Using Propagation Models to Build Fingerprint Maps and Assess Location Estimation Algorithms Performance

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***Abstract*—Performance of Fingerprinting-based Location Estimation Algorithms can be improved by using the user direction information when Fingerprint Maps are generated. Instead of using a single Map, multiple maps can be used, and the Location Estimation Algorithm can choose the best map or combine the information of a subset of best maps. However, collecting data to build the Fingerprint Maps is a very time consuming task, therefore, collecting data to build multiple maps is even more time consuming. Also, any change in the scenario (e.g. new furniture) implies that new data must be collected to update the Fingerprint Map. The time it takes to collect data for N directional maps, instead of only one, increases by a factor of N. A possible solution to cope with this problem is to generate those maps using propagation models. This is the technique proposed in this paper, which uses propagation models, that include information about the user influence on the Received Signal Strength, to generate the Fingerprint Maps. These propagation models can be used both to build the Fingerprint Maps and to generate data sets used to test Location Estimation Algorithms. It is possible to simulate RSS values, and eliminate the need of collecting real data, to test Location Estimation Algorithms, for example during the development phase.**

***Index Terms*—Fingerprinting, Location Estimation Algorithm, Indoor, Propagation Models.**

I. Introduction

FINGERPRINTING, one of the most used location estimation techniques for indoor environments [1], consists on collecting information about some property of wireless networks, and compare it to values previously stored in a set of data called the Fingerprint Map (FM) [2], [3], [4]. Although any property of the wireless signal can be used in Fingerprinting, usually the Received Signal Strength (RSS) value is used. Data to build the FM is collected during a phased called the off-line phase, at which several data samples are collected at each point of the spatial domain that will be used in the map.

With the objective of increasing the performance of Fingerprinting-based Location Estimation Algorithms (LEA), the authors presented in [5] a Fingerprinting-based solution that uses multiple Fingerprint Maps. Instead of collecting only data about the RSS values, it was also collected data about the user direction (azimuth), using the smartphone magnetic sensor. It was then possible to build multiple Fingerprint Maps, based on the user direction, e.g. North, South, East and West. Two approaches were proposed to select the map to be used during the on-line phase: the first consists in selecting the best FM, and do the location estimation based on that map; the other option consists on using the best N maps and then combine the solutions based on the contribution of each map (weighted average).

One of the drawbacks of Location Estimation using Fingerprinting is that collecting data to build the FM can be a very time consuming task, because data must be collected at multiple spatial domain points, and, at each point several samples must be collected. For example in [6], 20 sample per spatial coordinates were collected. If, instead of collecting data for a single FM, data is collected to build multiple Fingerprinting maps, then the time needed to collect data will be much longer.

The above mentioned problem can be solved if instead of collecting *in loco* data, to build the FM, propagation models are used. In this paper it is presented an extension to the methods proposed by the authors in [7], and Multiple Fingerprint Maps are generated by simulating both the expected RSS values and the user direction. The user direction will also have a direct influence on the RSS values.

When improving existing LEA, or when creating new ones, it is often needed to feed the Location Estimation Algorithm with test data sets. These data sets can be real data, collected at real scenarios, with the above mentioned drawbacks, or can be simulated data. This paper will also present a solution for generating test data sets based on propagation model data, the user position, and some randomness associated do wireless signals. Propagation models will be used to simulate RSS values used by the Location Estimation Algorithms.

To test the feasibility of building multiple Fingerprint Maps (with user direction information), and to generate data sets based on RSS values simulation, based on propagation

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models, three of the classic Location Estimation Algorithms are used: Nearest Neighbour; k-Nearest Neighbour; Weighted Nearest Neighbour. Results will also be compared to data obtained using real values that were acquired in the testing scenario.

II. Generating Fingerprint Maps using Propagation Models

With the objective of making the FM generation an easier and faster task, by eliminating the need to collect data *in loco*, it was proposed by the authors in [7] the use of Propagation Models to generate the Fingerprint Maps. Instead of collecting data at every point of the real scenario, a simulation was made using a blueprint of the scenario that includes information about obstacles (furniture, doors, walls, etc) and propagation models. One of the advantages of this technique is that if the scenario changes, it is only needed to update the blueprint information, run the simulation again and generate the new Fingerprint Map.

