Multi-device Map-aided Fingerprint-based Indoor Positioning using Ray Tracing

Akis Kokkinis*, Marios Raspopoulos†, Loizos Kanaris*, Antonio Liotta* and Stavros Stavrou‡
*Department of Electrical Engineering, Eindhoven University of Technology, Eindhoven, The Netherlands
e-mail: {a.kokkinis,l.kanaris, a.liotta}@tue.nl
†Sigint Solutions Ltd, Nicosia, Cyprus
e-mail:m.raspopoulos@sigintsolutions.com
‡Faculty of Pure and Applied Sciences, Open University of Cyprus
e-mail:stavros.stavrou@ouc.ac.cy

***Abstract*—The objective of this work is to investigate potential accuracy improvements in the fingerprint–based indoor positioning processes, by imposing map-constraints into the positioning algorithms in the form of a–priori knowledge. In our approach, we propose the introduction of a Route Probability Factor (RPF), which reflects the possibility of a user, to be located on one position instead of all others. The RPF does not only affect the probabilities of the points along the pre-defined *frequent routes*, but also influences all the neighbouring points that lie at the proximity of each frequent route. The outcome of the evaluation process, indicates the validity of the RPF approach, demonstrated by the significant reduction of the positioning error.**

I. Introduction

The accuracy achieved by any Real Time Localisation System (RTLS) is affected by the volume and quality of information that is available during the position estimation procedure. The more useful information can be provided, the higher the probability for producing a more accurate estimate.

Depending on the capabilities of the terminal or the overall RTLS, in retrieving, storing and processing location-specific information, advanced positioning algorithms can be developed in order to provide improved positioning services.

The location-specific information may include radio parameters, such as Received Signal Strength (RSS), Angle of Arrival (AOA), Time of Arrival (TOA) and Impulse Responses (IR) or non-radio parameters, such as inertial measurements, prior map/layout knowledge etc.

In many cases, the sole utilization of the radio parameters, during the position estimation, imposes limits that are hard to overcome. By introducing and fusing additional non-radio parameters to the localisation process, it is expected that one could potentially improve the positioning accuracy.

In this direction, the information retrieved from the inertial sensors can be used in conjunction with environment maps. The idea is to utilise the available environment description of building databases and blueprints/architectural drawings of indoor areas, for the purpose of aiding the localisation process. By using map–related information, the possible movement and location of the user is expected to be constrained and different probabilities can be assigned to different areas of the environment where the User/Mobile Station (MS) might reside. As a result, long–term error stability can be achieved when the map is sufficiently accurate and effectively constrains the motion.

Proper use of any available information into the positioning process, is definitely a challenge and can contribute noticeably to the minimization of the positioning error. In fact, the information retrieved from environment maps, can offer this extra knowledge. This paper describes how such environment knowledge can be extracted and exploited into a fingerprint-based positioning process. The proposed approach utilizes an a-priori knowledge of the likelihood of a user being at a specific location. This a-priori knowledge can be made available as a means of probabilistic map constraints.

The rest of the paper is organized as follows: In Section II the related background work is briefly summarized in terms of indoor positioning algorithms and map information extraction methods. In Section III, the methodology is analysed, describing the generation of the RSS fingerprint-based database and the implementation of the RPF in the positioning algorithms. The performance evaluation of the proposed approach is included in Section IV and the final conclusions are given in Section V.

II. Background

A. Fingerprint–based Positioning Algorithms

Fingerprint–based positioning using RSS can be classified into two main categories (1) Deterministic and (2) Probabilistic approaches. The *deterministic* positioning methods estimate location as a convex combination of the reference locations [1]. Usually, the K reference locations with the shortest distance between $\overline{r}_i$ and s in the n-dimensional RSS space are used and the estimated location $\widehat{\ell}$ is given by

$$\widehat{\ell} = \sum_{i=1}^{K} \left(\frac{w_i}{\sum_{j=1}^{K} w_j} \ell'_i \right). \tag{1}$$

The set $\{\ell'_1, \dots, \ell'_l\}$ denotes the ordering of reference locations with respect to increasing distance between the respective fingerprint $\overline{r}_i$ and the observed measurement during positioning s, i.e. $\|\overline{r}_i - s\|$. The distance can be calculated using standard norms, such as the Manhattan (1-norm) [2], the Euclidean (2-norm) [3], the general p-norm with modifications

[4] or the Mahalanobis norm that employs the sample means and variances of the reference fingerprint [5].

