Toward Environment Indicators to Evaluate WLAN-Based Indoor Positioning System

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Abstract—**In recent years, the indoor positioning systems using the existing wireless local area network and Location fingerprinting schemes are the most popular system. The accuracy of the system is the most important indicator. In this paper we present experimental studies to emphasize on location error. Two experimentation stages are realized. The first one is based on selected reference points. The second one is based on precision indicators. The obtained results give more insights for environment parameters and their impact on location error. Finally, we propose an optimization algorithm to effectively increase the location accuracy.**

I. Introduction

The increasing distribution of mobile devices leads to location based services (LBS) wind. LBS as a special context aware services provide information using the spatial context of the users. The main origin of LBS was the E911 (Enhanced 911) mandate. Nowadays the outdoor LBS has been realized by outdoor position systems like the Global Positioning System (GPS) or the upcoming European positioning system Galileo (planned start: 2010) [1]. But the indoor LBS still encounter numerous obstacles.

In recent years, the wireless local area network (WLAN) positioning systems as a promising technology in indoor LBS have been widely studied and deployed. Compared to other technologies, WLAN positioning systems have many advantages.

This technology need not any additional installations if a Wireless LAN infrastructure already exists. Moreover, a lot of mobile devices have built-in support for Wireless LANs. In the WLAN positioning systems, user is already connected to a Wireless LAN, so user can use the same infrastructure for positioning and communication.

WLAN positioning systems usually work in two phases: the offline training phase and the online location determination phase [2].

In the offline phase, the test area is decomposed into a grid. Each grid node is called Marking Position (MP). The location fingerprints are collected by performing a site-survey of the Received Signal Strength (RSS) from multiple access points (AP). The RSS is measured with enough statistics to create a database or a table of predetermined RSS values at each MP. This table is called radio map. The vector of RSS values at a grid point is called location fingerprint of that point.

In the on-line phase, a mobile station (MS) will report a sample which is the measured RSSs vector from different AP to a central server; otherwise a group of AP will collect the measured RSS from a MS and send it to a server. The server uses an algorithm to estimate the MS location and reports the calculated position back to the MS or to the application requesting the position information. The most common algorithm to estimate the MS location calculates the Euclidean distance between the measured RSS vector and each fingerprint in the database [3], [4], [5], [6]. The coordinates associated to fingerprint that provide the smallest Euclidean distance is returned as the estimated position.

Previous studies in the literature mainly focus on measurements stage and then results analysis such as those in [7]. Recent developments have been emphasizing the algorithms used for estimating the location that associates the fingerprints with the location coordinates [6], [8], [9], [10], [11], [12]. To explore influencing factors, some researchers performed experimentations regarding the orientation effects [7], [13], some others applied temporal prediction model to deal with the environmental variations of the signal [2]. However, there is a lack of clear understanding of how these systems may perform in terms of accuracy and precision, how to design these systems -what is the impact of the building architecture and thus the radio propagation characteristics- and what impacts the design -what should be the spacing of the grid where location fingerprints are taken.

In order to answer the above questions, we have implemented and tested a WLAN-Based Positioning System (WPS) to evaluate its performance. The objective is to explore first results related to accuracy and localization precision.

In recent work, we have implemented Centre of Mass (CM) and Time Averaging (TA) techniques [14] in the context of WPS. Testing the new programme denoted CMTA-WPS shows that these two techniques improve WPS performance [15].

We also realized a statistical study to emphasize the influence of the WLAN configuration on the precision of a WLAN-based positioning system. Afterwards, we have defined two indicators, Specific Error Ratio (SER) and Global Error Ratio (GER), to determine the best configuration which provides the smallest localization error [16]. The results show that while varying the AP number or the MP number our statistical programme is always able to determine the best configuration under a given precision constraint. Following these conclusions, we deduced that it is possible to improve these indicators. The new indicators were called Refined Specific Error Ratio (RSER) and Refined Global Error Ratio (RGER) and will be described later in section IV.

