Efficient design of indoor positioning systems based on optimization model

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Abstract— **In recent years, positioning systems for indoor areas using the existing wireless local area network infrastructure have become very popular and attractive. However, most systems only focus on the network deployment for positioning but overlook that the original purpose of these WLAN infrastructures is providing the required connectivity. Furthermore, experimental results related to such positioning systems have been presented while there is a lack of good analytical models that can be used as a framework for designing and deploying the positioning systems. In this paper, we propose an innovative approach where WLAN planning and positioning error reduction are modeled as an optimization problem and tackled together during the WLAN planning process. A Mono-objective algorithm called Variable Neighborhood Search (VNS) is implemented and the simulations demonstrate that this algorithm is highly efficient in solving the indoor positioning optimization problem.**

Keywords- Indoor Positioning System; communication quality demand; mono-algorithm, modeling

I. INTRODUCTION

Over the past ten years, indoor positioning system has won growing interest in emergency situation, public security, commercial and military applications. It has attracted a lot of researches from both academia and industry and much substantial work has already been done in the area of indoor positioning. Since the deployment of WLAN infrastructures are widely adopted and the Received Signal Strength (RSS) can be easily obtained and stabilized in multi-path and non-line-of-sight conditions, WLAN-based fingerprinting approach is considered now as the best choice for indoor positioning system.

The previous studies in the literature mainly focus on measurements stage and then results analysis [1]. Recent developments have been emphasizing on the algorithms which are used for estimating the location that associates the fingerprints with the location coordinates [2], [3], [4], [5]. However, our work here is trying to model the positioning problem as optimization problem. To our knowledge, this is the first time that designing a WLAN-based indoor positioning is dealt as a modeling and optimizing approach.

Since WLAN networks are widely deployed, WLAN infrastructures are chosen for indoor positioning in almost all the papers [6], [7], [8]. Nevertheless, almost all the papers neglect a fact that the original purpose of these WLAN infrastructures is to provide the required connectivity [9], so that, positioning becomes the only target of the network configuration design. In [10], a network configuration refers to the deployment of a given number of APs with their assigned parameters (i.e. the allocated frequency, the emission power and the azimuth). In fact, an increase of the density of AP can improve the system accuracy and precision, whereas the communication quality (due to frequency interferences) and the installation costs are increasing too. These are major drawbacks!

In this paper, we attempt to answer the following question: how to deploy a WLAN in order to guarantee the requested Quality of Service (QoS) while reducing the location error? Such a problem includes two aspects: WLAN planning and positioning error reduction. To provide users an optimal wireless access to their local network, WLAN planning does not only consists in selecting a location for each transmitter and setting the parameters of all sites, but also acts on allocating one of the available frequencies to each AP configuration. And toward the indoor positioning system, once RSS from all visible APs are measured and inputted, the location is estimated and outputted using the RSS distribution and machine learning technique. We propose a new approach where WLAN planning and positioning error reduction are modeled as an optimization problem and tackled together during WLAN planning process.

The rest of the paper is organized as follows. The next section introduces two indicators which are used to evaluate network throughput and positioning accuracy. Section 3 describes the problem definition of WLAN-based positioning model. Section 4 presents a Mono-objective algorithm. The experiments and results are given in section 5. Final section gives some conclusions and perspectives.

II. EVALUTION INDICATORS

To find a feasible network configuration satisfying QoS and positioning error constrains, one important step is to define two indicators in order to evaluate the actual network QoS as well as the positioning error. In the proposed model, the calculation area is meshed. Each mesh node is called Marking Position (MP). The defined indicators are calculated at each MP to evaluate the quality of the network configuration, i.e. the required QoS and positioning error. In this section, both indicators will be introduced.