One possible option for the non–negative weights w_i in Eq. (1) is the inverse of $\|\overline{r}_i - s\|$ and in this case the positioning method is known as Weighted K-Nearest Neighbour (WKNN) [2]. The K-Nearest Neighbour (KNN) method assumes equal weights for the candidate reference locations, while setting $K = 1$ leads to the simple Nearest Neighbour (NN) method [3], [6], [7]. In general the KNN and the WKNN methods have been reported to provide higher level of accuracy compared to the NN method, particularly with parameter values $K = 3$ and $K = 4$ [2], [3]. However, if the density of the RSS radio map is high, NN method performs equally well compared to more complicated methods [1]. Several variants of the KNN method have been discussed in the literature, including the Database Correlation Method (DCM) which introduces an additional term in the error function to penalize missing RSS values in the fingerprints [8], [9].

In probabilistic methods, location ℓ can be estimated by calculating and maximising the conditional posterior probabilities $p(\ell_i|s),\ i = 1, \ldots, l$ given an observed fingerprint s and a fingerprint database (l is the number of fingerprints in the database). These methods have been extensively used in the Maximum A Posteriori (MAP) approach [10]–[12] and the Minimum Mean Square Error (MMSE) approach [13] to estimate the expected value of ℓ.

The posterior probability $p(\ell_i|s)$ is obtained by applying Bayes' rule:

$$p(\ell_i|s) = \frac{p(s|\ell_i)p(\ell_i)}{\sum_{i=1}^{l} p(s|\ell_i)p(\ell_i)} \tag{2}$$

where $p(s|\ell_i)$ is a conditional probability calculated through statistics at the survey stage and $p(\ell_i)$ is the a–priori probability, a weighting factor based on the probability distribution of the target over the reference position candidates (database fingerprints). If we assume that we do not have any prior knowledge then this *prior* can be assumed to be unity providing equal a-priori probability to all the fingerprint candidates in the database.

B. Map Information Extraction

Most of the work carried out in the direction of utilization of map information for indoor positioning purposes is related to the robotics area and the enhancement of the respective mobility models. In this scope, Liao et al. in [14] and Evennou et al. in [15] proposed the use of particle filters to make use of the inherent structure of indoor environments. In order to simplify the calculation complexity of the unconstrained particle filters, they suggested the estimation of the locations of people on the Voronoi graph of the environment. By restricting particles to a graph, they achieved a more efficient algorithm and at the same time simulated a basic human motion in the indoor environment.

In our work, instead of adopting the Voronoi graphs and particle filters, we define the frequent –or most probable– routes, based on observations. The recording of the *frequent routes* based on simple observations, can be replaced by the adoption of supervised or unsupervised learning techniques. As the names suggest, in the case of supervised learning, the researcher must involve some supervision by an external source in order to improve the algorithm, while in the case of unsupervised learning, the algorithm will self-evolve, and gradually achieve a very representative snapshot of the most frequently used routes.

III. Methodology and Test Environment

A. Route Probability Factor

This section introduces a new map–aided method, using the Route Probability Factor (RPF). The RPF reflects the likelihood of a user to be located at a specific position instead of all other positions. This means that along a frequent route, the RPF will be increased, while in remote areas it will be decreased. The RPF does not only affect the probabilities along the specified route, but also the positions at its proximity. For this purpose, a normally distributed approach was implemented, at a radius ρ across the route, creating *route tubes*. For every location on each frequent route, the algorithm assigns a decaying probability to all those fingerprints in the fingerprint database, which reside within a circle with radius ρ around this location. This decaying probability is given by the following formula:

$$RPF_{\ell_i} = RPF_\ell \left(\frac{1}{\sigma_{route}\sqrt{2\pi}}\right) e^{-\frac{1}{2}\left(\frac{\|\overline{\ell}-\overline{\ell_i}\|}{\sigma_{route}}\right)^2} \tag{3}$$

where RPF_ℓ is the route probability factor at the location ℓ which lies exactly on the route and $\|\overline{\ell} - \overline{\ell_i}\|$ is the distance between location ℓ and any other location ℓ_i within the range of ρ. Finally, σ_{route} is given with respect to the selected ρ: for a 99% confidence level $\sigma_{route} = \rho/3$, since statistically 3σ provides this confidence level.

This iterative process results in a normalised probability matrix for every location along each frequent route tube. All these matrices are then summed up to result into an accumulated probability matrix which describes the likelihood of a user being in any location. This matrix has a one to one relation to the fingerprints database and is then used in conjunction with the positioning algorithm to improve the localisation accuracy.

In this paper, we employ the WKNN deterministic algorithm to perform fingerprint–based positioning, extended with the probabilistic part of the RPF. Our approach takes into consideration a-priori knowledge of the frequent user routes, as well as the weighted Euclidean distance of the observed location. The former allows to incorporate map constraints into the position estimation, by assigning the different probabilities of likelihood of each location in the environment, in the form of a matrix as described above. In this context each fingerprint in the database is given a prior probability $P_i = RPF_i$, which multiplies the Euclidean Distance as $P_i\|\overline{r}_i - s\|$. This gives less likelihood to fingerprints in constrained areas to appear higher in the ordered vector $\{\ell'_1, \ldots, \ell'_l\}$ which is then used in Eq. (1). These prior probabilities can also be combined with the probabilities explicitly set to a minimum, in areas that are not accessible by the user (e.g. locked rooms, dangerous and forbidden areas etc.).

The normalised distribution of RPF in our test environment is visually presented in Figure 1.

Fig. 1. Prior Probabilities

B. Generation of Fingerprint Database and Test Results

In the literature, two map generation methods are used; actual measurements and utilization of simulation tools. The actual measurements method is extremely time consuming, costly and more difficult to maintain, since in case of changes in the environment setup, new measurements are required. Examples of this method can be found in [3] and [13]. The simulated map generation method, is faster and easier to maintain. During this procedure, the indoor environment is created in a simulator and different probabilistic or deterministic propagation models are used to generate the RSS fingerprints. Examples include the adoption of *2D Ray Tracing (RT)* models in [16] and [17], and full *3D Ray Tracing Models* in [18], [19] and [20]. The 3D RT algorithm typically utilises the 3D electromagnetic formulation of reflection, refraction and diffraction based on the Uniform Theory of Diffraction (UTD). In this work, the generation of the fingerprint database of the testing environment was performed in *TruNET*, a 3D Ray Tracing (RT) Simulator. The 3D model of the building shown in Figure 2, including the furniture set up, was imported in the simulator in a digital form (.OBJ).

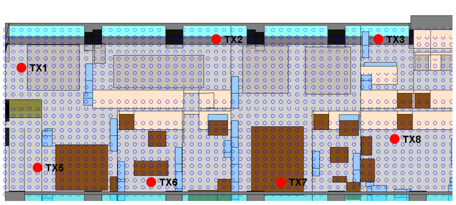

Fig. 2. 3D Model of the Indoor Environment with Fingerprint Locations

For the creation of the fingerprint database, 1584 isotropic receivers (Rx) were defined in the floor plan. They were equally-spaced with a step of 0.5m, at a height of 1.5m. The underlying wireless network included 8 Wi-Fi (2.4GHz) Access Points (APs) with an omni-directional antenna, installed at a height of 2.2m. The locations of the APs are depicted in Figure 2. Typical values of the electrical parameters obtained from literature [21], were used to characterise the morphology of the walls and other geometric features of the building.