Because in [7] the user direction was not considered, a single map was generated. Information on the generated FM was equivalent to that of collecting data in all directions (with the user rotating while acquiring data), but without considering the attenuation of the user's body (i.e. the influence of the user's direction).

From the several propagation models that could be used to build the FM, and to simulate the RSS values, because of the results obtained in [8], the modified Motley-Keenan model (Eq. 1) is going to be used:

$$PL(d) = PL(d_0) + 10nlog\left(\frac{d}{d_0}\right) + \sum_{i=1}^{N} k_i L\omega_i \tag{1}$$

The above equation models the total Path Loss, as a function of the distance between the transmitter and the receiver (d), the Path Loss at a reference distance ($PL(d_0)$), the Path Loss exponent (n), which may vary according to the structure of the building [9], the number of walls of type i (k_i) and the attenuation factor for walls of type i ($L\omega_i$).

When there are walls of the same type, but with different thicknesses, the adjusted model of Eq. 2 can be used instead:

$$PL(d) = PL(d_0) + 10nlog\left(\frac{d}{d_0}\right) + \sum_{i=1}^{N} k_i L_{0i} 2^{\log_3\left(\frac{\epsilon_i}{\epsilon_{0i}}\right)} \tag{2}$$

where:

- L_{0i}: is the attenuation of a reference wall with thickness ϵ_0;
- k_i: is the number of type i walls that have thinness ϵ_i.

A. Simulation of the Fingerprint Maps

Even though the above presented model can be used to predict the expected RSS values at each spatial point of the real scenario, and therefore be used to build the Fingerprint Map, it does not take into account the losses because of the user presence. The use of multiple Fingerprint Maps only makes sense if information about the user position is included in the Fingerprint Map.

To Equation 2 it must therefore be added the user attenuation (U_a), and the final model equation (considering the user influence) is as in 3:

$$PL(d) = PL(d_0) + U_a + 10nlog\left(\frac{d}{d_0}\right) + \sum_{i=1}^{N} k_i L_{0i} 2^{\log_3\left(\frac{\epsilon_i}{\epsilon_{0i}}\right)} \tag{3}$$

Relatively to the values for the user attenuation (U_a), in the literature several values can be found. According to [3], [10] a single human body can cause an attenuation in the range of $3.5dB$ to $5.0dB$.

In the simulations presented in this paper it will be considered that the user is always facing the mobile terminal, therefore the user will be an obstacle only for those references that lie behind him/her. For all Access Points that the user is facing, it is used Equation 2 to model the propagation data (there is no user-caused attenuation), otherwise Equation 3 is used.

B. Simulation of On-Line RSS Values

Another objective of this work is the simulation of on-line RSS values, i.e., values that are fed to the Location Estimation Algorithms for testing purposes. To simulate these values propagation models can also be used. Data, to simulate the RSS values, will be generated based on Equations 2 and 3, depending on the user direction relatively to the Access Points. However these equations, cannot be used as they are, to simulate on-line data, because they are deterministic, and wireless signals have a slight randomness.

Since Fingerprint Maps are usually built using many data samples, which are averaged, the randomness of acquired data fades. This means that deterministic models can be used to build the Fingerprint Map.

However, to mimic real data acquired from the wireless transceiver (e.g. during the on-line phase), some randomness must be added to the model. This characteristic is obtained by adding a random variable X_σ, that denotes a Gaussian variable with zero mean and standard deviation σ [11], to Equations 2 and 3.

III. Testing scenario and Conditions

For the tests, whose results are presented in section IV, it was used the scenario represented in the map of Fig. 1. It is located at the University of Trás-os-Montes and Alto Douro in Portugal, and it was used both to collect real data (using a smartphone), and to build the simulated data.

Both for simulated and data acquired in the testing scenario four directions were used (North corresponds to the top of the map): North, South, East and West.

At each of the 25 points of the grid shown in Fig. 1, 20 samples per direction were taken, and the acquired data consisted on the values of RSS and the azimuth.