To follow up this study, we proposed an optimization algorithm to improve positioning accuracy. Therefore, the positioning problem is considered as an optimization problem where the RSER indicator has to be minimized. A local search algorithm is applied to find the best results for our optimization. Considering different AP configurations, we realized several tests using an optimization algorithm. Comparing the obtained results with the former results obtained without optimization shows that the optimization algorithm improves the location error.

This paper describes ongoing work where we address the impact of building architecture together with the AP placement on mobile localization. The rest of the paper is organized as follows. Section II describes our experimental environments. Section III describes and analyses the experimental results. Section IV describes two precision indicators and proposes a new way to estimate the localization error. Section V presents our optimization algorithm and the performance estimation of this method. Section VI concludes the paper and proposes further work.

II. EXPERIMENTAL ENVIRONMENTS

This section outlines two experimental environments under different situations with different AP configurations. The first building architecture is simple; this means that the building has few obstacles. In this case, it is better to focus on the AP number of AP as well as their optimal placement. The second building is a typical example of offices architecture. It’s more complex than the first one and has more different type of obstacles. Exploring this type of building we can study obstacles effect on MS localization. Finally, the WLAN-based positioning system CMTA-WPS is briefly described.

A. *Building 1: A Simple Environment*

In the first stage of experimentation, we have measured the location error in a simple environment. To evaluate the positioning system CMTA-WPS, the objective is to understand how the variation in the AP number depending on the topology of the building influences the location error. The building layout is depicted by Fig. 1. The deployment covers an experimental area of approximately 80m x 40m and uses 802.11g wireless LAN infrastructure to provide coverage.

For the analysis need, we selected 8 reference points (RPs) where several measurements have been made. The RPs are distributed on the whole area as shown in Fig. 1.

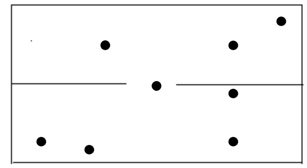


Figure 1. Building 1 layout.

Note that the few obstacles result in a complex environment for signal propagation. In other words, a WLAN composed of a little AP number, for instance less than four AP can not provide enough coverage for good location accuracy.

According to our previous work [15], we started from a 4-AP WLAN. We tested the positioning system by varying the AP number and their locations. We realized several series of measurements under different WLAN configurations inside the building. For shortness consideration, we will restrict the results description. Rather, we will only focus on three scenarios: two 4-AP WLAN configurations and one 5-AP WLAN configuration.

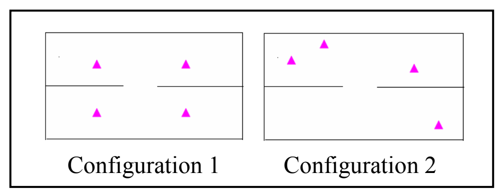


Figure 2. Building 1: the first scenario 4-AP WLAN configurations.

In the first case, we selected the same number of AP (see Fig. 2) but the selected AP sites (placements) are different. As shown in Fig. 2, AP in configuration 1 are placed symmetrically in the building, whereas they are scattered and unsymmetrical in configuration 2.

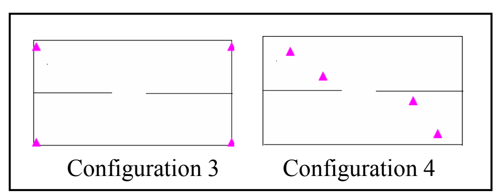


Figure 3. Building 1: the second scenario 4-AP WLAN configurations.

In the second case, we also select 4 APs. In configuration 3, AP are symmetrically placed in the building corners, whereas, in the configuration 4, they are scattered in a different way compared with configuration 2. Nevertheless, the average power of these RPs in symmetrical placement is lower than unsymmetrical placement.

In the third case, we added another AP to configuration 1 and 2 (see Fig. 2). In the configuration 5, the fifth AP was placed in the building centre resulting in a symmetrical configuration whereas in configuration 6, the fifth AP is placed in the left bottom corner as depicted by Fig. 4.