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A. QoS Indicator

Inside AP coverage area, the quality of service perceived by the user is of different levels because the interferences are not uniform. A user can loose his connection due to interferences while another user of the same AP may have high throughput. One indicator to measure interferences is the Signal-to-Interference-plus-Noise-Ratio (SINR). Its definition is local for each user, which is [11]:

$$SINR = \frac{P_{BestRSS}}{\sum P_{othersRSS} \times \gamma(\Delta f) + N} \tag{1}$$

Where:

$P_{best\ RSS}$ is the highest RSS in a MP. In IEEE 802.11 standard, the connection is usually established with the best RSS. $P_{other\ RSS}$ are other RSSs perceived by a MP with smaller values than the best RSS. *γ(.)* is the protection factor corresponding to the attenuation coefficient between channels. It is a function of Δf, the channel distance between the carrier signal and the interfering signal. *γ(.)* decreases when Δf increases: if $\Delta f = 0$, $\gamma(\Delta f)=1$ and if $\Delta f \geqslant 5$, $\gamma(\Delta f)=0$. All intermediate values depend on the receiver equipment features. N is the noise strength. Its value is around *-100dBm* in surrounding air.

B. Positioning Error Indicator

Recent indoor positioning system research has mainly focused on algorithms that compute the best match. Although, most research only provided experimental results, they neglected an in-depth analysis of the impact of different factors for position errors. At a first glance, it is nearly impossible to find an appropriate way to pre-estimate the positioning error. However, viewing from a statistical perspective, the location error can be divided into two parts. One comes from real environment disturbances, which belongs to a random error. There are many factors that can affect this kind of error, such as AP orientation, time of day (a lot of people or not), environment (tables, desks…), distance from transmitter, interferences from other AP, and sensibility of the wireless card. The error caused by these key factors is uncertain and time-varying, so that it can not be pre-estimated and eliminated efficiently. The other part is due to the drawback of the finger-printing technique, which is a system error. After studying the principle of positioning based on finger-printing technique, we noticed that there is only one drawback of finger-printing technique. We call this drawback "aliasing". Aliasing means, that there are several distinct locations receiving the same signal strength of one AP. Even worse, due to variations in the signal strength caused by obstacles, locations need not to be in the same distance to the AP. If aliasing appears at some MPs that receive the same RSS values from several APs, positioning based on finger-printing technique will become invalid. In other words, aliasing is a source of positioning error. Although some well-known approaches like bayes's theory, particle filter, and etc. are proposed to diminish or eliminate the effect of aliasing, they are only valid for the measurement-based indoor positioning system. The aliasing effect is unavoidable and especially significant in the positioning system based on a propagation model. During a measurement-based training phase, the process generating a radio map is not only labor-intensive and costly, but also very sensitive to possible sources of interferences in the building. Therefore, we chose a propagation model based method as a robust methodology to overcome this training phase, so aliasing effect becomes the emphasis of our research. According to our pervious study [12], if we increase the number of APs or change the placement of APs, the number of the reference points which contain aliasing will reduce till disappear.

To sum up, we may draw the conclusion that the error induced by aliasing is suitable for being a part of the fitness of our optimization problem. In other words, the objective is to optimize the positioning error generated by aliasing. An indicator, called Refined Specific Error Ratio (RSER), was proposed in [12] and is used to evaluate the aliasing error. The expression of RSER at MP k is as follows:

If n = 1 so RSER (k) = 0

otherwise,

$$RSER(k) = \frac{1}{(n(n-1))} \sum_{i} \sum_{j \neq i} dist(i, j) \tag{2}$$

where:

i, j: the sequence number of MPs having the same RSS vector at the position k.

n: the number of MPs having the same RSS vector at the position k.

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

The above equation indicates that RSER computes an arithmetic mean of the distances by twos among a set of MPs having the same RSS vector. Namely, RSER is essentially a statistical aliasing error on a MP.