To have a comparison method, simulated and acquired data were tested using three of the classic Location Estimation Algorithms:

- Nearest Neighbour (NN) – which considers that the spatial coordinates of the nearest neighbour (in the signals domain) are the spatial coordinates of the mobile node;

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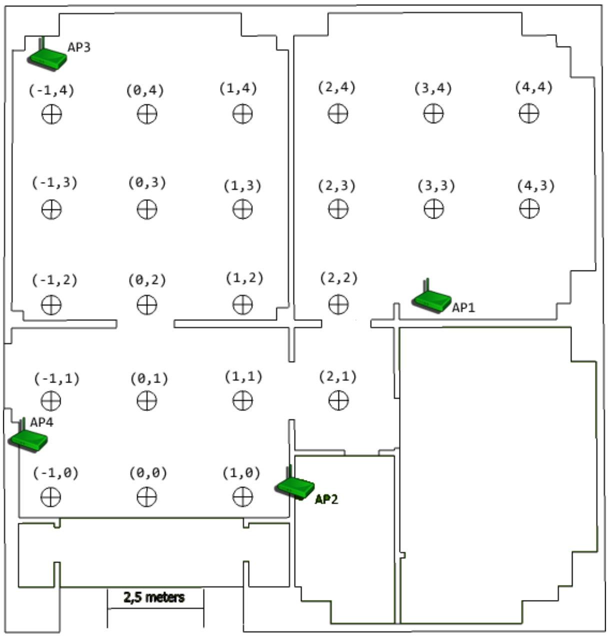

Fig. 1. Map of the testing scenario.

- k-Nearest Neighbour (kNN) – finds the k nearest neighbours, in the signal domain, and assumes that the spatial coordinates of the mobile node are the average of the spatial coordinates of these k neighbours;
- Weighted k-Nearest Neighbour (WkNN) – similar to the above LEA, but it uses a weighted average of the k nearest neighbours coordinates, in the spatial domain, to estimate the node coordinates.

All the above LEA are based on the euclidean distance in the signals domain between the coordinates of the mobile device and the points that belong to the Fingerprint Map.

IV. Numerical Results and Discussion

In this section are shown the results obtained with the set of tests made using the proposed propagation models. For comparison purposes it will also be presented some data obtained with RSS values acquired in the real testing scenario.

For all these tests Fingerprint Maps with fours directions were used, and the algorithm used to select the map was the Direct Maps algorithm, which consists on selecting a single map, the one that matches the user direction [5].

Through the rest of the paper it will appear two different designations for Fingerprint Maps generated using propagation models: Maps Generated using Propagation Models; Maps Generated with Simulated Data.

While the first corresponds to the FM built using the propagation models presented in Equations 2 and 3, the latter corresponds to an FM built as if it was generated using real RSS data, i.e. this FM is obtained using several samples of the data generated by the propagation model including the random variable X_σ. This is an approach to simulate Fingerprint Maps built with real data, where we might not have enough samples to neutralise data randomness.

In all tests that use simulated results, it will be used the above mentioned boundary values, reported in the literature, for the human body absorption of electromagnetic waves, i.e., $3.5dB$ and $5.0dB$. All the values presented in the tables are normalized values.

A. Reference Values

To assess the feasibility of the proposed methods, data obtained using simulations must be compared with real data. Values that will be used as reference for such comparisons are presented in Table I.

These data correspond to the values obtained using a Fingerprint Map based on real data collected in the testing scenario, and the Location Estimation was also made using real data.

These are not optimal values, but they are the "real life" Location Estimation Algorithm results, at the chosen testing scenario, without any simulated data.

TABLE I
Reference Values

	NN	kNN	WkNN
Prec.	1,36	1,27	1,29
St. Dev.	0,97	0,72	0,79
Max. Err.	6,40	5,21	5,76
Min. Err	0,00	0,00	0,10

Table I shows the normalized values for the Precision (Prec.), Standard Deviation (St. Dev.), Maximum Error (Max. Err.) and Minimum Error (Min. Err.) for the three Location Estimation Algorithms.

B. Fingerprint Map Generated using Propagation Models and LEA using Real Data

In this subsection are presented the results obtained for the tests made with the Fingerprint Map built using propagation models, and the location estimated using real data.