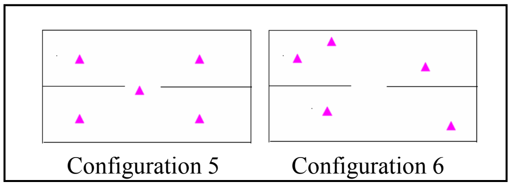


Figure 4. Building 1: the third scenario 5-AP WLAN configurations.

B. *Building 2: A Complex Environment*

In the second stage of experimentation, we considered a more regular building (see Fig. 5) which is an office building having an experimental area of approximately 80m x 40m. It consists of seven rooms and a corridor. The deployment uses 802.11g wireless LAN infrastructure to provide coverage. It should be noted that both experiments are based on the same surfaces. Although, for this building there are more obstacles such as load-bearing walls, bulkheads and doors that may affect the wave propagation.

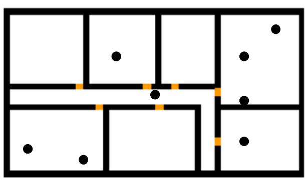


Figure 5. Building 2 layout.

Despite the different number of obstacles, we used the same RPs in the building 2 as shown in Fig. 5 since the two buildings cover the same surface.

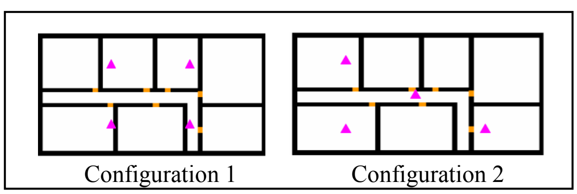


Figure 6. Building 2: the first scenario 4-AP WLAN configurations.

As in the first experimentation, we also varied the AP number and AP locations in order to evaluate the performance of our positioning system. We conducted several series of measurements under different WLAN configurations. Here again, we will restrict the results description and will only focus on three scenarios: two 4-AP WLAN configurations and one 5-AP WLAN configuration.

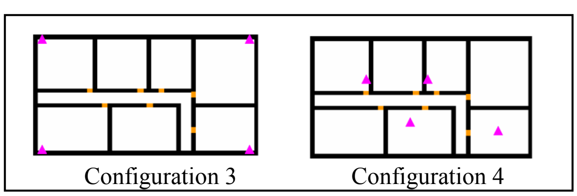


Figure 7. Building 2: the second scenario 4-AP WLAN configurations.

Note that, in these scenarios, AP placements of configuration 1, configuration 3, configuration 5, in building 1, respectively in building 2 are symmetrical, and AP placements of configuration 2, configuration 4, configuration 6, in building 1, respectively in building 2 are asymmetrical.

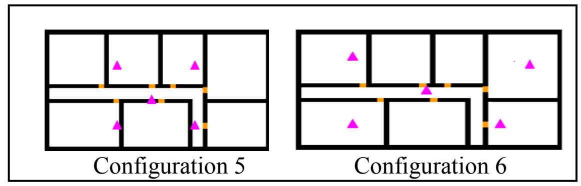


Figure 8. Building 2: third scenario 5-AP WLAN configurations.

C. *WLAN-Based Positioning System (WPS)*

The implemented WLAN-Based Positioning System CMTA-WPS is a probabilistic location determination system which can perform location estimation and tracking of stationary and mobile users.

CMTA-WPS stores information about the signal strength distributions from AP in a radio map and uses probabilistic techniques to estimate the user location. CMTA-WPS uses a discrete-space estimation process that returns the radio map location having the maximum probability given a RSS vector from different AP. A continuous-space estimation process takes as input the discrete-space estimated location and one of the radio map locations, and returns a more accurate estimate of user location in the continuous space.

As described in [14], [15], CMTA-WPS is based on probability distribution of the signal calculated during the training phase. Unlike other systems collecting radio map from measurements, our radio map is generated by propagation model that takes as input the building topology and the WLAN network configuration. During the working phase, the mobile device detects a signal from each AP and uses the deployed position-determination model to calculate a real time position.