III. MODELLING OPTIMIZATION PROBLEM

An indoor WLAN-based positioning system modeling process is based on a mathematical description of several objectives. WLAN design is widely studied, and some mathematical models of WLAN planning are worth learning from [13], [14], [15], [16]. In indoor WLAN-based positioning system, the basic objective is to provide radio coverage on all assigned areas, which is a common requirement for communication and positioning. One complementary objective concerns the positioning accuracy, which mainly relies on the aliasing error. Another complementary objective concerns the efficiency and the throughput of the network, which mainly relies on the interfering signals level and the communicating signal level between cells.

A. AP Location Model

In this model [13], the AP location is defined as a vector of N items $S= (s_1,\ldots,s_i,\ldots,s_n)$. Each item s represents a candidate site which is a geographical location where an AP may be assigned. The sites define places in the studied building and more than one AP may be installed to provide higher bit rate in strongly congested zones. Thus, we also define the sectors $L=(l_1,\ldots,l_i,\ldots,l_m)$ as the list of available sectors per site.

B. AP Parameters Model

In this model [13], since different types of APs have different parameter values, we predefine a list of AP types provided for user choice. When one AP is selected, we define its set of parameters that is, azimuth, emitted power and frequency. Summarily, the AP setting is characterized by the following parameters (s,l,a,p,h,f). Where (s,l) defines the location, a is the type of AP used, p is the emitted power, h is the azimuth or the horizontal orientation and f is the number of the frequency channel used.

C. Radio Signal Model

To achieve a communication or positioning service, a user terminal needs to receive the radio transmission of an AP at an adequate level of power. The radio signal model defines the RSS expression and the different service demands related to the RSS level. For each candidate location, a three dimension coverage map is computed with a propagation model. The propagation model considers a discrete space, thus the coverage map is defined as a set of mean RSSs associated with the meshes. The element of the set p_{slm} is the RSS in the centre of the mesh m and coming from the location (s, l). This power is expressed in *dBm*. For the coverage criterion, we define three kinds of RSSs according to different power thresholds. The lowest power threshold $p_{interference}$ is called interference threshold, which is the minimum signal power a client can receive as interference. The medium power threshold $p_{positioning}$ is called positioning threshold, which is the minimum signal power a client must receive for positioning estimation demand. The highest power threshold $p_{reception}$ is called reception threshold, which is the minimum signal power a client must receive for communication.

D. Qos Model

The QoS model in [13] consists of two sub-models. One is called traffic model, which defines the way of representing the network load demand and gives a framework to the expression of the desired QoS. The other one is named throughput model, which transcribes SINR values into service level provided by the network, that is, the bit rate offered to the clients.

In the traffic model, we define service zones, which are represented by polygons covering parts of the building. Several essential characters of service zones are defined: n_z is the number of users inside the service zone z, and d_z is the bit rate in *kbps* desired by user for the service zone z. The service zones overlap each other, so the desired bit rate per user is computed taking into account the overlapping area. To integrate these service zones into our model, these service zones are represented by a set of meshes or MPs called Test Point (TP). The characters of service zones can be analyzed by d_t the total bit rate desired on the TP t. The mathematic formulation is given by: $d_t=argmax\{d_z:z\in Z\}$. Z is the set of service zones covering the TP t.

The principal parameter in throughput model is r_t, the real bit rate provided on the TP t, whose quality is defined by SINR on that TP.

E. Positioning Model

Like the service zones considered in the traffic model, we define, in the positioning model, the positioning zones where we aim to reduce the positioning error. These positioning zones are also represented by a set of meshes or MPs called Reference Points (RPs). The key parameter for the model is the positioning error, denoted e_t, which represents the aliasing error at the RP t. As mentioned previously, we consider the aliasing error as the positioning error and RSER is used to calculate the aliasing error.

IV. IMPLEMENTATION

The WLAN-based indoor positioning optimization problem can be clearly identified as a multi-objective (MO) optimization problem where positioning accuracy and QoS need to be concurrently optimized [17]. There are two commonly used approaches to solve a multi-objective optimization problem. The first one reduces the multiple objectives to a single objective by generating a composite objective function, usually from a weighted sum of the objectives. This composite objective function can be optimized using existing mono-objective optimization algorithms. In this case, the quality of the indoor positioning system relies on the optimization of several objectives and the optimal solution is the result of a fixed trade-off between them. The second one relies on a MO search strategy and looks for a set of Pareto-optimal solutions, each solution representing a different trade-off between the objectives that is involved. In this paper, we use the first approach. The second approach will be implemented in our further work.