In Table II are presented the results that were obtained using $3.5dB$ and $5.0dB$ as the user attenuation values in the propagation model.

TABLE II
FM built using Propagation Model Map and Location Estimated using Real Data

	User Atten. 3.5dB			User Atten. 5.0dB		
	NN	kNN	WkNN	NN	kNN	WkNN
Precision	1,58	1,41	1,46	1,55	1,39	1,44
Std. Dev.	0,99	0,83	0,87	0,99	0,81	0,86
Max. Err.	5,83	5,68	5,82	5,83	5,68	5,66
Min. Err.	0,00	0,00	0,10	0,00	0,00	0,10

If we compare the obtained values with those achieved using the Fingerprint Map using real data (Table I), it is obvious that the results are worse. However, taking into account that these values were obtained using a simulated Fingerprint Map, we cannot say that they are significantly different.

For the worse case (Attenuation of $3.5dB$) we have a difference in the precision values of about 16% for NN, 11% for kNN and 13% for wKNN. Comparing the results when considering an user attenuation of $3.5dB$ and $5.0dB$ the differences can be considered as minimal.

C. Fingerprint Map Generated with Simulated Data and LEA using Real Data

This set of tests consisted in generating the Fingerprint Maps based on simulated RSS values, both for an user attenuation of $3.5dB$ and $5.0dB$.

Results presented in Table III were obtained using a random variable with standard deviation $2dB$ and in Table IV it was used a standard deviation of $4dB$. These values for the standard deviation were chosen empirically.

TABLE III
FM BUILT USING SIMULATED RSS VALUES WITH $\sigma = 2dB$ FOR THE RANDOM VARIABLE AND LOCATION ESTIMATED USING REAL DATA

	User Atten. 3.5dB			User Atten. 5.0dB		
	NN	kNN	WkNN	NN	kNN	WkNN
Precision	1,59	1,41	1,46	1,57	1,40	1,45
Std. Dev.	0,99	0,84	0,87	0,99	0,81	0,86
Max. Err.	5,83	5,68	5,82	5,83	5,68	5,66
Min. Err.	0,00	0,00	0,10	0,00	0,00	0,10

TABLE IV
FM BUILT USING SIMULATED RSS VALUES WITH $\sigma = 4dB$ FOR THE RANDOM VARIABLE AND LOCATION ESTIMATED USING REAL DATA

	User Atten. 3.5dB			User Atten. 5.0dB		
	NN	kNN	WkNN	NN	kNN	WkNN
Precision	1,58	1,40	1,45	1,54	1,41	1,44
Std. Dev.	0,98	0,82	0,86	0,98	0,80	0,85
Max. Err.	5,83	5,68	5,66	5,83	5,47	5,77
Min. Err.	0,00	0,00	0,10	0,00	0,00	0,14

Even though there are slight differences when comparing to the results presented in the previous section (Table II), these difference are not significant.

As a first conclusion, despite the fact that maps were generated with the objective of mimicking the behaviour of an FM generated with real RSS values, i.e. have some randomness, there are other factors that must be taken into account besides adding a simple random variable, at least to generate the Fingerprint Map.

On the other hand, the simulated RSS values can be used by Location Estimation Applications (e.g. in unit or integration tests), to build the Fingerprint Map. In he next section it will be presented the tests made to assess if they can also be used to test the LEA.

D. Maps generated using Propagation Model and LEA using Simulated Data

Tables V, VI, VII and VIII show results of a set of tests that have as objective to verify if it is possible to use Fingerprint Maps obtained using Propagation Models and Simulated RSS values to assess the performance of Location Estimation Algorithms.

In all these tables, the columns $3.5dB$ and $3.5dB$ correspond to the results obtained using an user attenuation of $3.5dB$ and $3.5dB$, for the simulated RSS values.

For the results in Table V and VI, the FM was generated considering a user attenuation of $3.5dB$. In Table V the value of the used standard deviation for the random variable is $\sigma = 2dB$, and for Table VI the values of the standard deviation is $\sigma = 4dB$.