IV. Performance Evaluation

In order to assess the performance of the proposed approach, two separate simulations have been carried out for positioning estimation of a user moving along the test route shown in Figure 3. The purpose of the test route is to evaluate the positioning accuracy before and after imposing the map constrains. It consists of 520 equally spaced (0.25m) locations at a height of 1.5m. When a positioning platform is deployed under real operating conditions, several factors affect the positioning accuracy. The user might not be using the same device as the one used to collect the database fingerprints (device diversity issues), or even the geometric environment might have changed (displacement of furniture, new partitions etc.). Moreover, the movement of people create a more dynamic environment. To incorporate this profile variability onto the RSS values estimated along the test route, we have introduced an uncertainty factor (normally distributed with standard deviation $\sigma = \pm 3dB$) on the RSS values of the Mobile Station (MS) [22], [19]. The WKNN positioning method was tested iteratively for various values of K in the case where no map constraints are used and it was found that the optimum one that minimises the mean error was $K = 5$. This value was then also used for the case where map constrains are incorporated into the positioning process.

The results from the two aforementioned positioning estimations (with and without map constraints) are summarized in Table I, while the respective graphs showing the CDF of the obtained localisation accuracy are depicted in Figure 4.

TABLE I
Positioning Accuracy with and w/o map Constraints

Positioning Estimation	**Parameter**	**Error m**
Without Map Constraints	Mean	2.03
	CEP 50%	1.79
	CEP 67%	2.35
	CEP 95%	4.53
	Max	17.09
With Map Constraints	Mean	1.46
	CEP 50%	1.09
	CEP 67%	1.62
	CEP 95%	3.77
	Max	5.95

From the above findings we note that, when the map constraints are used, a significant improvement of 28% occurs on the mean positioning accuracy (from 2.03m to 1.46m). We also observe a radical reduction of 65% on the maximum error (5.95m instead of 17.09m). The improvement is sustained in the whole range of Circular Error Probable (CEP), as it can be seen in Figure 4. The position estimation for all

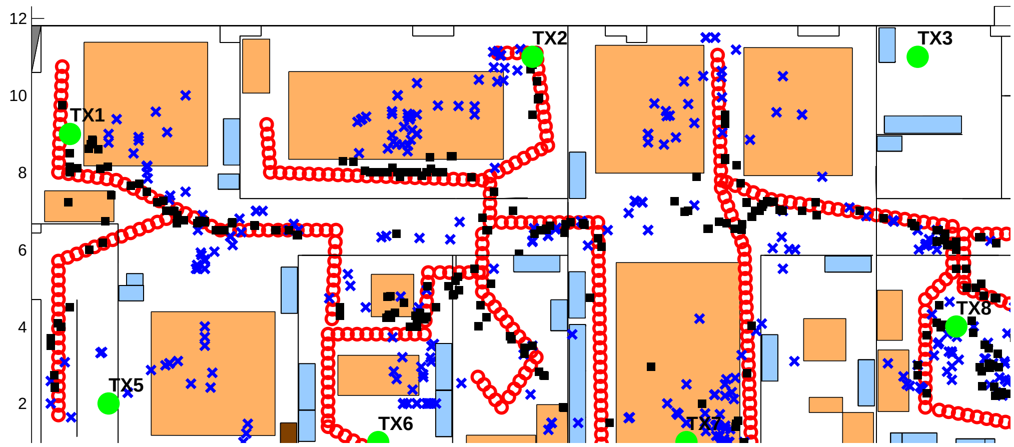

Fig. 3. Estimates along the test route

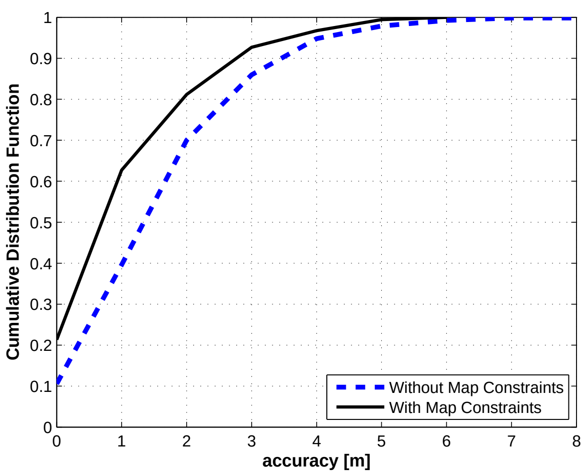

Fig. 4. CDF of Localisation Accuracy

points along the test route in the map-aided scenario, is presented in Figure 3 with square symbols. It can be observed that, as a result of the implementation of the RPF in the positioning procedure, the estimated locations were shifted from the areas captured by furniture (asterisk symbols) towards more reasonable positions, near the test route.

