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LOCALIZATION APPROACH BASED ON RAY-TRACING INCLUDING THE EFFECT OF HUMAN SHADOWING

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Abstract—This work presents an accurate and realistic positioning approach for indoor environments based on fingerprinting and ray-tracing techniques. Fading caused by multipath seriously degrades the performance of communication systems operating inside buildings. For this reason, the proposed localization method considers multipath effects due to reflections and diffraction from walls, roof and floor. However, fading in indoor environments can also be caused by the movement of people or the presence of furniture. Because people are the primary absorption agents in indoor channels, their influence on the radio propagation channel must be considered. The proposed localization method takes into account the effects of human body shadowing to provide a realistic estimation of the mobile station position. Numerical calculations in real indoor scenarios show reasonable results.

1. INTRODUCTION

Currently, localization of mobile terminals is one of the most popular topics in mobile radio research and development. In recent years, several localization methods have been presented [1–9]. Most of them consider data from the indoor propagation channel, such as the received signal strength (RSS), the direction of arrival (DOA), the time of arrival (TOA), the time differences of arrival (TDOA), etc. These parameters are obtained by exchanging radio signals with N fixed base stations or access points, which are placed in known positions. However, only a few works [10, 11] take into account realistic considerations existing in indoor environments such as mixed Line of Sight (LoS) and Non Line of Sight (NLoS) conditions, multipath due

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to reflections and/or diffractions and fading due to moving people or the presence of furniture. As an example, Nelson et al. in [10] is a recently published work that describes an expectation maximization algorithm for localization under lognormal shadowing. On the other hand, [11] presents an approach based on maximum likelihood methods for location estimation using received signal strength measurements in wireless fading/shadowing channels. In both works, shadowing is modeled by means of a lognormal function, but they do not define clearly the unwanted effects as “body shadowing”. The only treatment of body shadowing effects is presented in articles on the characterization of indoor propagation channels.

Research on the influence of the human body on radio channels has been in progress in recent years. For example, a statistical model for human body shadowing in offices and factories that can be included in an existing propagation prediction method is proposed in [12]. Another deterministic propagation prediction model is introduced in [13] to investigate the human body-scattering effects in the indoor channel using the Uniform Theory of Diffraction (UTD). In the model, the human body is approximated with a perfect conducting circular cylinder and then combined with the ray tracing technique to deal with particular indoor propagation scenarios. A very similar approach is proposed in [14], in which the human body is approximated by conducting sphere and cylinders, and the ray tracing technique is used to find the surface diffracted ray path while the UTD surface diffraction coefficients are used for calculating the RSS. On the other hand, there are also some works that analyze the effect of the human body interaction with a close proximity Ultra Wide Band (UWB) antenna, as in [15]. UWB propagation was investigated again in [16], in which it is demonstrated that human body shadowing directly affects the root mean square delay spread.

The main contribution of the current paper is to present a novel radiolocalization method that focuses on the fading caused by the presence of people to obtain better performance and minimize errors in the localization process. In an earlier published work [17] we considered estimating the locations of multiple mobile stations in the presence of mixed LoS/NLoS conditions and multipath contributions. However, we did not consider the influence of human body shadowing. Here, the old method is improved by including the realistic effects that exist in any indoor environment. Because people are the primary absorption agents in the indoor channel, their influence on the radio propagation channel must be considered. The relevance of this paper is not only that it considers realistic effects but also that there is not enough information about this topic in the literature. As mentioned before, there are only a very few works that consider the fading due to the presence of people when developing location approaches. As discussed above, several propagation prediction methods include models to describe human body shadowing. However, in this work, the influence of the movement of people has been considered by means of a statistical model independent of the propagation prediction method. It is worth noticing that the proposed method is able to estimate the location of a mobile station under mixed LoS and NLoS conditions. In fact, this model is the most representative situation when analyzing the indoor radio propagation channel. Reflected and diffracted rays contribute to the computation of the estimated position. In order to validate the proposed 3D-radiolocalization method, several realistic indoor scenarios have been analyzed. Numerical results demonstrate higher positioning accuracy with respect to traditional approaches.

This paper is organized as follows. In Section 2, the basic concept of the statistical model to characterize the attenuation due to shadowing and fading is explained. The main features of the localization approach are described in Section 3. In Section 4, the estimation results obtained from the experimental data analysis are shown. Finally, Section 5 contains concluding remarks and directions for future work.

2. STATISTICAL MODEL TO DESCRIBE BODY SHADOWING

Although there are several works that analyze the influence of the human body on the radio propagation channel, there are not enough contributions dealing with the effects of human body shadowing on localization methods. Due to the fact that most of the papers related to positioning methods in the literature do not consider the influence of the presence of people in indoor environments, the proposed approach focuses on this important and fundamental aspect. Therefore, it can be stated that the proposed approach is more realistic because the presence of moving people is very common in indoor environments such as offices, airports, hotels, etc. It is almost impossible for those places to be empty, without people or furniture.