TABLE V
FM BUILT USING PROPAGATION MODELS WITH $3.5dB$ FOR USER ATTENUATION AND $\sigma = 2dB$ FOR THE RANDOM VARIABLE

	User Atten. 3.5dB			User Atten. 5.0dB		
	NN	kNN	WkNN	NN	kNN	WkNN
Precision	0,04	0,68	0,34	0,08	0,70	0,36
Std. Dev.	0,25	0,30	0,19	0,34	0,31	0,23
Max. Err.	2,24	1,41	1,75	2,24	1,41	1,93
Min. Err.	0,00	0,00	0,00	0,00	0,00	0,10

TABLE VI
FM BUILT USING PROPAGATION MODELS WITH $3.5dB$ FOR USER ATTENUATION AND $\sigma = 4dB$ FOR THE RANDOM VARIABLE

	User Atten. 3.5dB			User Atten. 5.0dB		
	NN	kNN	WkNN	NN	kNN	WkNN
Precision	0,28	0,74	0,48	0,33	0,77	0,51
Std. Dev.	0,61	0,33	0,38	0,63	0,34	0,40
Max. Err.	3,00	2,43	2,50	3,61	2,69	3,11
Min. Err.	0,00	0,00	0,00	0,00	0,00	0,00

For the results in Table VII and VIII, the Fingerprint Map was generated considering that the user attenuation is $5.0dB$. In Table VII it was considered $\sigma = 2dB$ for the random variable, and for Table VIII, $\sigma = 4dB$ was used.

TABLE VII
FM BUILT USING PROPAGATION MODELS WITH $5.0dB$ FOR USER ATTENUATION AND $\sigma = 2dB$ FOR THE RANDOM VARIABLE

	User Atten. 3.5dB			User Atten. 5.0dB		
	NN	kNN	WkNN	NN	kNN	WkNN
Precision	0,07	0,69	0,36	0,03	0,69	0,34
Std. Dev.	0,32	0,32	0,22	0,23	0,31	0,19
Max. Err.	2,24	1,49	1,81	2,24	1,41	1,75
Min. Err.	0,00	0,00	0,00	0,00	0,00	0,00

TABLE VIII
FM BUILT USING PROPAGATION MODELS WITH $5.0dB$ FOR USER ATTENUATION AND $\sigma = 4dB$ FOR THE RANDOM VARIABLE

	User Atten. 3.5dB			User Atten. 5.0dB		
	NN	kNN	WkNN	NN	kNN	WkNN
Precision	0,33	0,74	0,50	0,30	0,76	0,50
Std. Dev.	0,64	0,35	0,40	0,62	0,35	0,40
Max. Err.	3,00	2,69	2,50	3,61	2,85	2,80
Min. Err.	0,00	0,00	0,00	0,00	0,00	0,00

Making a first comparison between all these data, it can be concluded that there is a slight overall difference between the values obtained when considering a user attenuation of $3.5dB$ and $5.0dB$, both for the FM and for the simulated

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RSS. The higher the value of the user attenuation that is used in the simulations, the more the results approach those values obtained with real data.

Another conclusion is that higher values for the random variable standard deviation also produce better results (more similar to those with real data). This is particularly noticeable for the Nearest Neighbour algorithm.

To verify if the systems is behaving as if it was using real data, the first parameter to be checked are the values for the precision (localisation error) of Nearest Neighbour. One of the characteristics of NN is that the output value is always a point of the grid. This means that the output of NNb either has zero error or an error equal to the distance of two points of he grid.

If the precision values are too close to zero this means that either we are using a spatial grid too sparse, or the RSS values are very similar to those used to build the Fingerprint Map. In the first case, the points of the grid are so distant that the probability of error is to low, which is not the case of our testing scenario (because of the results presented in Table I). The second case means that the simulated RSS values are too similar to those without the random variable added.

Analysing Table V and Table VII we can see that, for these tests, the precision values are too low, this means that the simulated RSS values cannot be used to test the LEA.

Values for kNN and WkNN give little information about the simulation feasibility because in kNN the error is zero only when the k points are collinear and in WkNN we do not have error equal to zero for $k > 1$.

On the other hand, despite the fact that values presented on Tables VI and VIII are different of those shown in the reference table, they have a behaviour similar to what is expected of real RSS values.

With a higher value of randomness in the model, it is possible to simulate RSS values to test Location Estimation Algorithms.

