.

VI. Conclusion

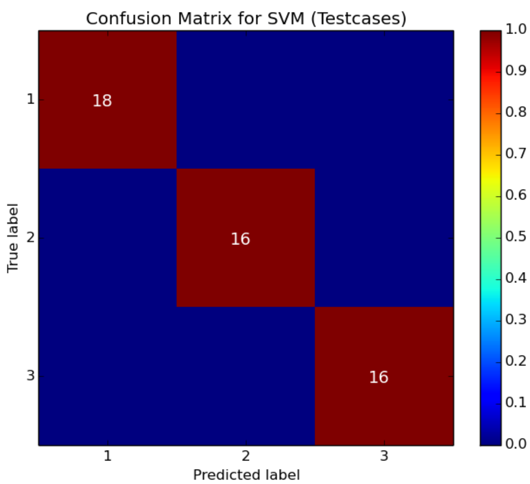
In this paper we have conceptualized and implemented a low-power, cheap and unobtrusive Bluetooth based presence detection, localization and identification system that requires extremely low maintenance using common, everyday items to use in the smart homes of tomorrow. A set of decision



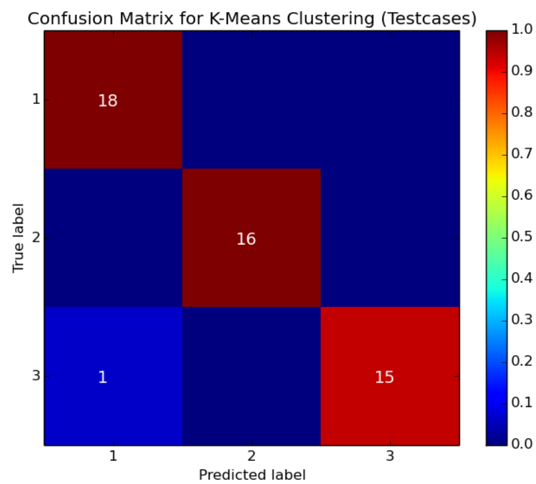
(a) Peak RSSI algorithm



(b) Multilayer Perceptron



(c) SVM



(d) K-Means Clustering

Fig. 5: Confusion Matrices of the result data

algorithms has been tested in order to achieve the highest possible accuracy for the system. In this work, we have shown that a solution based on Bluetooth technology was the most viable option to satisfy the goals of our project and hence went about designing and implementing a system based on it. Bluetooth was chosen over WLAN primarily because of lower power drain on the mobile devices, and also since Bluetooth signals are weaker than WLAN [2], better room level localization can be achievable. Moreover and with regard to the decision algorithms which have been used, we draw the conclusion that all the algorithms seemed to work quite well offering almost 100% accuracy and prediction for room level localization, with the multilayer perceptron and the SVM performing marginally better. Any of them can be used for this purpose subject to computing constraints.

Next steps in the problem deal primarily with implementing a system that achieves better resolution for presence localization i.e. beyond room level. To achieve this satisfactorily, we will need to combine the basic Bluetooth system with some of the other previously mentioned techniques such as PIRs, Ultrasound rangers (as in [9]) etc. Another future objective is to try out the system in more varied, challenging environments to accentuate the differences in capabilities of each of the data processing algorithms.

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