Positioning accuracy is the main goal for the location approaches. Erroneous locations are due to parameter estimation errors, over-simplified assumptions about the propagation channel, multipath effects and NLoS conditions. Usually, the mobile station may not be visible from a determinate access point. Furthermore, in indoor scenarios characterized by dense multipath and mixed LoS and NLoS conditions, these errors become more critical. For these reasons, a positioning method that considers these unwanted effects is compulsory.

It is well known that the movement of people within indoor scenarios can cause temporal channel variations. That is to say, the presence of people in the indoor scenario can influence the RSS distribution in different ways: it may cause the RSS to decrease, increase or remain constant. The explanation of these changes is the scattering and shadowing effects of human bodies in indoor environments. The user acts as an obstacle that obstructs the propagation path between the access point and the mobile station and therefore causes changes in the RSS value. Moreover, the WLAN signal is absorbed when the body obstructs the signal path, causing extra attenuation leading to a lower RSS value.

It is worth noticing that the influence of body shadowing is included independently of the ray tracing technique. It is considered through a statistical model that is applied to every received ray in mobile stations and fingerprints. The RSS value is attenuated by a certain level that represents the effects of body shadowing. The statistical model applied is based on [18]. In this paper, the effects of random human traffic on path loss in the communications channel at 1.8 GHz have been experimentally measured. Such effects account for an increase in path loss up to 5 dB when the transmitting and receiving antennas are not in very close proximity to the human body.

The parameters of the Gamma probability density function have been extracted from a measurement campaign. According to [18], before each measurements session, samples were taken in the absence of human traffic to know the attenuation in these conditions and then calculate the attenuation in excess. The attenuation in excess over the average without traffic yielded the following parameters statistics:

Mean attenuation in excess: 2.6 dB, standard deviation: 2.09 dB, maximum attenuation in excess: 9.18 dB, minimum attenuation in excess: -1.02 dB. The parameters of the Gamma distribution are obtained as follows:

$$E[X] = k \cdot \theta = 2.6 \tag{1}$$

$$V(X) = k \cdot \theta^2 = 2.09^2 \tag{2}$$

The resulting values are:

$$k = 1.54 \tag{3}$$

$$\theta = 1.68 \tag{4}$$

Figure 1 shows the statistical behavior of the attenuation in excess in terms of the Gamma probability density function.

As mentioned before, [18] demonstrates that the Gamma distribution models the attenuation in excess due to body shadowing

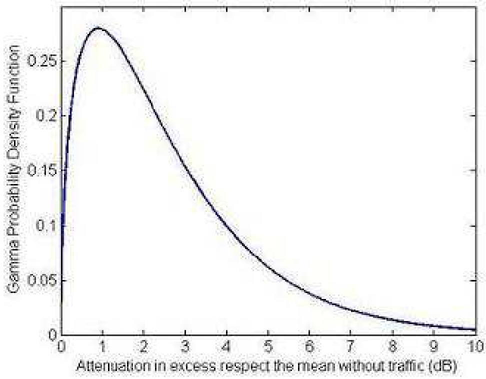

Figure 1. Statistical behavior of the attenuation in excess.

quite well. It is worthwhile to point out that the results are very similar under LoS or NLoS conditions. Therefore, the attenuation due to the presence of people in the area of propagation is independent of the direct vision conditions between the access points and the mobile stations.

3. LOCALIZATION APPROACH

Normally, propagation prediction models are given either through measurement campaigns or by analytical models. In this case, a ray tracing technique that provides information about multipath effects is used to model the indoor radio channel via deterministic methods [19]. The ray tracing tool is based on geometric optics and the uniform theory of diffraction (UTD). The electric field levels can be obtained using the direct, reflected, transmitted and diffracted fields. Therefore, taking into account this variety of effects, the tool provides good predictions. The proposed indoor localization method is based on the fingerprinting technique because fingerprints may store information about multipath effects, and therefore the estimation position will be more accurate. As explained above, the ray tracing model is used to provide the information about multipath effects required in the fingerprinting technique. This information is stored in a dataset during the first stage of the fingerprinting method. The localization estimation is calculated while taking into account the Euclidian distance between the RSS from each unknown position and the information of the fingerprints. The location of a mobile station is evaluated using the following cost function, which uses the RSS of the received signals:

$$D(X,Y,Z) = \sum_{n=1}^{N} \left(R\hat{S}S_n - RSS_n^{RT} \right)^2 \tag{5}$$

where

$$R\hat{S}S_i = \sqrt{|E_x^m(i)^2 + E_y^m(i)^2 + E_z^m(i)^2|} \tag{6}$$

$$RSS_i{}^{RT} = \sqrt{|E_x^f(i)^2 + E_y^f(i)^2 + E_z^f(i)^2|} \tag{7}$$

E^m is the received electric field value in the mobile station,and E^f is the received electric field value in the fingerprint.