V. Conclusion

Comparing the results obtained in the testing scenario, it can be concluded that it is possible to replace the off-line phase of Fingerprinting by a simulation using Propagation Models, provided that some minimal information about the scenario are known, such as the blueprint, location of furniture, thickness and type of walls and location of the Access Points. This last is very important when using multiple Fingerprint Maps because the model considers two situations: the user is an obstacle between the Acess Point and the mobile phone; the user is not in the path between these devices.

Obviously that this is not an universal solution suitable for all real life situations. For example if it is not possible to know where the Access Points are, or, it is impossible to do a mapping between Access Point and MAC address, this solution cannot be used. Instead the traditional approach to Fingerprint Map generation must be used. On the other hand, if the minimal requirements are known, at any time when small changes occur, it is possible to easily generate a new FM.

Comparing the techniques used to generate the Fingerprint Map, the use of propagation models without the random variable is simpler and has similar results to those obtained

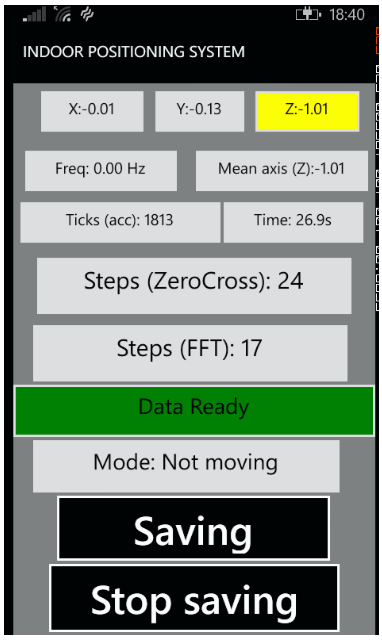

Fig. 2. Prototype of Mobile Application to detect user steps using accelerometer data.

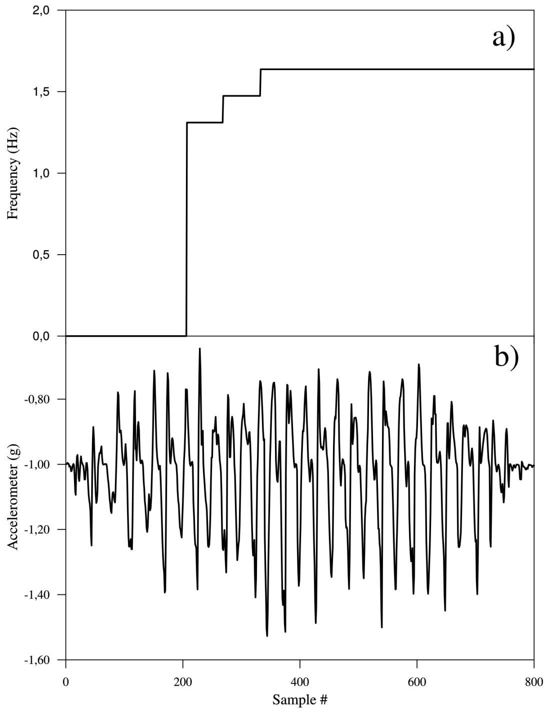

Fig. 3. Fundamental Frequency information (a) obtained from the accelerometer data (b).

with the simulated RSS values. In fact this was already expected because of the average properties.

As a tool to generate simulated RSS values to test Location Estimation Algorithms, propagation models are feasible. Analysing the presented tests, for the higher values of the user attenuation and the standard deviation of the random variable, we can conclude that even though some more tunning is needed in the model values, the results are promising.

Combining the information related to the above two paragraphs we can conclude that the generated RSS values mimic the behavior of real data because when used with an FM it is

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possible to test the LEA, and these values can also be used to build a valid FM.

Regarding to the value of the random variable standard deviation, it is not the same for all spatial points, nor for all values of RSS or even between the scenarios that the authors have been using to test the Algorithms. As future work it would be interesting to model the uncertainty of this random variable, to achieve an even more robust model that can mimic in perfection what we are expecting in the real scenario.

