A Multiobjective Optimization Methodology of Tuning Indoor Positioning Systems

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***Abstract*—How can the collected data from testing an indoor positioning deployment be transformed into information concerning the optimal tuning of a positioning system in this deployment? How can such kind of accumulated information from several deployments be transformed into more generic knowledge regarding the system's performance, with respect to several performance goals? In this work, we present a multiobjective optimization methodology of tuning indoor positioning systems, based on real data recorded onsite. Selecting the appropriate tuning for a positioning system is a challenging task, which depends on many factors: the specific deployment, the devices used, the evaluation metrics and their order of significance, the user-case scenarios tested, etc. In order to handle these multiplicities, we introduce the use of multiobjective optimization which allows several objectives to be simultaneously satisfied. We exemplify the methodology performing tests with the GpmStudio platform, a desktop tuning and evaluation platform that supports our Global Positioning Module (GPM). The methodology proves to be a very useful tool in the hands of testers who are designated to optimally tune the positioning system in a variety of scenarios.**

***Keywords*—Multiobjective optimization, Indoor positioning, Tuning, Ground truth definition, Positioning evaluation, Tracking, Indoor positioning deployment**

I. Introduction

During the last years, the indoor positioning community has identified the need to establish well defined methodologies of evaluating the performance of indoor positioning systems [1]. A series of works [2], [3], [4], [5], [6], has offered several well defined alternatives, some of which are the formal ways of performing indoor positioning competitions, like the ones held in the IPIN [4], [5] and the IPSN [6] conferences.

Furthermore, apart from the evaluation methodologies that have started to draw significant attention by the indoor positioning community, the methodologies of optimally tuning a system form also a domain worth discussing, sharing ideas on and improving. Assume a positioning expert called to deploy a positioning system, tune it properly, present it and report its performance. While the part of the evaluation and its relevant methodologies have started to be extensively discussed, the step of how the system is tuned accordingly does not appear to have gained the same popularity. It is not rare that, regarding the optimal tuning of the system, an empirical selection of the appropriate tuning is mentioned, or a manual test-and-set procedure.

The question of how to tune a positioning system at a new deployment has drawn our interest. We have approached the domain of evaluating and tuning positioning systems with a trilogy of works. In the first work of this trilogy [2], we established a methodology of ground truth definition and position evaluation of online positioning solutions. In the second work [7], we presented an offline tuning and evaluation methodology based on recorded data. By presenting in that work our offline parameter optimization platform (GpmStudio), the way that the methodology excepts the tester from the obligation to repeatedly revisit the deployment environment to test-and-set the IPS parameters was exemplified. The current study is the natural continuation and a significant expansion of the latter [7], concluding the trilogy with the introduction of multiobjective optimization techniques.

The broad goal of optimally tuning a positioning algorithm, may be composed of a multitude of objectives to be satisfied. This multitude of objectives may concern different kinds of multiplicities. It is generally accepted [6] that it is very hard to fully capture the effectiveness of an indoor localization algorithm with a single metric. Using a unique metric might not be representative of a system's performance, and could be unfair when used for comparisons. A more holistic evaluation would be an appealing field of research. Thus, one kind of multiplicity is the use of several evaluation metrics, as different objectives to be satisfied. This approach can provide a more complete evaluation of the performance of a system under test.

Moreover, selecting a parameter tuning based on a single recording introduces the risk of overfitting. Combining several recordings (with each recording being another objective) of the same deployment could minimize this danger, by strengthening the robustness of the parameter setting suggestion. Lastly, using recordings from a variety of environments to infer a parameter setting that handles a good trade-off in all of them, could lead to a good selection of the default setting of the system to be deployed in an unknown environment.

The rest of this paper is organized as follows. In Section II, we introduce preliminary information, necessary for the rest of

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the work. In Section III, the related work is discussed, along with the contributions of this study. The proposed methodology is theoretically presented in Section IV, along with the implementation of the method with the related software tools. The experimental results based on a multitude of recorded data are presented and discussed in Section V. Lastly, conclusions drawn and future directions of this work are discussed in Section VI.

