Converting context to indoor position using built-in smartphone sensors

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I. Introduction

While outdoor positioning via GPS is widely used, indoor positioning without the aid of costly infrastructure still remains an area of active research, the practicality of indoor positioning is often hindered by the need for expensive and cumbersome sensor systems [1] [2] [3]. Moreover, they compromise user's privacy, and cannot deal with dynamic situations (e.g., disasters). To date there has been no solution that overcome these limitations and provides an autonomously indoor positioning system.

One possible solution in this direction is to rely on the capabilities of recent smartphones coupled with indoor maps. Fortunately, there is a recent interest from several location based service providers to create and distribute detailed digital indoor maps. For example, Google has launched a new initiative in 2011 to create indoor maps for most large shopping malls, airports, and other buildings in 10 different countries [4]. Within this initiative, the building owners will be able to upload the floor plans and add many details through the map, including the location of useful facilities, such as lifts, escalators, telephone booths, coffee shops, etc.

Although digital maps formats might lack standardization, this problem can be overcome by utilizing the Scalable Vector Graphics (SVG) format described in [5] and then preloaded in the smartphone. Therefore, the context of the user in terms of which facility he/she is using at the moment, have the promise of significantly providing very accurate indoor positions frequently and independently from any infrastructure, Such context can be detected using the built in sensors in the smartphones. Between two instances of opportunistic positioning from context detections, pedestrian dead reckoning [6], which tracks current position accurately for a short distance if started from a known position, could be employed to realize a continuous indoor positioning system that remains completely self-contained. Moreover, augmenting the identification of the facility used by the user, the direction of movement, and the distance traveled will determine the position of the user with high accuracy without relying on any interaction with the infrastructure.

II. Problem Statement

The main problem is to accurately detect the context and in an energy-efficient manner. More precisely, the smartphone needs to classify the sensor data into a set of known facilities, such as lifts, escalators, travelators, ramps, stairs and so on. This has to be done with minimal computational overheads so that the continuous use of it does not drain the limited battery of the smartphone. Several challenges are facing the context detection using smartphone. First, given that the user may perform the same activity in different facilities, such as standing on a lift, standing on an escalator, standing on a floor, the smartphone sensors may not provide much information to differentiate between these facilities. This makes the context detection very challenging compared to previous works that used sensor data to detect different health monitoring activities, such as walking, standing, running, jumping, etc. [7]. Second, to minimize the computational complexity of the context detection, we need to restrict ourselves to only simpler statistical features and classification models. Finally, given that a particular type of facilities is correctly detected, multiple facilities of the same type may exist in close proximity in the same floor (e.g., several lifts next to each other), a situation that would make it more difficult to identify the correct one among them.

III. Approach and Methodology

To address the first challenge of this research; namely the similarities among the signals, features with high discriminative abilities are needed to extract the relevant hidden information from the sensor data. Besides, the noisy smartphone accelerometer signals may need to be de-noised before extracting features to get better results.

A large number of possible features which could be extracted from the accelerometer signals are mentioned in the literature. These features include time-domain, frequency-domain, correlation-based, etc. However, coping with the minimization of the computational complexity, as a second challenge in this research, will require the use of alternative feature selection algorithms (like particle swarm optimization, principle component analysis, auto regressive models, etc.) to remove irrelevant and redundant features. Also, the most suitable classifier (in terms of having simpler settings and providing high accuracy) needs to be identified among the many existing classifiers.

Finally, more detailed architectures of the facilities, like their dimensions and ramp slopes might be used to identify

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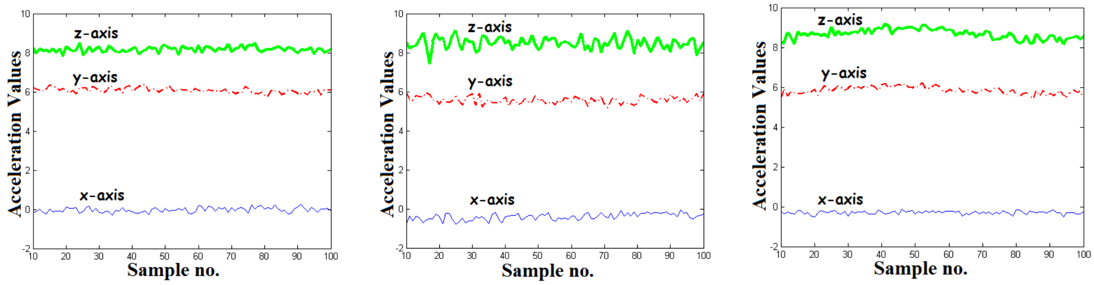

(a) Standing on the floor (S) (b) Standing on an Escalator (E) (c) Standing in a Lift (L)

Fig. 1. Accelerometer samples of standing on three different facilities (a) Standing on the floor, (b) Standing on an Escalator and (c) Standing in a Lift

the specific facility used among the multiple facilities of the same type in the same floor. I also intend to consider some self-learning techniques, so the peculiarities of each building can be learned automatically. This will create a flexible autonomic framework that will adapt itself based on each building characteristics.

IV. Expected and Achieved Contributions

Two distinct contributions have been achieved in the preliminary studies of this research. First, using the Sydney Airport map, I have shown that existence of multiple facilities of the same type on the same floor may lead to large inaccuracies in correctly identifying the facility in question [8]. Second, I have collected Android accelerometer data from five volunteers holding the smartphone on the right or left palm of the hand in front of the body while standing on the floors, lifts, and escalators in nine different buildings. This smartphone holding position is chosen since it is the most natural holding position when using the phone for applications that may need positioning information. Figure 1 shows a snapshot of one sample from each category. Although there were some minute differences in signals, which may be caused by different vibration patterns exhibited by lifts and escalators standards of riding quality [9], it can be seen that the signals are very similar to each other. After applying many different feature selection and classification models, I was able to classify these three categories with 94% accuracy using a multi-layer perceptron classifier and only five simple time-domain features: Mean of x-axis, Standard Deviation (SD) of z-axis, SD of x-axis, Average Absolute Deviation of z-axis, and the Kurtosis of y-axis.

The preliminary results indicate that accurate and energy-efficient context detection in smartphones may be possible to achieve. However, much work remains to be done in terms of extending the set of facilities to many other types, such as ramps, moving ramps, travelators, and stairs. Besides, detecting more detailed structural features of those facilities, like the slope of the ramp, will pave the way towards more accurate identification of a specific facility. This will certainly require additional mathematical modeling to estimate the slopes of ramps relying only on the accelerometer sensor or using other low-power sensors like gyroscope. The above challenges constitute the focus of the remaining terms of my PhD research.

V. Conclusions

This paper describes the work in progress of converting context to indoor position using built-in smartphone sensors. This research will ultimately contribute towards a self-sufficient indoor positioning system that works without any interaction with a pre-deployed communication infrastructure. Such self-sufficiency is desired from several points of view. It makes the system more scalable, privacy-preserving (no communication means less chances of privacy leakage), and energy-efficient (radio interfaces consume orders of magnitude more energy than MEMS sensors, such as accelerometers).

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