The results presented in this paper using real data are valid for the smartphone used in the tests, however in a "real life" scenario it is possible to adapt the Location Estimation Algorithm to the smartphone and the Fingerprint Map, using LEA calibration based on Direct Search Methods as presented in [6].

As future work, the proposed methods will be integrated with complementary techniques that will allow to minimize the localisation errors in tracking applications. One of such techniques is the use of other sensors included in the smartphones (besides the compass and the wireless transceiver), such as the accelerometer, to predict to where the user is heading.

For example, the compass and the wireless transceiver information can be used together to obtain a location estimation point (or subset of points), and the information provided by the compass and the accelerometer can be used to estimated to where the user as moved relatively to a previous well known position. Making the fusion of these two pieces of information the location method can become more robust.

A prototype of an application, that could be integrated with the localisation techniques here presented, is depicted in Fig. 2. This application estimates the user activity (e.g. walking) and number of steps, by extracting the fundamental frequency information of the accelerometer data, using the Fast Fourier Transform. Plots of Fig. 3 represent the output of the frequency domain analysis (a) and data collected from the accelerometer (b).

References

[1] G. Deak, K. Curran, and J. Condell, "A survey of active and passive indoor localisation systems," *Computer Communications*, vol. 35, no. 16, pp. 1939 – 1954, 2012. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S014036641200196X

[2] A. Taheri, A. Singh, and E. Agu, "Location fingerprinting on infrastructure 802.11 wireless local area networks," in *LCN '04: Proceedings of the 29th Annual IEEE International Conference on Local Computer Networks*. Washington, DC, USA: IEEE Computer Society, 2004, pp. 676–683.

[3] P. Bahl and V. N. Padmanabhan, "Radar: an in-building rf-based user location and tracking system," pp. 775–784, 2000.

[4] C. Serodio, L. Coutinho, H. Pinto, and P. Mestre, "A comparison of multiple algorithms for fingerprinting using IEEE802.11," in *Lecture Notes in Engineering and Computer Science: Proceedings of The World Congress on Engineering 2011, WCE 2011, 6-8 July, 2011, London, U.K.*, 2011, pp. 1710–1715.

[5] P. Mestre, J. Cordeiro, and C. Serodio, "Multi fingerprint map for indoor localisation," in *Lecture Notes in Engineering and Computer Science: Proceedings of The World Congress on Engineering 2015, WCE 2015, 1-3 July, 2015, London, U.K.*, 2015, pp. 599–604.

[6] P. Mestre, L. Reigoto, A. Correia, J. Matias, and C. Serodio, "RSS and LEA adaptation for indoor location using fingerprinting," in *Lecture Notes in Engineering and Computer Science: Proceedings of The World Congress on Engineering 2012, WCE 2012, 4-6 July, 2012, London, U.K.*, 2012, pp. 1334–133.

[7] P. Mestre, C. Serodio, L. Coutinho, L. Reigoto, and J. Matias, "Hybrid technique for fingerprinting using ieee802.11 wireless networks," in *Indoor Positioning and Indoor Navigation (IPIN), 2011 International Conference on*, Sept 2011, pp. 1–7.

[8] C. Serodio, L. Coutinho, L. Reigoto, J. M. A., Correia, and P. Mestre, "A Lightweight Indoor Localization Model based on Motley-Keenan and COST." in *Lecture Notes in Engineering and Computer Science: Proceedings of The World Congress on Engineering 2012, WCE 2012, 4-6 July, 2012, London, U.K.*, 2012, pp. 1323–1328.

[9] F. Evennou and F. Marx, "Improving positioning capabilities for indoor environments with WiFi," in *IST Summit*, 2005.

[10] M. Youssef, M. Mah, and A. Agrawala, "Challenges: Device-free passive localization for wireless environments," in *Proceedings of the 13th Annual ACM International Conference on Mobile Computing and Networking*, ser. MobiCom '07. New York, NY, USA: ACM, 2007, pp. 222–229. [Online]. Available: http://doi.acm.org/10.1145/1287853.1287880

[11] J. Andersen, T. Rappaport, and S. Yoshida, "Propagation Measurements and Models for Wireless Communications Channels," *IEEE Communications Magazine*, vol. 33, no. 1, pp. 42–49, January 1995.