II. Preliminaries

A. Multiobjective optimization

The goal of mathematical optimization is the selection of the best element from a set of available alternatives, with regard to an accurately defined criterion. The function which evaluates the suitability of each candidate solution is called *objective function*. The space of feasible solutions is called *search space* or *decision space*. Many real life problems (in engineering, economics, operational research, logistics, etc.) contain more than one objective that needs to be satisfied. Multiobjective optimization is the domain that is applied where optimal decisions need to be taken, at the presence of more than one objectives. In multiobjective optimization, the evaluation of a candidate solution is a vector in a space with a number of dimensions equal to the number of objectives. This space is called the *objective space*.

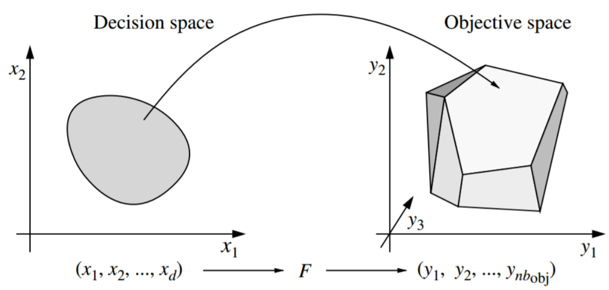

Fig. 1. The decision space and the objective space in a multiobjective optimization problem (Image from [8]).

In this category of problems, these multiple objectives can often be contradictory. Therefore, a trade-off among all relevant objectives is usually needed. The preferences concerning all objectives (their relative significance, their importance ranking, constrains, etc.) might often be unclear when stating the problem.

The principle solution concept used in multiobjective optimization is the notion of *Pareto Optimality*. With this solution concept, a small optimal subset is selected from the set of all candidate solutions. A solution A is said to *Pareto-dominate* another solution B, if A is better (or equal) than B in all objectives. A solution A belongs to the *Pareto Optimal Set* if there exists no other feasible solution that Pareto-dominates A. The image of the *Pareto Optimal Set* in the *objective space* is referred to as the *Pareto Front*. Each candidate solution of the population can be assigned with a *Pareto Rank*. All solutions of the *Pareto Front* form the first rank. Excluding the first rank from the population, and recalculating the *Pareto Front*, provides the solutions of rank two. All following ranks are calculated with the same procedure.

There is a plethora of algorithms and solution concepts, that may use the notion of *Pareto Optimality* or not. A simplistic approach is to transform the problem into a single objective problem, by defining a linear combination of the multiple objectives as the unique objective function. This simple, practical and straightforward method has significant limitations. Initially, it might be unclear to the designer how to relatively weight all objectives, in a precise way. Moreover, the objectives might be non-commensurable (the units of each objective may be incomparable among them), and an effort of normalizing them in order to combine them might not be practical, feasible or desired.

The result provided by the solution concept of the *Pareto Optimality*, is a set of non-dominated solutions that are considered optimal. The selection of a unique solution among the *Pareto Optimal Set* (in case such is needed to be selected) is left to the discretion of a Decision Maker (DM), who chooses according to the current needs, and based on their own criteria [9], [10].

Overall, a variety of algorithmic approaches allows the designer to decide and precisely define how the trade-off among conflicting objectives can be handled, in order to arrive to a unique, optimal solution. The designer is free to define priorities, relative weights or restrictions among the objectives. Furthermore, it is also possible that a small list of optimal solutions is calculated (*Pareto Optimal Set*), which can then be given to a DM who has the expertise to select the most preferable of these few optimal solutions. Decision support systems aim to facilitate the DM in the final selection of a unique solution. The flexibility in the ways of defining preferences regarding the structure of the problem and the characteristics of the desired optimal solution is a key element of multi-objective optimization.

B. Data gathering

In contrast to works that are based on a simulation of a deployment's environment, this work is based on real data collected in IPS deployments. The data that need to be collected are of two main types:

- the timestamped measurements of raw signal receptions
- the spatiotemporal ground truth

The first category, concerning raw signals, is to be used as an input of offline positioning algorithms that output timestamped position estimates. These estimates are compared with the spatiotemporal ground truth, in order evaluate the performance of the system. In our previous works [2],[7], we have fully characterized a dynamic data gathering methodology. Here, we shortly describe this method, mentioning also other similar methods that are broadly used, as in the positioning competition of the IPIN [11] conference, and could be also used to feed the tuning methodology of this work. Both our proposed method and the one used in the IPIN competition belong to the category of dynamic evaluation (e.g. a moving tester) with predefined geometrical paths.

