Phone application for indoor localization based on BLE signal mapping

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Abstract. Indoor position of devices and persons is a very valuable information for context aware devices and human activity recognition. The need of such information grow bigger by the advancement of IoT technologies. In this paper we discuss existing indoor positioning approaches and their applications, give specific interest to the signal strength mapping approach based on Bluetooth low energy beacon packets, and the implementation in smart system for elderly health care. The goal of this research is to adopt the indoor localization approach to a phone application that can collect data, build position model, and estimate the position of the elderly. Then share the information with care givers through a cloud service.

Keywords: Indoor localization, data mapping, beacon, mobile computing.

1 Introduction

GPS technology allows the privilege of determining the location of a mobile device is great accuracy. Although we have access to such information in almost all around the globe, emerging technologies requires it where GPS is incapable [1], which is indoors areas. In this new era of ubiquitous computing, the exact location of a person curry a significant importance because most approaches uses it as a base for determining this person's context and estimating the activity [2-5], recently employed for human behavior monitoring [6], in the growing domain of smart elderly care.

Different approaches have been proposed to solve indoor localization, each has advantages and shortcomings that can be summarized in a trade-off between precision, cost, complexity, and privacy issues [7, 8], wireless-sensor-network based techniques are the most widely used since they overcome the privacy issues related to vision-based positioning systems.

From the strategy point of view, there exist two categories: range-free, where it is usually assumed that the network is isotropic and the hop count between two nodes is proportional to their distance. And the range-based methods which are more realistic due to the presence of various anisotropic factors [9], these techniques, instead, assume that the inter node distances can be measured by ranging using the Reserved Signal Strength Indication (RSSI) measurements, they suffer from the intrinsic ranging noise, which affects the localization accuracy.

WiFi-Based approaches have been widely investigated due to the widely available infrastructure, but Bluetooth Low Energy (BLE) have gain more interest recently by the arrive of Beacon technologies, which relatively lowering the cost [10, 11].

BLE-based triangulation methods describe the distance between the beacon and the received by a theoretical model based on the RSSI, which makes their performances very poor when there is no direct sight of the beacon, and suffer from large estimation error. Signal mapping method (also called finger printing) has been adopted widely because it handle will with non-line of sight issue and has higher accuracy [12]. Also it has been noticed that the major characteristics of signal strength diversity is not only characterized by the distance but also by the signal absorption by humans, or reflection on wall, which is problem that can be avoided by single mapping methods [13].

2 Motivation

In one hand, despite the fact that commercial systems like Ekahau [14] or UbiSense [15] are accurate, the costs of installation, maintenance are still high. Moreover, most commercial systems require to purchase and install specific hardware which means they cannot be used with portable devices already at hand.

And from another hand, a lot of research have been dedicated to finding an accurate and robust approach to determine the location of mobile devices indoors using data mapping [16-20], but most of these systems require a designated training phase that can take an extended period of time [21, 22], Moreover, the accuracy based on these systems is according to the training phase, and can no longer improve later.

Form a technical point of view, most of the existing methods makes the offline computations in a cloud server or in different device than where the online computation is made, which makes the indoor localization approach less practical when used in bigger system. A few researcher have tackled the need for updatable indoor localization mapping systems, and even fewer commercial systems addressed this need.

3 Project goals

Based on the argument presented above, we set an objective to build a fingerprinting-based indoor localization system that covers the following requirements:

- Easy to setup and to maintain
- Provide higher estimation accuracy

• Must be able to adapt to changes in the environment

• Collect data, compute offline model and estimate position in the same mobile device

• Share information with observers through a cloud server

• Develop a system that uses the location information, like personal identification, behavior analysis, emergency prediction and protocols.

The main goal of our project is make an adaptable localization system for smart remote elderly association.

4 Data collection

At the first stage study, we intend to use beacon signal strength as data, we employ a configuration where there are one beacon at each wall of a square room, collect data from different places as depicted in figure 1, which allows us to build a model that describe the real relation between signal strength and distances, or in the case shown in the figure, the coordinates according to left bottom corner reference. At the presence of obstacle, this way of collecting data will prevent falling into errors due to signal deviation and non-line of sight. One more information will be taken into consideration is the orientation of user, we consider taking at each point, four orientations (facing each wall).

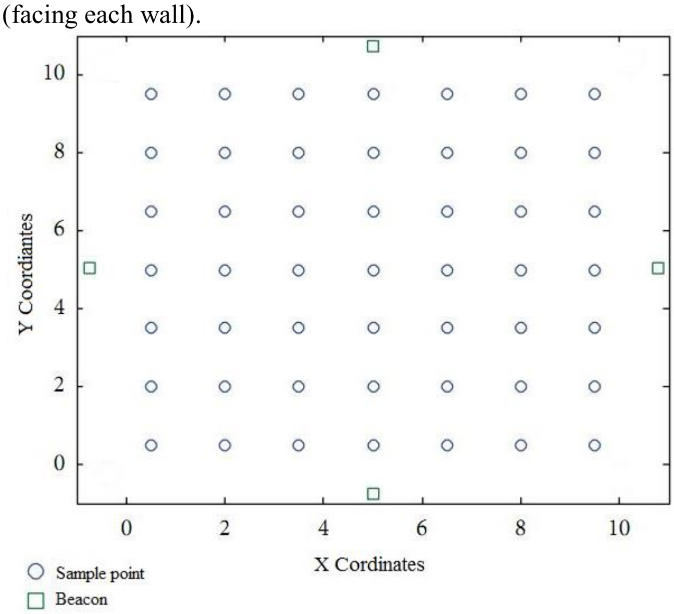

Fig. 1. Beacon configuration and signal mapping

From the phone application perspective, the user collaboration is required at this stage. The user is allowed to collect as many data as wanted and at any place, but it is advised to cover the whole room with moderate density of sample points. Ones positioned and started receiving data, the phone application will automatically filter the data, then ask the user to change position when a sufficient amount of signal is received from all beacons. The user has the freedom to follow a predetermined pattern of positions of set the position coordinates manually.

4 Phone application

Most currently used fingerprinting systems run a neural network training after collecting the data, this phase is time consuming and most importantly very hard to implement in a phone app, we intend to adopt a strategy that allows understanding the relation between cordialness and signal data by costume interpolation, which makes the offline phase very quick. And by allowing farther data collection while use, data collection is incorporated, which makes it an ongoing process that allows the model to learn more and more about the relation between signal and position and adapt to signal map changes, when the environment of the indoor location had changed, like furniture being moved for example.

The final vision of this phone application is to be very interactive, to make its use as natural as possible, since the precision of the estimation relies on the collaboration of the user. In case the estimation wasn't precise enough, the observer can launch a process that will make the phone application ask to collect more data, than automatically construct a new model based on both old and new data.

Since different phones are associated to the users, the personal identification is easy in this case, and the observer is able to remotely check the state of many elderly simultaneously even if they are located in the same room.

5 Conclusion

Most existing indoor localization methods are hard to implement in human activity recognition, due to their requirement of a certain technical knowledge, and interactive phone application that can handle all stages of signal mapping indoor localization, and presented as a sort of game, seem to be promising idea for remote elderly association, since it allows the observer to be aware of the context in which the elderly exist, and keeps the elderly challenged and active.

The accuracy of the described method is being examined at this stage, where we are still at the stage of determining the filtering and interpolation parameters. It is insured that the accuracy of the estimation will increase by the number of sample points. For the final vision of this application, we want to make the system able to concentrate on some hot points, where the user is frequently located. Also to make the application less technical as possible, we intend to determine the location with a different system than the coordinates of the position.

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