III. STUDYING LOCATION ERROR USING REFERENCE POINTS

We explored two situations for position determination: stationary MS and tracking (i.e. moving MS). We run CMTAWPS programme on both building 1 and 2, each time a unique configuration is considered. We based the analysis on location error as a criterion to evaluate CMTA-WPS. The location error is defined as the average error of all the RPs.

The errors of the first experimentation inside building 1 are described in the chart of Fig. 9. The left graphic describes the results relating to stationary mobile; the right graphic describes those of tracking. For each graphic, the bars numbered from 1 to 6 correspond to the 6 tested configurations.

As we started by building 1 where there are few obstacles, we aimed to better focus our research on the ideal AP placement and AP number. The experimentation shows that the location accuracy for tracking is better than for stationary mobile. Indeed, tracking take advantage from prior knowledge of the building layout as well as previous positions of the mobile device.

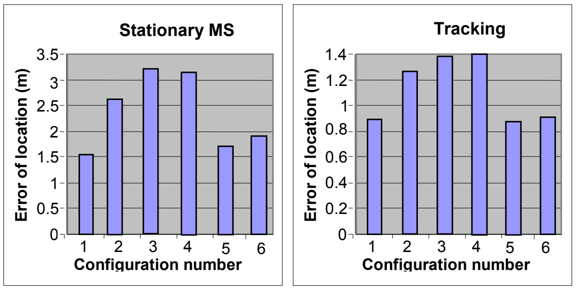


Figure 9. Location error inside building 1.

A second observation is that the best results are obtained with 4 AP for stationary mobile or tracking particularly when the APs are placed symmetrically. So, adding a new AP does not always improve the accuracy. It depends on the position of the added AP. We can also conclude that the placement of the added AP was not chosen judiciously and, as a matter of fact, the central position of the AP generates more perturbation than improvement.

Symmetric configurations are better than asymmetric configurations except the configuration 3 in Fig. 3. In this case, we can observe that the average signal power of the RPs is very low as shown in table 1.

The experimentation in building 2 reveals very different results as described in the chart of Fig. 10. Unlike the pervious experimentation, the accuracy of the stationary MS is always better. Since tracking is based on prior knowledge, bad performance may come from errors accumulation at each previous position.

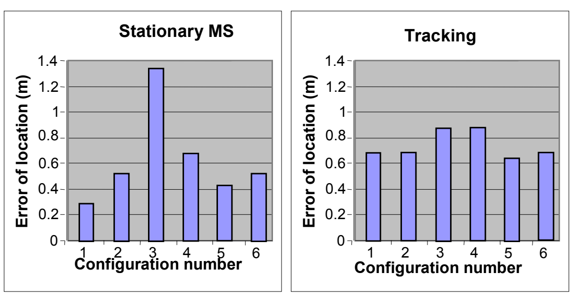


Figure 10. Location error inside building 2.

More generally, the best results are obtained with a 4-AP WLAN and configuration 1 for stationary mobile and with a 5-AP WLAN and configuration 4 for tracking. In these configurations, the APs are placed symmetrically in the building. Here again, the configuration 3 in Fig. 7 is still the worst performance in stationary MS and tracking although it is the symmetrical configuration. That is also due to the low average signal power.

Since building 2 has many obstacles, the wave propagation is disturbed. Therefore, it is most unlikely to have RP with the same maximum probability for a given RSS vector.

Besides above observed findings, we are interested in the relationship between the average signal power of the RPs and the average location error.

Table 1 provides the average signal power in milliwatt of these RPs for different configurations in both buildings. High values of the average signal power reflect high RSS values and reciprocal. Since RSS values are very low in case of configuration 3 in both buildings, the location error is very high.