In these methods, a predefined path needs to be specified. This path consists of a list of positions that will be followed, one after the other, by a tester and will serve as checkpoints. A tester has to follow this predefined path, holding the mobile device that will continuously record all the raw signals that it receives during the path (and/or the position estimates that the positioning system produces), along with the timestamp of each reception. The tester should move on the path, which is composed of the straight linear segments that connect these checkpoints, at a steady pace. The tester has to simply to indicate to the recording application the moment at which he passes over each checkpoint. In this way, every predefined checkpoint is marked with the exact timestamp indicating when the tester passed over it. These methods are subject to a small error that is introduced by the human factor (imprecision of the time or the location of clicking).

At the IPIN competition, the estimates that are evaluated are the most recent estimates obtained before each checkpoint. In our previous works [2],[7], we have proposed a continuous evaluation of all received position estimates. This is achieved by interpolating the ground truth between checkpoints, to obtain the true position of the user for the time of the reception of each position estimate. Assuming a steady pace of the tester throughout the linear segment connecting two checkpoints, the interpolation would introduce no error. It is noteworthy that the tester is not required to maintain the same pace among different segments, but only during each segment.

This method has the disadvantage of adding to the human error that the tester may introduce by the imprecision in the time or the location of clicking (an inherent disadvantage of all similar methods), the interpolation error when not maintaining an actual steady pace between two checkpoints. The range of this possible error can be reduced by a dense checkpoint placement. Overall, despite this minor error addition, the benefits of this method are important for certain use cases. For instance, this continuous evaluation method can fully capture the experience of a user that would actually follow the path while receiving position estimates, as the complete trajectory estimation produced is evaluated. Also, it can provide metrics that concern the totality of the estimated trajectory. These metrics may evaluate the smoothness of the estimated trajectory, offering an indication of how pleasant the produced outcome may be to a user.

Nonetheless, the rest of this work does no assumption about the method used to collect the data, as long as a spatiotemporal ground truth and timestamped raw signal measurements are present. The tests of this work were done with our methodology previously discussed in [2],[7]. It is left to the discretion of the designer though to use the data gathering method that suits their needs and preferences.

III. Related Work

The field of IPS evaluation has attracted the attention of researchers of the field over the last years. Indoor positioning competitions have started becoming popular in relevant conferences [4], [5], [6], [12]. Works have proposed methodologies where a robot replaces the human tester who traverses the test environment defining the ground truth and collecting data [3], [13], [14]. Such robots are equipped with a high accuracy positioning system, whose accuracy is higher by at least one order of magnitude comparing to the system under test. A recent interesting study [15] has focused in measuring the error introduced by humans when they are called to statically place a hand-held device over predefined points, defined by floor or ceiling markers or defined relatively to landmarks of the environment. People unfamiliar with the process participated as a test group, achieving in all three cases (floor, ceiling makers and landmarks) a median error lower than $10cm$. In the floor markers case, that is the one commonly used in competitions, the median error was only $7.1cm$, and the 95th percentile of the error $15cm$. The authors also present the accuracy of a series of benchmarks that use high accuracy positioning systems (as reported in the relevant publications), ranging between 6.7 and $25cm$. The results indicate a similar accuracy between the human defined ground truth and the commonly used reference systems.

Apart from the evaluation methodologies, the creation of testbeds has gained popularity over the last years. In [13], a visual testbed is introduced, in which a robot spans an area recording both the raw signals and the ground truth information throughout the area. These data are offered to be used as a testbed for positioning systems. Moreover, the creators of the IndoorLoc Platform [16], present a testbed based on data collected by humans. This method is used for the offsite track of the IPIN competitions, where the IPSs of different teams compete by running positioning algorithms offline, based on recorded data that they receive.

The metrics used to evaluate positioning systems can be numerous. The statistics of the Euclidean error (mean, median, percentiles, standard deviation, etc.) are the most commonly used. Other metrics, such as the room, floor, or building hit rate [12], the latency of estimation [3] or the smoothness of the estimated trajectory [2], [17] are also used. It is not rare that these metrics are combined in a unique final score [3], [4] based on subjective criteria, introducing a simple case of multiple objective handling.