As mentioned before, RSS measurements are subjected to random errors due to channel nonidealities such as multipath and shadowing. In the absence of such nonidealities, RSS measurements accurately represent the distances between the unknown node and the reference nodes. For this reason, a statistical attenuation model must be applied over the RSS values. Because the cost function in (5) guesses an ideal channel, a realistic cost function that considers nonidealities must become a new expression.

Note that Equation (5) compares the non-attenuated RSS values, that is to say, the RSS is computed by considering the electric field values received in fingerprints and mobile stations from the access points without taking into account the presence of moving people. In order to include these realistic effects, RSS values are attenuated applying the conclusions obtained in [18]. According to the previous section, the statistical behavior of the attenuation in excess introduced by the presence of people in an indoor environment can be modeled as a Gamma function. Therefore, only a portion of the total power generated at the access points is received at each fingerprint or mobile station when considering body shadowing. The percentage of attenuation is obtained by using the Gamma function as follows: first, a random number between 0 and 10 is calculated; second, the Gamma probability density function is evaluated considering the random number. As shown in Figure 1, the resulting value is between 0 and 0.28; thus the worst scenario for the RSS level is to suffer an attenuation of 28 per cent. However, this attenuation may happen only when the random number is near 1. If the random number is higher than 5, the attenuation percentage will be practically zero. Once these previous considerations have been performed, the cost function is:

$$D(X,Y,Z) = \sum_{n=1}^{N} \Big((1-\mathrm{Gamma}(k,\theta)) R\hat{S}S_n - (1-\mathrm{Gamma}(k,\theta)) RSS_n^{RT} \Big)^2 \tag{8}$$

An attenuation factor modeled by the Gamma statistical distribution has been added to the initial expression so that the Gamma distribution fit more closely to the measured data when considering the presence of people.

Finally, changing (X, Y, Z) inside the testing area, which is the point that minimizes the cost function, is used to estimate the position of the mobile station. Therefore, the estimated position is obtained as follows:

$$(\hat{X}, \hat{Y}, \hat{Z}) = \min D(X, Y, Z) \tag{9}$$

According to this expression, the position of the mobile station corresponds with the fingerprint whose Euclidian distance is the smallest.

4. EXPERIMENTAL RESULTS

In order to evaluate the localization performance of the proposed approach, an indoor environment (Politecnica building in Madrid) has been analyzed with different grid densities. The 3D view of the scenario is depicted in Figure 2. The tests were performed for LoS and NLoS situations and considering the presence of people in movement. The experiments consider two grids consisting of 36×36 and 72×72 fingerprints at a frequency of 1.8 GHz. The distance between the fingerprints is 0.8 m in the grid of 36×36 fingerprints and 0.4 m in the grid of 72×72 fingerprints. The simulations also use 9 access points and 99 mobile stations randomly distributed over the grids.

These simulations were performed in an earlier published work [17] without considering the presence of moving people. The localization

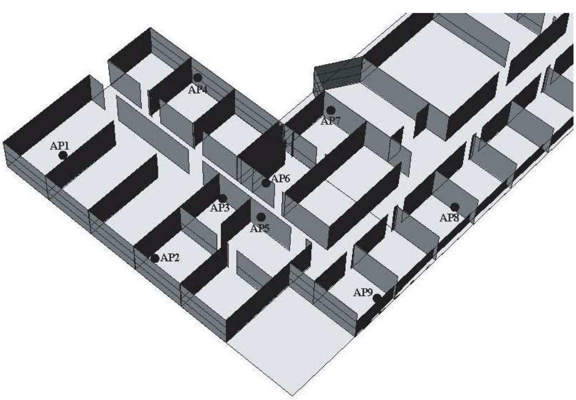

Figure 2. 3D view of the Politecnica building. (Taken from [17]).

method provided quite good results, as it can be observed in Figures 3–6 (solid red line). However, these results are not very realistic, since they do not take into account realistic assumptions such as the common movements of the people inside a public building.

Therefore, in order to compare the results considering or not considering human body shadowing, two different simulations have been performed: the first one utilizes expression (5), which is provided in [17], and the second one utilizes expression (8). Figure 3 shows the mean error in the location process depending on the number of rays in both cases for the grid of 36×36 fingerprints.

