Investigations on mobility models and their impact on indoor positioning

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ABSTRACT

This paper proposes a new mobility model more suitable for an user that moves in a 3D indoor space. A fingerprinting method is used to compare the performance of the new model with others found in literature. The software implementation is made available at [8].

Categories and Subject Descriptors

H.4 [**Information Systems Applications**]: Miscellaneous

General Terms

Theory, Algorithms

Keywords

Indoor positioning, mobility models, fingerprinting

1. INTRODUCTION

Knowing the location of an user in an indoor scenario can enable and lead to the creation of novel services and applications. Nevertheless, knowing the user location with an accurate position would certainly contribute to the possibility of understanding the users mobility patterns. Knowing the expected behaviour of an user could help with localization algorithms, by increasing the probability of an user being in a certain area. However, collecting such kind of information raises several ethical and privacy concerns and such a thing should be addressed and clarified by the governing entities.

Despite that, mobility models can be classified as synthetic or traces-based and with or without memory [6]. The synthetic models are based on empirical parameter assumptions. Traces-based models are models with numerous samples of data from real life, thus traces provide reliable information about human trajectory patterns. Due to the privacy and ethical concerns, this paper focus solely on synthetic models. The models analysed in this study are as follows:

1. **Random Walk (RWK)**, the user moves from the current position to the next one with random velocity, direction and duration. This study assumes simulations of this model with fixed time and fixed distance [1, 2];
2. **Random Waypoint (RWP)**, the user stays stationary for a random period in time, before it moves to the following position with random velocity and direction [1, 4, 3];
3. **Random Direction (RD)**, the user is constrained inside a boundary and once it is reached, the user changes direction and speed [1];
4. **Boundless Simulation Area (BSA)**, the user moves in an bounded space, but once the limits are reached, the user appears on the other end of the boundary [1];
5. **Hybrid Model (HM) (the proposed method)**, the user moves inside a bounded area and mostly roams inside a small part of it. Parameters such as the state of the stationary and the minimum distance to the nearest boundary are added to the model. The height dimension distributes uniformly.

The HM is proposed as a better alternative to model user behaviour in indoor buildings, where they spend the majority of time in small constrained areas. This study compares the HM with the RD model, which was considered by the authors to be the most suitable for modeling movement in a 3D indoor environment. This comparison is done by comparing the performance of a Wi-Fi based fingerprinting method [7, 5] when each of these methods is used.

1.1 3D Hybrid Model

Physical spaces where user's spend their majority of time are usually small areas, such as individual and shared offices. Therefore, user's are mostly constrained to corridors and small offices and by reviewing the several methods above, the authors were unable to find a suitable candidate to represent this. For example, the most suitable candidate, the RD model, assumes the user moves all over the area with equal probability. The authors believe this is most of the

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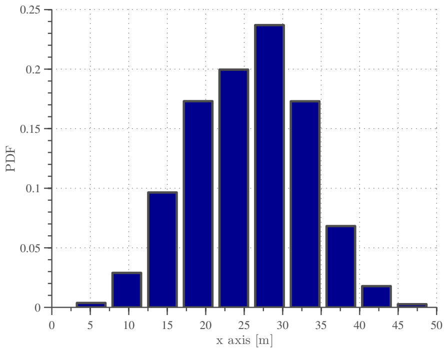

Figure 1: PDF of positions on X axis.

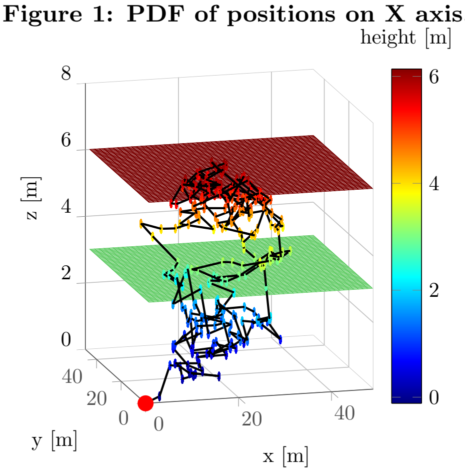

Figure 2: Simulation of one trace using 3-D Hybrid Model.

times not the case in indoor scenarios and propose the HM as an alternative. The main goal of the HM is to model user's movement over small areas, an equivalent to office areas. Figure Fig. 1 illustrates this feature of the model, by presenting a probability density function (PDF) of the positions of the user in the X axis.

In the HM, the user moves from a random point inside the simulation area, with random speed, direction, and duration. When the movement duration expires, the user enters into a stationary state for the duration of the defined pause duration. Through the whole simulation process, a parameter, called the minimum distance to the nearest boundary, checks if the user reaches this minimum value, and if the user reaches the value the direction changes but the speed remains the same. The speed only changes when the moving duration expires.

Figure Fig. 2 shows a simulation of one trace obeying 3-D Hybrid Model, the green and brown facets represent the floors. The simulation is under a building with 50 meters width, 50 meters length and 9 meters height (3 floors and 3 meters each floor).

2. RESULTS AND CONCLUSION

Fig. 3 contains the mean values of the root mean square errors (RMSE) for different values of the Wi-Fi signal shadowing. The upper cluster of lines shows the performance when using the RD model, while the lower curve cluster

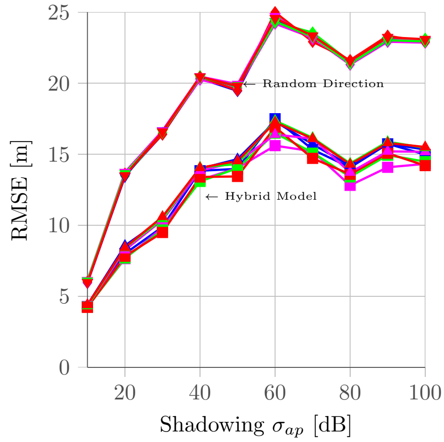

Figure 3: Fingerprint RMSE results.

refers to the HM. These results were obtained by considering 20 user segments inside the building model, where the starting point and velocities were randomised. By comparison of the two clusters, the HM model leads to a better RMSE positioning accuracy than the RD model. The reason behind this is that the user in the Hybrid Model mostly moves within a small certain area while the user in the Random Direction Mobility Model moves with the trend to quickly cover the whole simulation area.

As conclusion, the choice of a mobility model influences the positioning performance of the user, but, on the other hand, the velocity ranges and starting points of each mobility model have no influence on it.

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