It is common in the community to discuss the parts of deploying and its requirements, the positioning methods, as well as the ways of evaluating the system's performance. It is not rare though, that the step of how the system is tuned accordingly is left undescribed, mentioning for example an empirical selection of the appropriate settings. For instance, among the five competing teams in the offline track of the 2016 IPIN competition [4], only one focuses in explaining the procedure of optimizing the parameters of their system, according to several objectives. The BlockDox team [4], chose to optimize the hyper parameters of their algorithm hierarchically and greedily, by firstly optimizing the parameters of the floor classification, and only then the location parameters. In this way, when the optimum of each parameter was found, it

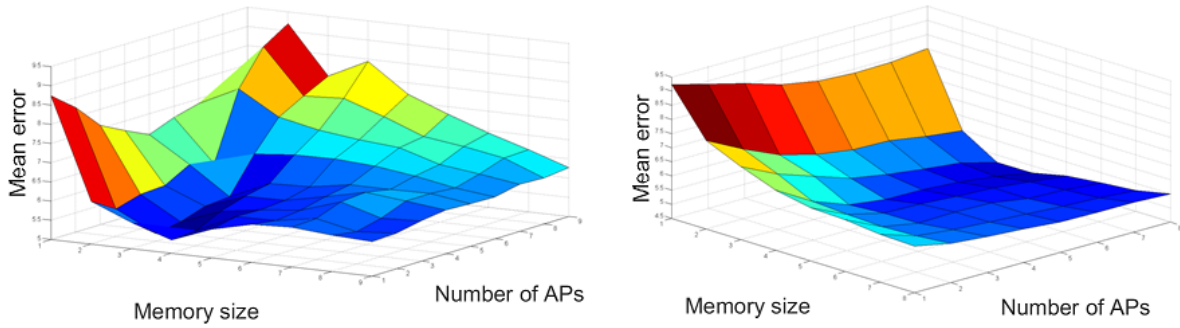

Fig. 2. Average positioning error, depending on two parameters, based on reckornings in two diferent environments.

was turned into a constraint and the optimization procedure continued to optimize the next parameter.

So far, advanced multiobjective optimization techniques have not been extensively use in the field of indoor positioning. In a very interesting sequence of works [18], [19], [20], [21], Domingo-Perez et al. and Martin-Gorostiza et al. introduce multiobjective optimization techniques to solve the optimal sensor placement problem. An adaptation of the state of the art NSGA-II algorithm [22] is used, to infer the *Pareto Optimal Set* of sensor placements, from which a decision maker can choose. Contrary to our current work, these studies concern a pre-deployment task, and therefore are based on simulations of the resulting deployment. To the best of our knowledge, our work is the first that brings the principal solution concept of multiobjective optimization, the *Pareto Optimality*, in indoor positioning problems based on real recorded data.

During the last decades, Multiobjective Optimization Evolutionary Algorithms (MOEA) have been greatly studied. State of the art algorithms, such as SPEA2 [23], NSGA-II [22] and recently its evolvement NSGA-III [24], [25], have been widely used in problems with many objectives, in search of the *Pareto Optimal Set*. The goal of such algorithms is finding the *Pareto Optimal Set* of non-dominated solutions, among which a decision maker should choose one according to their preferences [9], [10]. In this approach, preferences are expressed *a posteriori*. On the other hand, in *a priori* methods the decision maker expresses preferences regarding the objectives in advance and in a formal way. For instance, in some cases the tester is able to combine the objectives *a priori* into a single objective function, or may define a desired reference point in the objective space [26]. Lastly, *interactive methods* allow the DM to intervene during the search, steering the development of the search, as for instance by responding to pairs of comparisons of candidate solutions [27].

According to relevant surveys [9], [28], the *a posteriori* methods are the most used ones. Recent works of the field, have tried to facilitate the task that remains for the DM, that is choosing a final solution among the optimal set of non-dominated solutions. Efficient visualization techniques for *Pareto Front and Set* analysis have been proposed for helping DMs in the selection task [28],[29]. Moreover, methodologies of reducing the number of members in the *Pareto Front* have been proposed to help the DM identify their preferred solution [28].

IV. Proposed Methodology and its Implementation

A. Concept

In our previous work [7], we presented a methodology that allows the tester to make consistent comparisons of parameter settings, or even of different positioning algorithms, by running positioning algorithms offline based on the same recorded data. In this way, a tester is exempt from the tedious task of repeatedly traversing the environment in order to tune the parameters of the positioning system. Furthermore, the offline running of optimization algorithms provided the parameter tuning that gives the best performance of the selected evaluation metric based on a specific recording.