TABLE I. AVERAGE SIGNAL POWER

Configuration	Building 1 (mW)	Building 2 (mW)
1	26.43×10^{-6}	27.71×10^{-6}
2	1.45×10^{-6}	20.34×10^{-6}
3	0.64×10^{-6}	0.53×10^{-6}
4	1.15×10^{-6}	6.79×10^{-6}
5	20.34×10^{-6}	21.36×10^{-6}
6	18.69×10^{-6}	20.96×10^{-6}

Synthesizing Fig. 9, Fig. 10 and table 1, it is possible to reliably establish a relationship between the average signal power of the RPs and the average location error. The location error of stationary MS decreases while the average signal power increases. On the other hand, for tracking, the prior knowledge of previous positions is an important parameter which can influence the location error. This is why the relationship is not reliable in some experimentation.

Another indicator to assess this relationship is the RPs proximity of the deployed AP and the location error. Indeed the average signal power is higher when RPs are closer to APs.

IV. STUDYING LOCATION ERROR USING REFINED PRECISION INDICATORS

In the previous section we chose only 8 RPs in the experimentation area, so this may result in early conclusions which are valid in some area parts. In this section, we explore our refined precision indicators to estimate the location error in the global area.

A. Refined Precision Indicators

The calculation of precision indicators is based on the set of the predefined marking positions of the experimentation area. For SER and GER indicators, the error estimation is based on the number of marking position (MP) having the same maximum probability for a given RSS. The estimation error for the refined indicators is the distance between the MPs having the same maximum probability.

1) Refined specific error ratio: To We calculate the refined specific error ratio (RSER) in two steps.

First, we define μ as the local error of each MP k as follows:

If $n = 1$ so $\mu(k) = 0$;

Otherwise

$$\mu(k) = \frac{1}{(n(n-1))} \sum_{i} \sum_{j \neq i} dist(i, j) \tag{1}$$

where

i, j: The sequence number of the MPs having the same maximum probability P (l_i | O) at the position k.

n: The number of MPs having the maximum probability P (l_i | O) at the position k.

dist (i, j): The Euclidean distance between the MP i and the MP j.

Then in order to provide the percentage of error ratios, we normalized the local error μ based on statistical studies and proposed the definition of the RSER as follows:

$$RSER = \left[\frac{e^{\frac{\mu}{2}}}{e^{\frac{\mu}{2}} + 1} * \left(\frac{2\mu}{2\mu + 1} \right)^5 \right] * 100 \tag{2}$$

From the above formulation, we determine the relationship between the local error μ and RSER as follows:

When μ = 0 meter RSER = 0%;

When μ = 1 meter RSER = 8%;

When μ = 5 meters RSER = 58%;

When μ > 11 meters RSER > 80%.

2) Refined global error ratio: The refined global error ratio (RGER) was defined as the average of all RSER relating to each MP of the experimentation area.

$$RGER = \frac{1}{n} \sum_{i=0}^{n} RSER(i) \tag{3}$$

where:

n: The number of MPs in the experimentation area.

B. Exploring the Experimentation Environments Using RSER and RGER

Now we can explore the APs configurations deployed in both buildings. As mentioned above, we will focus on three scenarios: two 4-AP WLAN configurations and one 5-AP WLAN configuration.

Fig. 11 and Fig. 12 show the results obtained from the experimentations. The cell (or point) colour relates the RSER value. According to above RSER formulation, we can know the relationship between the location error and RSER.

The colour values are summarized in the table 2. The green cell colour corresponds to a location error of about one meter. The red cell colour is relative to a location error of more than five meters. All the other colours stand for a location error between one and five meters.

TABLE II. RSER CELL COLOURS CORRESPONDENCE

RSER	Cell Colour
0 % ~ 10 %	
10 % ~ 20 %	
20 % ~ 30 %	
30 % ~ 40 %	
40 % ~ 50 %	
50 % ~ 60 %	
60 % ~ 100 %	

The colour values are summarized in the table 2. The green cell colour corresponds to a location error of about one meter. The red cell colour is relative to a location error of more than five meters. All the other colours stand for a location error between one and five meters.