Given the above improvements in the positioning accuracy, it is interesting to investigate what would be the effect of the radius ρ around each of the locations of the frequent route used for the generation of the a-priori probabilistic knowledge by the RPF method. In this context, for the optimization of the RPF, different values of route radius ρ were investigated. As it is illustrated in Figure 5, the value of ρ affects the localisation accuracy and should be $\rho \geq d_{Rx}$, where d_{Rx} is the fingerprint radiomap resolution (step between the receivers).

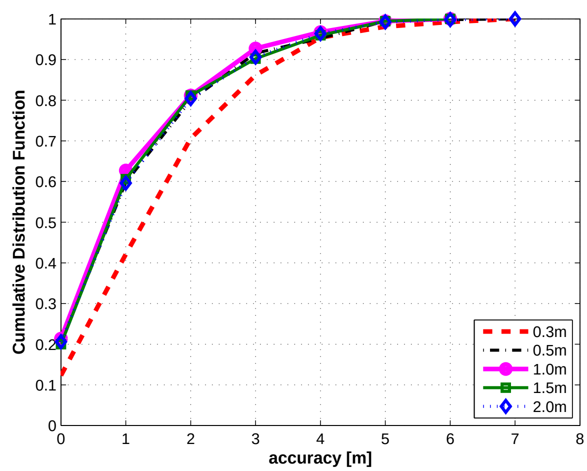

Fig. 5. Effect of RPF radius ρ on accuracy

V. Conclusion

The introduction of weight coefficients in the form of a–priori knowledge that reflect the map constraints can result in significant improvements of position estimation in indoor environments. In this direction we proposed the implementation of RPF as a matrix, which can be either populated manually, by observing the human movement behaviour, or through the implementation of supervised or unsupervised learning methods. The value of the radius ρ which defines the range of effect of the frequent routes, depends on the fingerprint radiomap resolution and should be optimized accordingly to minimise positioning error.

Acknowledgement

This work has been performed in the framework of the ICT-248894 WHERE2 project funded by the European Union.

References

[1] V. Honkavirta, T. Perala, S. Ali-Loytty, and R. Piche. A comparative survey of WLAN location fingerprinting methods. In *6th Workshop on Positioning, Navigation and Communication (WPNC)*, pages 243–251, 2009.

[2] B Li, J Salter, AG Dempster, and C Rizos. Indoor positioning techniques based on wireless LAN. In *1st IEEE International Conference on Wireless Broadband and Ultra Wideband Communications*, pages 13–16, 2006.

[3] R. Bahl and Venkata N. Padmanabhan. Radar: An in building rf-based user location and tracking system. In *INFOCOM*, volume 2, pages 775–784, 2000.

[4] et. al. P. Prasithsangaree. On indoor position location with wireless lans. In *Personal, indoor & Mobile Radio Communications, 2002, The 13th IEEE International Symposium*, volume 2, pages 720–724, 2002.

[5] Wilson Yeung, JunYang Zhou, and Joseph Ng. Enhanced fingerprint-based location estimation system in wireless LAN environment. *Emerging Directions in Embedded and Ubiquitous Computing*, pages 273–284, 2007.

[6] P Bahl, VN Padmanabhan, and A Balachandran. Enhancements to the RADAR user location and tracking system. *Microsoft Research, Tech. Rep. MSR-TR-00-12*, February 2000.