The goal of this work is to move further on, by doing the extra step of combining different kinds of multiplicities, and providing a result that efficiently handles a trade-off of multiple objectives. These multiplicities may concern multiple recordings at the same environment, multiple mobile devices, multiple environments, etc. In Figure 2, we see the performance of an IPS in two environments. It is evident that the best performance for each environment (the lowest mean error in this case) is not achieved by the same parameter values. How should the designer of the system choose among a big variety of parameter settings? This problem becomes even harder when considering hybrid systems, where apart from the parameters that serve the positioning algorithm of each technology used, additional parameters concerning the hybridization of the technologies need to be also properly tuned. To address these issues, we propose the introduction of multiobjective optimization techniques, for optimally tuning an indoor positioning system.

A first approach is to use the simplistic method of reducing the problem to a single objective one, where the single objective is a linear combination of the objectives. In cases where the units of the objectives can easily be combined, and that the designer is certain about the relative relevance of the objectives, this method may be an appropriate way to approach the problem. On the other hand, when combining many objectives, or non-commensurable objectives, the solution concept of the *Pareto Optimal Set* is more appropriate. The notion of *Pareto Dominance* excludes all dominated solutions from the *Pareto Optimal Set*, as it would be irrational to choose them. From the resulting optimal set, the designers/decision makers are free to choose according to their preferences.

Sum of ranking at each objective: In many cases, a supporting system to the final decision making process is required, either to help the DM or to replace them in case the process of selecting a parameter tuning needs to be automated. As a supporting system, we propose a sum of the rankings of each solution according to each objective. The candidate solutions of the optimal set are sorted according to their performance in each objective, and are assigned a ranking at each objective accordingly. Summing the rankings of a solution in all objectives, can give a unitless impression of how well the solution performs in all objectives. Weights can be introduced to the summing of rankings, in order to express a potential difference of importance among the objectives.

B. Implementation

The GpmStudio platform, presented in our previous work [7], is a desktop application that allows a tester who interacts with a user friendly GUI, to access a database of recorded data and run optimization algorithms which calculate optimal parameter settings for the positioning algorithms used. In this work, GpmStudio has been enriched with the addition of the mutliobjective optimization module. The mutliobjective optimization module of GpmStudio supports several algorithms and solution concepts. The main solution concepts of multiobjective optimization and relevant decision support methods discussed in this work (*Pareto Optimality*, *Linear Combination of Objectives*, *Sum of Ranking at Each Objective*) are implemented and supported by GpmStudio.

In the following Section V, we present the results of tests performed with the mutliobjective optimization module of GpmStudio. Several recordings from different test environments are used, along with different evaluation metrics. Each recording contains all receptions throughout a predefined path that traverses all accessible areas of each test environment. All tests are performed utilizing Bluetooth Low Energy (BLE) receptions. The Received Signal Strength (RSS) is used by a weighted centroid algorithm, used and discussed in previous works [30],[31].

The focus of our tests is not on the specific positioning algorithm used and its parameters, but rather on the method with which the performance of the candidate solutions in multiple objectives is handled. Thus, our analysis focuses on the *objective space* and the relevant analysis therein, that holds in any other relevant context without loss of generality, rather than focusing on the *search space* which is bound to the specific example. For the sake of completeness, we mention that the *search space* of the tests of this work is composed by the valid values of the main parameters of the RSS positioning algorithm used. Such parameters are the number of closest APs included in the position estimation calculation, the memory size of the buffer storing the latest RSS, as well as parameters of the filtering used to smooth the sequence of position estimates. Regardless of the specific algorithm and its parameters, in the following section we proceed with a generic exemplification of the proposed methodology, focusing on the tester's selection options regarding the objectives to be used, and the relevant analysis in the *objective space*.