We notice that performing RGER values according to WLAN configurations we considered is a way to choose the best configuration relative to building architecture, for instance, selecting the configuration having the minimal RGER seems to be the more convenient. The colours mapping of RSER values reflects the error ratio at each MP. Note that, to determine location error, RSER and RGER do not take into account the prior knowledge of previous positions. Thus both indicators reflect only the performance estimation of stationary MS in the global experimentation area.

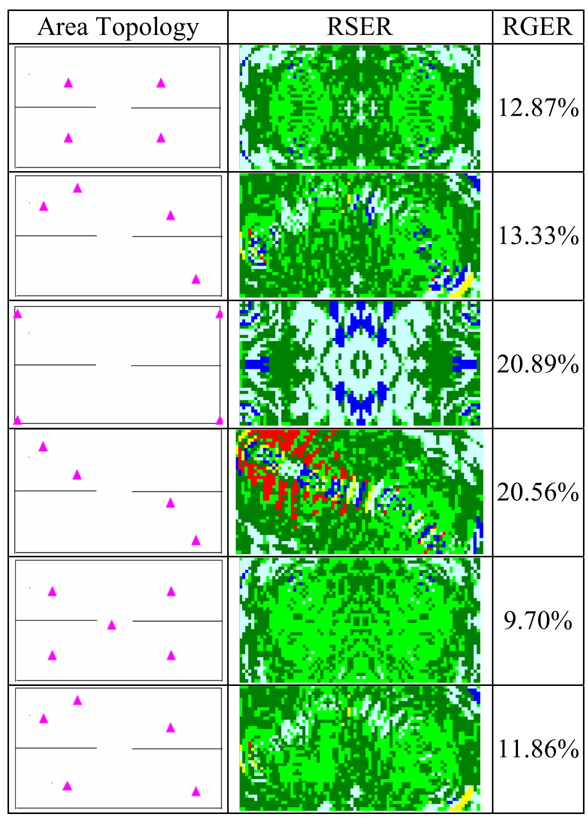


Figure 11. Indicators variation in building 1.

Fig. 11 shows the results obtained from the experimentations in the first building. Two major observations emerge.

Firstly, in the previous section, we concluded that adding a new AP does not always improve the accuracy. But studying the RGER, we can adjust the conclusion as follows: adding a new AP does not always improve the accuracy in some area parts but improves it globally. For example, the RGER value is 12.87% in the configuration 1 whereas it equals 9.70% in the configuration 5. Looking at the RSER colours mapping of these two configurations, we observe centered symmetrical green parts which are more extended in configuration 5 compared to configuration 1.

Secondly, both conditions of symmetrical configuration and high average signal power give better results in the global experimentation area. Here, the RGER of configuration 1 is lowest in all the 4-AP configurations since it is symmetrical and has high average signal power. For the same reasons, RGER of configuration 5 is lower than the one of configuration 6.

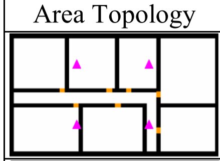
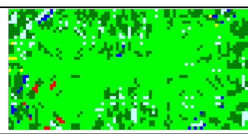
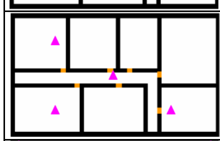
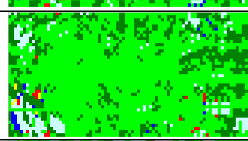
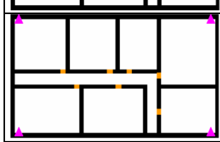
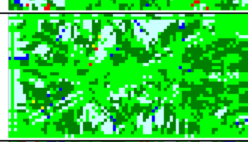
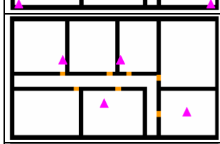
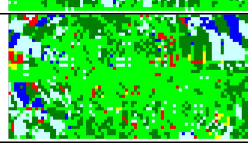
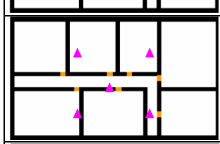
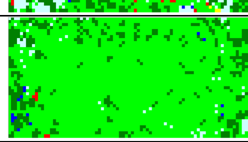
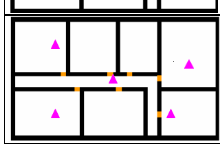
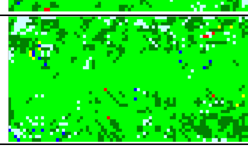
Area Topology	RSER	RGER
		6.36%
		6.76%
		10.84%
		13.31%
		3.67%
		5.68%

Figure 12. Indicators variation in building 2.