[7] S. Saha, K. Chaudhuri, D. Sanghi, and P. Bhagwat. Location determination of a mobile device using IEEE 802.11b access point signals. In *IEEE Wireless Communications and Networking (WCNC)*, volume 3, pages 1987–1992, 2003.

[8] H. Laitinen, J. Lahteenmaki, and T. Nordstrom. Database correlation method for GSM location. In *53rd IEEE Vehicular Technology Conference (VTC2001-Spring)*, volume 4, pages 2504–2508, 2001.

[9] P. Kemppi and S. Nousiainen. Database correlation method for multi-system positioning. In *63rd IEEE Vehicular Technology Conference (VTC2006-Spring)*, volume 2, pages 866–870, 2006.

[10] M.A. Youssef, A. Agrawala, and A. Udaya Shankar. WLAN location determination via clustering and probability distributions. In *IEEE International Conference on Pervasive Computing and Communications (PerCom)*, pages 143–150, 2003.

[11] Moustafa Amin Abdel Azim Yousief Abdel Rehim. *Horus: a WLAN-based Indoor Location Determination System*. PhD thesis, University of Maryland, Department of Computer Science, 2004.

[12] Moustafa Youssef and Ashok Agrawala. The Horus WLAN location determination system. In *3rd ACM International Conference on Mobile systems, applications, and services*, pages 205–218, 2005.

[13] Teemu Roos, Petri Myllymaki, Henry Tirri, Pauli Misikangas, and Juha Sievanen. A probabilistic approach to WLAN user location estimation. *International Journal of Wireless Information Networks*, 9(3):155–164, July 2002.

[14] Lin Liao, D. Fox, Jeffrey Hightower, H. Kautz, and D. Schulz. Voronoi tracking: location estimation using sparse and noisy sensor data. In *Intelligent Robots and Systems, 2003. (IROS 2003). Proceedings. 2003 IEEE/RSJ International Conference on*, volume 1, pages 723–728 vol.1, 2003.

[15] F. Evennou, F. Marx, and E. Novakov. Map-aided indoor mobile positioning system using particle filter. In *Proc. IEEE Wireless Communications and Networking Conf*, volume 4, pages 2490–2494, 2005.

[16] Yiming Ji, Saad Biaz, Santosh Pandey, and Prathima Agrawal. ARIADNE: a dynamic indoor signal map construction and localization system. In *4th ACM international conference on Mobile systems, applications and services*, pages 151–164, 2006.

[17] A. Hatami and K. Pahlavan. Comparative statistical analysis of indoor positioning using empirical data and indoor radio channel models. In *3rd IEEE Consumer Communications and Networking Conference (CCNC)*, volume 2, pages 1018–1022. IEEE, 2006.

[18] K. El-Kafrawy, M. Youssef, A. El-Keyi, and A. Naguib. Propagation modeling for accurate indoor wlan rss-based localization. In *Proc. IEEE 72nd Vehicular Technology Conf. Fall (VTC 2010-Fall)*, pages 1–5, 2010.

[19] M. Raspopoulos, C. Laoudias, L. Kanaris, A. Kokkinis, C.G. Panayiotou, and S. Stavrou. 3d ray tracing for device-independent fingerprint-based positioning in wlans. In *Positioning Navigation and Communication (WPNC), 2012 9th Workshop on*, pages 109–113, March.

[20] Marios Raspopoulos, Christos Laoudias, Loizos Kanaris, Akis Kokkinis, Christos Panayiotou, and Stavros Stavrou. Cross device fingerprint-based positioning using 3D ray tracing. In *Mobile Computing Symposium (IWCMC2012-Mobile Computing)*, Limassol, Cyprus, August 2012.

[21] S. Stavrou and SR Saunders. Review of constitutive parameters of building materials. In *Antennas and Propagation, 2003.(ICAP 2003). Twelfth International Conference on (Conf. Publ. No. 491)*, volume 1, pages 211–215. IET, 2003.

[22] Jun geun Park, D. Curtis, S. Teller, and J. Ledlie. Implications of device diversity for organic localization. In *INFOCOM, 2011 Proceedings IEEE*, pages 3182–3190, 2011.