A. Mono-objective Formulation

To achieve several objectives simultaneously, our optimization problem, which is to determine a feasible AP configuration satisfying QoS and positioning error constrains, should be formulated as a sum of objectives in order to minimize the following single evaluation function:

$$\sum_{\mathrm{Site}} C_{\mathrm{Site}} + \sum_{TP} \beta \times \Delta_{tp} + \sum_{RP} \gamma \times \mathrm{E}_{rp} \qquad (3)$$

Where, C_{Site} is the network installation cost of a site. β is the penalty coefficient assigned to the TP. Δ_{tp} is the deviation between the required bit rate and the real bit rate. γ is the penalty coefficient assigned to the RP. E_{rp} is the magnitude of positioning error. In this function, the first term is the network installation cost; the second term is the cost of unsatisfied demands on QoS and the third term is the cost of unsatisfied demands on positioning. All components are in Euros. So, the indoor positioning challenge is completely changed into an economical challenge.

In addition, our optimization must be done under the following constraints:

- The network covers all MPs with a minimum guaranteed communication and positioning service by the user. That is to say that RSS of each MP should be equal or higher than reception threshold.
- The maximum number of newly installed AP does not exceed a given number fixed by the user.
- In each MP, the number visible APs should not less than three.
- All AP parameters such as type, emitted power, azimuth and frequency should be included in their domain of definition.

B. *Mono-objective Algorithm*

Variable neighborhood search (VNS), jointly invented by Mladenovic and Hansen in [18], is a meta-heuristic for solving combinatorial and global optimization problems. Unlike many standard meta-heuristics where only a single neighbor-hood is employed, VNS systematically changes different neighborhoods within a local search. Our implemented algorithm is based on basic General Variable Neighborhood Search (GVNS) scheme, a variant of VNS algorithm.

First, an initial solution is built based on the coverage criteria. It is generated by a simple greedy algorithm. After selecting the initial neighborhood, a solution is generated randomly from the selected neighborhood. Then, variable neighborhood descent search (VND) is implemented. VND is a method to change the neighborhoods in a deterministic way, which is applied to the current solution until no further improvement with respect to all defined neighborhood. Once the VND output is obtained, the next step is neighborhood changing. In this step, two enhanced strategies are incorporated: One strategy is the double control of the degradation to avoid falling into a local minimum. The other strategy is the dynamic probabilistic neighborhood ordering strategy, which can increase the solution quality and speed up the search.

V. EXPERIMENTATION

A. *Test environment*

Some experiments were realized with the objective to study the model and the algorithm. The experiments were held in the environment described by the Figure 1. The test bed is composed of a two-floor building. Each floor size is 120m x 40m. We defined 94 candidate sites for AP installation. AP parameter settings are one type of AP with a unidirectional pattern and 2 possible values of power. For the frequency allocation, each site must use one frequency among the 13 which are available in France. Then, the WLAN AP configuration design consists in installing some AP configurations among 188 candidate configurations and in assigning frequency channels that is 188x13 combinations. To focus on the different strategies, optimization does not take into account the financial requirements. We limit at 30 the maximum selected AP for a solution.

In order to define the traffic demand and positioning demand, we set several service zones and positioning zones respectively. And In order to ease the test analysis, we set several service zones and positioning zones of the same size which are presented by the green areas on Figure 1. Each zone is defined on each floor of the building. For the service zone, 300 users are uniformly distributed on each service zone and each user demand is about 500 kbps real bit rate. Then, the global demand for the whole building is 300 Mbps. Those two kinds of zones correspond to 7728m², and then 7728 TP are defined for SINR computation and 7728 RP are defined for RSER computation.