Besides the two observations mentioned above, Fig. 12 also reveals that the global accuracy of the closed-space (the second building) is better than open-space (the first building) with the same AP configuration. Indeed, in a closed-space environment, the probability to have RP with the same signal vector is very low.

V. Decreasing Location Error Using Optimization Algorithm

In the previous section, we presented the refined precision indicators to estimate the different APs configurations. In this section we will try to improve the RSER of MPs by our optimization algorithm.

A. The principle of optimization algorithm

Like mentioned before, RGER is defined as the average of all RSER relating to each MP, whereas RSER is the average distance between points having the same signal vector. The idea of our optimization algorithm is to take advantage from the neighborhood that has better RSER. Considering a MP i, when the local error of its neighbor cumulated with the error caused by the distance between them is less than its own local error, we can use the signal vector of this neighbor instead of the signal vector of the MP i.

The mathematical expression is as follows:

There are two points **i** and **j** which are geographical neighbors.

If Error (i) > Error (j) + Dist (i, j)

Then Vector (i) = Vector (j)

where:

Error (i) is the local error μ at MP i defined in the previous section.

Vect (i) is the vector of signal power at MP i.

Dist (i, j) is the Euclidean distance in meter between the MP i and MP j.

The optimization process uses a local search algorithm. This algorithm uses a search graph where the vertices are the AP configurations and the edges connect neighbour configurations. Two configurations are neighbours if we may move from one configuration to another configuration due to elementary configuration modification.

In our case, we start the search from a root node corresponding to the signal vectors of all MP with their local error μ. The other nodes are signal vectors of all MP where the signal vectors between neighbor nodes are permuted. The threshold of the search depth can be fixed in advance. The goal of our search is to find a node of minimum local error μ.

The local search algorithm must satisfy two constraints. The first constraint concerns the threshold neighbor. Here, we just consider the closet neighbor MP which satisfy the substitute condition. The second constraint concerns the choice of the MP which are separated by an obstacle. Indeed, their Euclidean distance is short, but their geographical distance is long. Currently, we use the shortest geographical distance instead of Euclidean distance.

B. The application of the optimization algorithm for the different configurations

We have implemented a C++ program to perform our optimization algorithm.

We explored the APs configurations deployed in all our experimentations. We also focused on the same scenarios described in the second section.

Fig. 13 shows the RGER of different configurations in the first building before and after application of our optimization alogrithm.

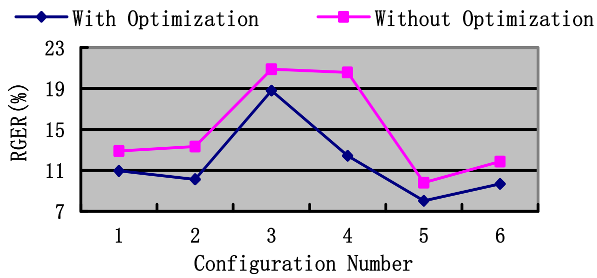


Figure 13. RGER improvement in building 1.

Fig.14 shows the RGER of different configurations in the second building before and after application of our optimization algrithm.