V. Experimental Results

In this section, the results of a variety of tests exemplifying the proposed methodology are presented. In each test, more than one objectives are set to be satisfied. The differences among the objectives can be the different evaluation metrics chosen to evaluate the system, the different recorded data that the offline algorithms utilize, or a combination of them. Concerning the evaluation metrics, usual statistics of the estimation error are used (mean, median, percentiles, etc.). Moreover, a metric concerning the smoothness of the estimated trajectory was desired. As such, the Travelled Distance Ratio (TDR), which was discussed here [2], is used. In short, the TDR is equal to the ratio of the length of the estimated path over the length of the ground truth path. A value close to 1 indicates a smooth trajectory, while a higher value implies that the trajectory suffers from abrupt changes.

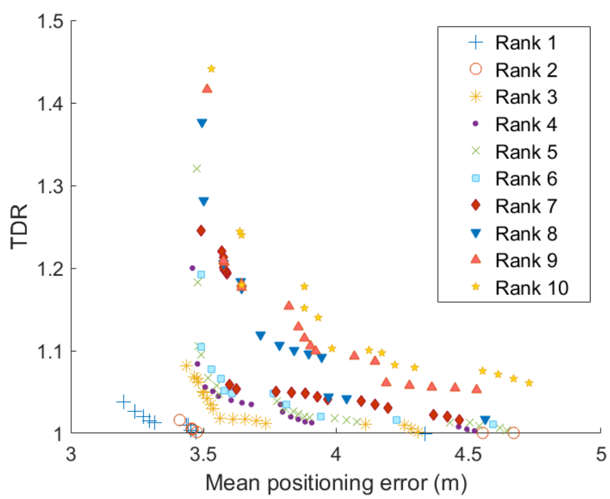

Fig. 3. The 10 first Pareto Ranks of a 2-objective problem.

As a first simple exemplification of our method we present a problem with two objectives. The two objectives are two evaluation metrics: the mean error and the TDR. The recorded data used for both objectives are the same, recorded at an underground parking environment of size $120m$ by $40m$. In Figure 3, the first ten *Pareto Ranks* are presented in the objective space of the problem. The *Pareto Front*, is the set of solutions in the first rank. We see in this plot that the solution of the first two ranks are quite distinguishable from the next ranks, thought really close to each other. The leftmost solutions of Figure 3 have a mean error of $3.2 - 3.3m$, while the solutions of the third rank are mostly above $3.5m$. At the

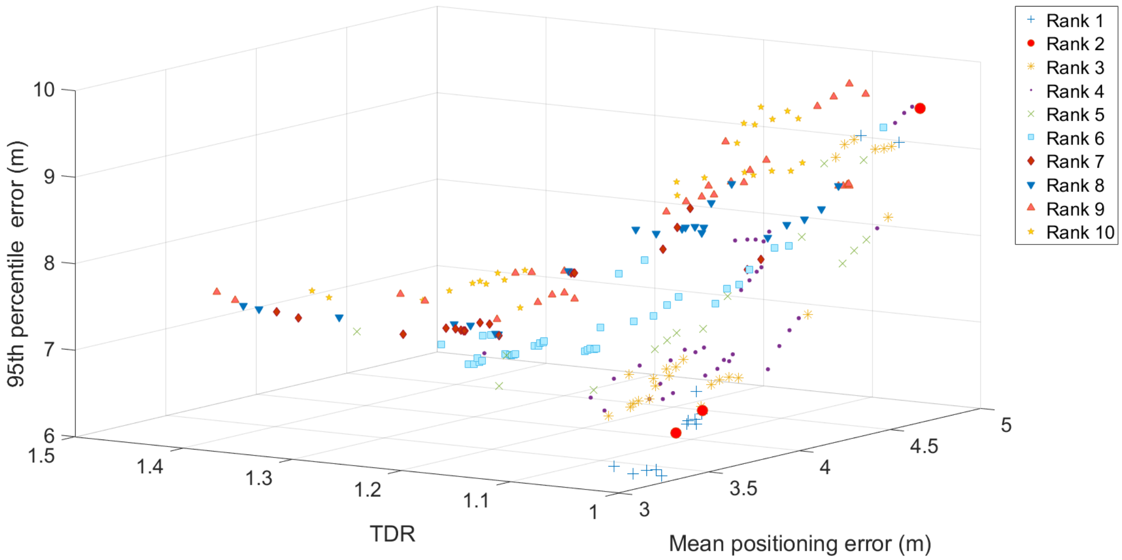

Fig. 4. The 10 first Pareto Ranks of a 3-objective problem.

same time, all TDR values in the range of $1 - 1.1$ can be considered as very satisfactory, setting the leftmost solutions of the *Pareto Front* eligible and appealing for the decision maker. Having this result, the DM may either choose from the front based on the objective values and the relevant preferences or repeat the test adding more objectives, to obtain a more holistic view before selecting a solution.