The mean error is calculated as the Euclidian distance between the real position of the mobile station and its estimated position. The variance of the mean error is shown in Figure 4.

Obviously, it can be observed that the mean error is a bit higher when considering the influence of body shadowing. People within indoor environments are not always stationary, and their movement will lead to temporal channel variations that dramatically affect the quality of indoor communication systems. Therefore, the propagation losses due to body shadowing strongly affect the RSS of the received rays and significantly degrade the transmission quality. For this reason, the accuracy when estimating the mobile position is lower. Very similar results have been found when using the grid of 72×72 fingerprints. In this case, results are shown in Figures 5 and 6.

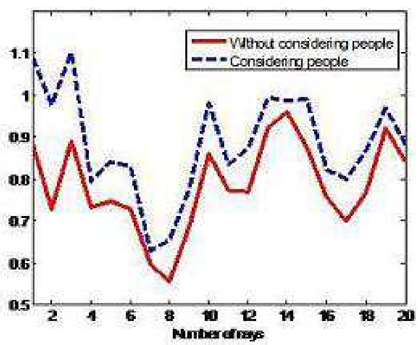

Figure 3. Mean error (meters) obtained by varying the number of rays taken into account to compute the cost function. Results obtained for a 36×36 grid of fingerprints in the Politecnica building.

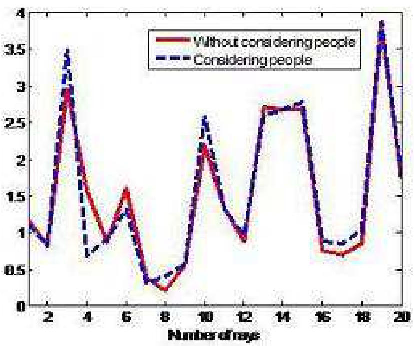

Figure 4. The variance of the mean error (meters) for various numbers of rays in order to compute the cost function. Results obtained for a 36×36 grid of fingerprints in the Politecnica building.

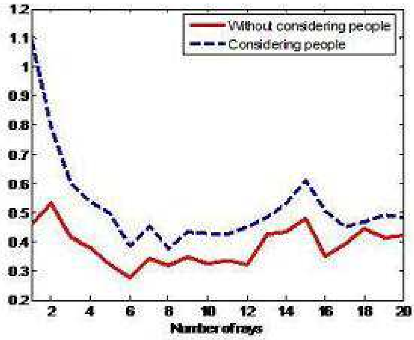

Figure 5. Mean error (meters) obtained by varying the number of rays taken into account to compute the cost function. Results obtained for a 72×72 grid of fingerprints in the Politecnica building.

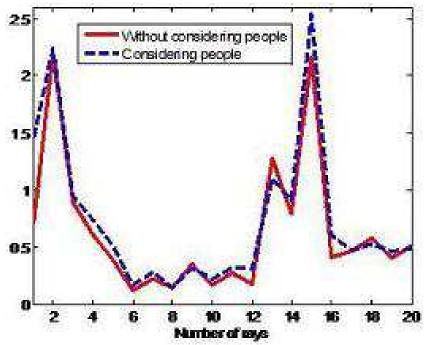

Figure 6. The variance of the mean error (meters) for various numbers of rays in order to compute the cost function. Results obtained for a 72×72 grid of fingerprints in the Politecnica building.

The best results are found when considering 8 rays for both grids. The explanation has already been given in [17], where the reader can find more information about the ray tracing and fingerprinting techniques.

Basically, the reason why the best results are provided when the number of rays is between 6 and 8 is that the cost function is evaluated only when some conditions are satisfied. First, the number of rays in the mobile station must be the same as the number of rays in the fingerprint. Second, the rays from the access points must be in the same order. For instance, if a mobile station receives two rays (from the access points 3 and 7) and the fingerprint receives also two rays (from the access points 3 and 8), the cost function is not evaluated and the information of that fingerprint is not taken into account to estimate the position of the mobile station. When the number of rays is higher (from 15 to 20), it is probable that fingerprints and mobile stations do not contain information for more than 15 rays. Hence, it is quite difficult to find enough information and the results are not so good when the number of rays is increased.

5. CONCLUSIONS

While a great deal of time has been spent developing new localization methods, the effects of human body interactions on the position estimation remain unexplored. There are several factors that affect the propagation channel in an indoor environment such as path loss, shadowing and multipath fading. These factors directly affect the quality of the received signal. The proposed localization method considers the effects of human body shadowing to provide a realistic and accurate estimation of the mobile station position in indoor scenarios.

Numerical simulations in realistic scenarios have been carried out to verify the benefits of the proposed localization method. It can be concluded that in contrast to outdoor environments, human body shadowing is a significant propagation effect in indoor scenarios.

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