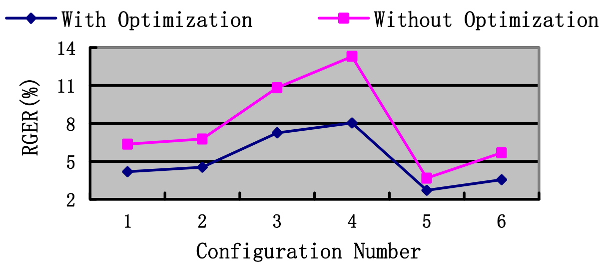


Figure 14. RGER improvement in building 2.

According to above figures, the RGER of all configurations in both buildings decreases after the application of optimization algorithm. The improvements vary from 1.69% up to 8.14 % in the first building, and from 0.95% up to 5.26% in the second building. These variations of the improvements depend on several factors.

The topology of the building:

In fact, the topology of the building and the number of barriers may be involved in signals distribution between the neighbors in our optimization algorithm. For example, let us consider two close MPs in the same room. The signal vector of one MP could be replaced by the other without interfering with the topology knowledge of the radio map.

The distribution of signal vector:

Assume that there is a homogeneous RGER region having many high RGER MP. So the optimization algorithm will try to improve the RGER of these MP. But the problem is that if these MP are condensed, the error improvement will not be very effective. This result is shown in Fig.15.

Here, the red area represents the MP which have a RGER more than 60%. Thus, we observe that the red area persists even after applying optimization algorithm. The improvements are effective only around the edges of the area where neighbors have a lower RGER.

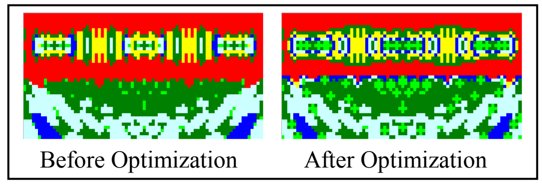


Figure 15. Improvement for the homogeneous high RGER MP.

On the contrary, this algorithm is greatly effective if these high RGER MP are scattered. Fig. 16 illustrates such a situation. We can see that most red dots disappear after applying optimization algorithm. These improved MP have the same characteristic: they are scattered. It means neighbours around them have a lower RGER.

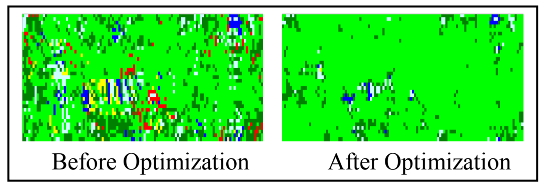


Figure 16. Improvement for the scattered high RGER MP.

VI. CONCLUSION AND PERSPECTIVE

In this paper, we selected two buildings and conducted several experimentations using our WLAN-based indoor positioning system to give more insight of the impact of AP placement on location error. For the first building, we focused on the influence of the placement and the number of APs on location accuracy. The experimental performance shows that if we place the AP in symmetric positions distributed over the experimentation area in such a way that the average signal power is high it is likely to be the best choice for reducing location error.

For the second building, we focused on the influence of the obstacles on the location error. The stationary MS and tracking performances are entirely different. Due to the positive effects of obstacles which make RSS vectors diverse, stationary MS are located more accurately. On the contrary, for tracking, location accuracy sometimes decreases. This is caused by the cumulated errors in the previous positions of the mobile device.

Since our former study are based on 8 selected RPs, we explored refined precision indicators to extend the analysis to the whole experimentation area. We defined two indicators called RSER and RGER to estimate the location error using the same experimentation environment. On one hand, considering the lowest RGER values is a way to choose the best WLAN configuration relative to building architecture. On the other hand, increasing the AP number improves the global accuracy of our WLAN positioning system.

Finally we applied a local search method to optimize the global location error. We recalculated RSER values of each configuration in both buildings after using the optimization algorithm. Comparing the RSER values obtained after optimization with those obtained without optimization, we conclude that the local search method improves the location error. This optimization algorithm is specially effective if the high RGER MP are scattered.

Realizing these experimentations was based on different indicators (AP number, AP placement, obstacles number, average signal power, etc.) to estimate the location error. When modeling the indoor positioning problem, these indicators will be used to set the optimization parameters.

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