For some applications, apart from the mean performance of the system, the worst case performance might also be crucial. For this reason, a third objective is added to the previous test: the 95th percentile of error. This objective adds to the calculation the notion of a ‘worst case performance’. In Figure 4, the fronts of this 3-objective problem are presented. It is visually clear that two of the objectives (mean, 95th percentile) seem to have a strong correlation. Nevertheless, the addition of this objective can help the decision maker to potentially reject some solutions. For instance, those members of the *Pareto Front* that seem to have a significantly higher error at the 95th percentile ($> 9m$) than others ($\sim 6m$), could be removed by the DM from the set of candidate solutions, simplifying his decision making.

Another interesting task is to comparatively evaluate the performance of the parameter settings in different environments. In Figure 5, we see the mean positioning error in three test environments: an underground parking of $\sim 4800m^2$ with a sparse access point (AP) deployment, an office environment of a $\sim 450m^2$ common space and a house environment of $\sim 60m^2$. The elements of rank 1 appear spread out in the plot. Using the *Sum of ranking at each objective* method discussed in Subsection IV-A, the rightmost solution of Figure 5 is proposed, which achieves $(3.2m, 2.1m, 1.4m)$ in the three respective objectives, having the lowest sum (equal to 18) among the solutions of the *Pareto Front*. Moreover, the linear combination of objectives could be used in this case, as the objectives are commensurable. Using a simple average of the three objective scores as a unique objective, the same solution results having the lowest value among the solutions of the Pareto Front. It is noteworthy that the same solution, meaning the same parameter setting, appears in the Pareto Front of the two previous problems (Figures 3 and 4).

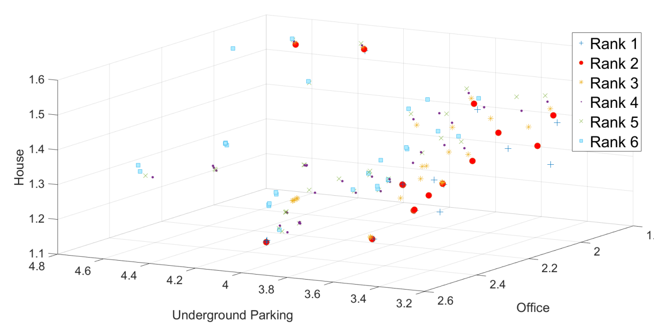

Fig. 5. The 6 first Pareto Ranks of the mean error at 3 deployments.

Several tests were executed either by combining pairs and triads of objectives, or by combining many objectives. For instance, three different devices were used to record data at the environment of the underground parking. The mean error values of the three objectives formed another test that was performed. In Figure 6, the *objective space* of this problem is presented, along with the ten first Pareto ranks. The solutions, especially those of the *Pareto Front*, are much less spread out in the *objective space*, when compared with Figure 5, as the recordings of three devices in the same environment seem to be less contradictory objectives, comparing to recordings at three environments of very different characteristics.

When combining all the objectives of all previous tests in a single problem, the nature of the problem changes drastically. In problems with more than three dimensions, a graphical representation is possible only for a subspace of

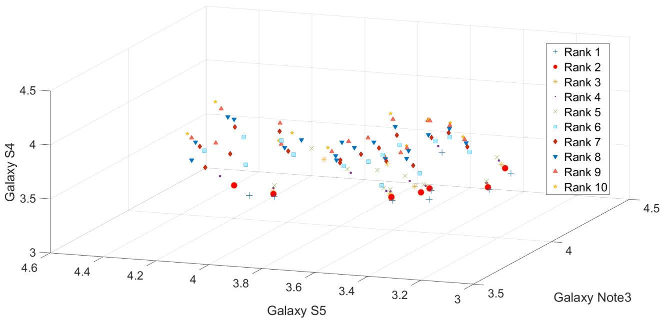

Fig. 6. The 10 first Pareto Ranks of the mean error with 3 devices.

the multidimensional objective space, not allowing a reliable visual overview to the decision maker. Moreover, the number of solutions appearing in the *Pareto Front* increase drastically. The four problems of Figures 3-6, have $10, 13, 17$ and 8 members in their *Pareto Fronts* respectively. On the other hand, when running the problem with 18 objectives, produced by combining 3 evaluation metrics (mean, $95th$ percentile, TDR) with 6 recordings (3 devices at the parking, 2 at the office and 1 at the house environment) the results are not really helpful for the DM. Out of 1125 possible solutions defined as the search space of the problem, 843 appear in the *Pareto Front*, offering no significant information to the DM. Similarly, the problem with 6 objectives (the mean error of the 6 recordings) has 72 members in its *Pareto Front*.