Figure 1. The topology of the test building

B. *Test Results*

In mono-objective, the penalty coefficients of the evaluation function must be pre-set. Setting the penalty coefficients implicitly introduces the designer's requirements on the relative trade-off between objectives. To avoid some undesirable effects, we will study the impact of these penalty coefficients on optimization process through following experiments.

Three test scenarios have been defined to evaluate the mono-objective search:

$$\sum_{TP} 100 \times \Delta_{tp} + \sum_{RP} 1 \times \mathrm{E}_{rp} \tag{4}$$

$$\sum_{TP} 10 \times \Delta_{tp} + \sum_{RP} 1 \times \mathrm{E}_{rp} \tag{5}$$

$$\sum_{TP} 1 \times \Delta_{tp} + \sum_{RP} 1000 \times \mathrm{E}_{rp} \tag{6}$$

In these three test scenarios, we vary the γ to β ratio to study the relationship between QoS and the positioning accuracy. From figure 2, different scenarios show different variation. We easily conclude that a high γ to β ratio of 1000 can guarantee a small positioning error while leading to a high total Δ_{tp} (black curves: good positioning accuracy, bad QoS). In the same way, a low γ to β ratio of 0.01 only guarantees a low total Δ_{tp} but gives a high total positioning error (blue curves: bad positioning accuracy, good QoS). These results completely match our expectation. On one hand, the objective associated with a high penalty coefficient is emphatically optimized. On the other hand, a high penalty coefficient also prevents the improvement of other conflicting objectives. However, people usually do not have a preference for a certain objective. Under such circumstances, treating these objectives equally is the best choice. With an appropriate value of 0.1 for the γ to β ratio, our approach could find an AP configuration which might provide a good improvement not only on QoS demand but also on positioning accuracy.

Typically, since the WLAN infrastructure is mainly used for communication, the objective of QoS is assigned a high penalty coefficient to grantee its prior level in optimization.

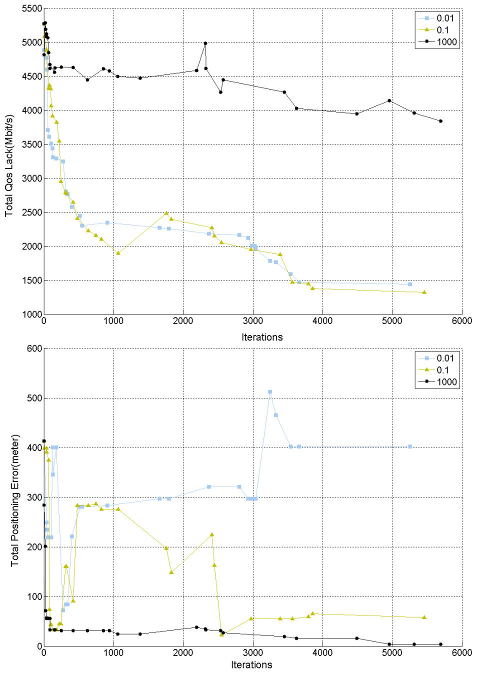

Figure 2. The variation of total Δtp and total Erp by different γ to β ratio in each improvement.

VI. Conclusions and Perspctives

In this paper, we provide a solution where WLAN planning and positioning error reduction is dealt with simultaneously as an optimization problem. QoS and positioning accuracy goals can be evaluated thanks to two evaluation indicators. The AP model, the RSS model, the QoS model and the positioning model have been defined according to our propagation model. A global formulation based on a penalty function has been proposed in order to transform a multi-objectives problem to a mono-objective problem. The problem has been solved with the VNS algorithm. In the experimentation part, this paper has highlighted the importance of penalty value assigned to each objective. The tuning of the mono-objective takes several launches to get the desired trade-off.

To overcome this weak point of the mono-objective, in our future work, we will focus on implementing a multi-objectives algorithm to solve this problem.

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