On the other hand, a solution that appears in the Pareto Fronts of all (or of most of the) smaller tested problems that have $2-3$ objectives, can be a solution to be chosen, as it efficiently handles the trade-off. For instance, there is only one solution appearing in the *Pareto Fronts* of all four problems previously presented (Figures 3-6). This fact sets this parameter setting as a perfect candidate for the default tuning of the tested system.

VI. Conclusions and Future Work

In this work, a complete formal workflow of a tuning methodology for indoor positioning systems has been presented. The first step to be performed is the recording of the required data (spatiotemporal ground truth and timestamped raw signal receptions) at the test environment. Having collected those data, the tester can make consistent comparisons of different parameter settings, by running offline positioning algorithms. In this way, the tester is exempt from the tedious task of traversing repeatedly the test environment for testing different settings of the system. In addition, contrary to the repetitive online testing procedure where the conditions of the test cannot be fully controlled (the noise level, the environment conditions, etc.), running offline positioning algorithms over the same recorded data guarantees the consistency of the tests.

The innovative step forward of this work is the ability to combine many objectives to be simultaneously optimized, offered by the introduction of multiobjective optimization techniques. With this approach, multiple evaluation metrics, several recordings at the same environment, different environments or devices, and other kinds of multiplicities can be combined in the effort of finding a more holistic evaluation for optimizing the system's performance.

Data recordings collected from three test environments with different devices, have been used to centrally perform tests and extract information in a formal way regarding the optimal parameter selection for an IPS under test. In the absence of methodologies such as the proposed one, this procedure is usually simplified in being the outcome of an empirical parameter selection by the system's expert. With the proposed methodology, new algorithms can be quickly tuned based on existing recorded data, while the empirically selected default parameter setting of existing algorithms can be evaluated and potentially improved. The trade-off of different evaluation metrics can be efficiently handled by selecting solutions from the resulting *Pareto Optimal Set*. Similarly, trade-offs among different environments or devices used can be also efficiently addressed.

To facilitate the decision maker in choosing a unique solution, we have tested two support systems: the *linear combination of objectives* for commensurable objectives and the *Sum of ranking at each objective*. When combining a large number of objectives (> 4) in a single problem, the number of solutions appearing in the *Pareto Optimal Set* increases significantly. To simplify such cases, the big problem can be decomposed to smaller ones, with fewer objectives each. The final selection can be done by choosing solutions that appear in the *Pareto Fronts* of all (or most) smaller problems.

In the future, we intent to systematically collect data from all new environments where we deploy positioning systems and further investigate efficient ways of handling 'big data' in a unique problem. Moreover, we are investigating the potential use of crowdsourced data, and evaluating the feasibility of utilizing existing crowdsourcing platforms [16], [32].

So far, we have been collecting in our recordings all type of data that could be useful for a hybrid provider. Apart from the BLE receptions utilized for the tests of this work, sensor data (accelerometer, barometer, light sensor, etc.), as well as WiFi and GPS recordings were stored. One future goal is to integrate hybrid providers in the calculations of the multiobjective optimization module of the GpmStudio platform.

In problems that the whole *search space* can be searched in feasible time frames, the *Linear combination of objectives* and the *Pareto Optimal Set* can be calculated by a full spanning of the whole search space. For very big problems, heuristic approaches come to address the issues of computational complexity. The commonly used *NSGA-II* algorithm [22] is implemented in GpmSudio, with a view to address computationally challenging scenarios. All tests performed in this work had a computational complexity that sets the full search of the search space to be feasible. Nevertheless, as the search space may increase in the future with the addition of hybrid algorithms, state of the art heuristic methods should prove to be efficient in providing good approximations of the *Pareto Optimal Set*.

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