Best Practices for Model Calibration in Smartphone-based Indoor Positioning Systems

Francesco Furfari, Antonino Crivello, Paolo Baronti, Michele Girolami and Paolo Barsocchi
Institute of Information Science and Technologies (ISTI-CNR)
Email: name.surname@isti.cnr.it

***Abstract*—User location and tracking information are increasingly used for contact tracing and social community detection. Indoor positioning and indoor navigation systems are reaching good performances in several realistic scenarios. After an evaluation exclusively done through simulations, nowadays, these systems are trying to reach robust performances and good accuracy in heterogeneous environments. Problems are manifold as each environment presents a structure that strongly affects inertial sensors and radio signal propagation. Generally, systems showing the best performances rely on an extended knowledge of the indoor map. Moreover, they implement a model for pedestrian dynamics in terms of e.g step length, stride and the behaviour of the target users. Experimental results obtained during realistic indoor competitions, clearly show that performances drop when such systems are used in unseen scenarios in which an external user test the proposed solution. In fact, many parameters that are generally calibrated and set to maximize the performances might not work as expected. In this paper, we highlight which best practices should be applied for model calibration in smartphone-based indoor positioning systems. We describe a reference system based on a particle filter, and we show the most relevant parameters and the main factors that are generally in common with all similar systems in the literature. We also present the *Run-Once* tool for reaching optimal parameters, highlighting those best practices that should be applied to indoor positioning systems to maximize their performances and improve their robustness.**

***Index Terms*—model calibration, indoor localization, smartphone-based, particle filter, system evaluation**

I. Introduction and motivation

In the last decade, we have witnessed the growing interest of the scientific community regarding indoor localization systems (ILS) [1], [2]. In particular, easy-to-use smartphone-based indoor localization systems have been gaining the attention of the community [3]. As a matter of fact, the evolution of on-board sensing technologies makes the smartphone a valuable alternative to infer the user position. The user's location is essential in many application scenarios, ranging from contact tracing system, to tracking and navigation services. In [4], we started analysing how on-board sensing technologies have evolved in the last years, from 2014 to 2019 and we showed a trend towards the improvement of the overall performance. Lastly, we provided insights into the role that sensing units and software algorithms play in the evolution of smartphone-based indoor localisation solutions [3], [5], [6]. In particular, by reviewing eleven leading applications, we observed that the current trend shows a massive use of IMU sensors [7], wireless interfaces, and context data (such as indoor maps) in order to infer and track the user's position. All these kinds of sensed and retrieved information are then put together with a data-fusion strategy, such as particle or Kalman filters [8], [9].

However, we observe that such technological trend strongly relies on the environment and on the person's behaviour using the system [10], [11]. As a result, it is often required a time-consuming calibration phase (based on a ground-truth path) in order to identify the optimal parameters to use in a specific environment. In practice, the user repeats the same ground-truth path several times, changing the setting parameters and finding those with the best localization error performance. While, in this work, we propose an alternative approach to the traditional ground-truth calibration phase. We propose a two-step methodology: i) to perform one single raw-data collection phase, ii) to exhaustively explore the collected data to find the optimal parameters leading to optimal performance in terms of localization error. Furthermore, in this paper we highlight the best practices that should be applied to indoor localization systems in order to maximize their performances and improve the robustness of the system. We describe which best practices should be applied for model calibration in smartphone-based indoor localization systems, describing a reference system based on particle filtering, and showing those parameters and the main settings that are generally in common with all similar systems in the literature. We finally provide a novel perspective to the calibration problem as, to the best of our knowledge, we are not aware of *Run-Once* tools capable of evaluating the overall performance of the localization system by evaluating both the uncertainties introduced by the environment and the uncertainties introduced by user behaviour.

II. Working principles of smartphone-based indoor positioning systems

Smartphone-based systems for indoor positioning relies on accurate knowledge of environmental factors which are accurately modelled [12]. In fact, information about distances from Wi-Fi Access Points, anchors or any details about the indoor map are essential to obtain good accuracy. Nowadays, the main challenge in the field of indoor positioning and indoor navigation is reaching a robust generalization, which means

Corresponding author: A. Crivello {antonino.crivello@isti.cnr.it}

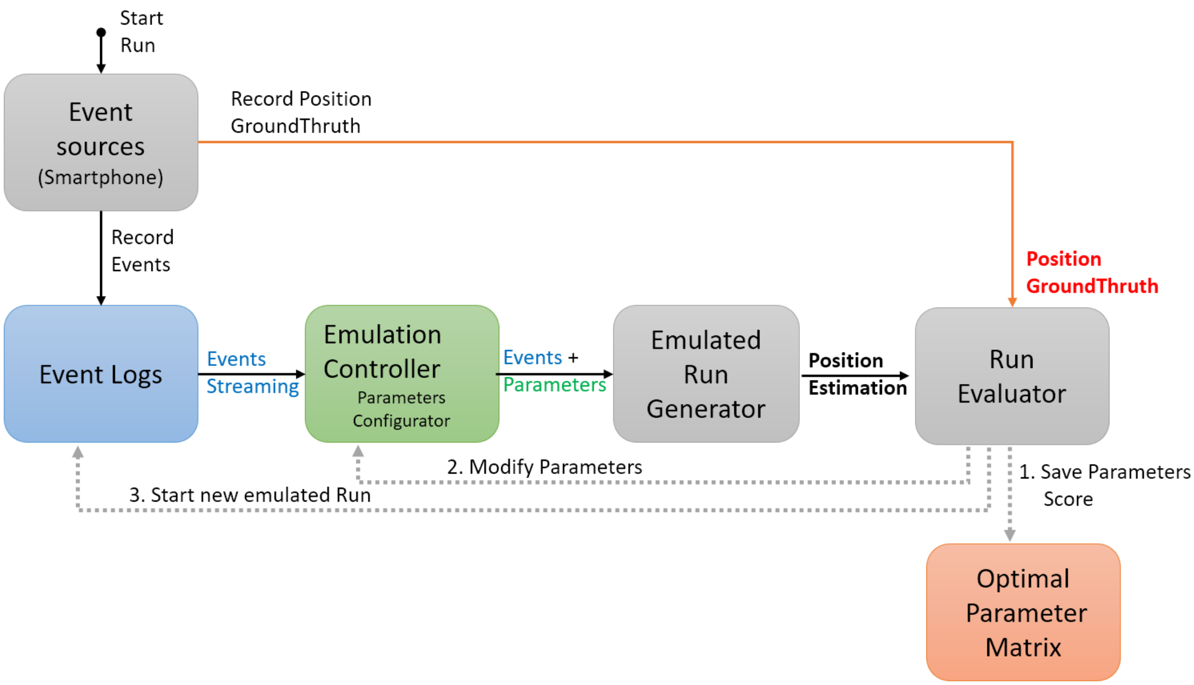


Fig. 1: The process to calibrate smartphone-based indoor localization systems: saving all the occurred events during the trial, fixing the ILS parameters, emulating the IL algorithm, evaluating the performance, and closing the loop with new ILS parameters.

the systems' capability to well perform also under uncertain circumstances given by factors that change dynamically. An example of these uncertainties is the unknown number of people in the environment, which strongly affects radio signals and their propagation. Furthermore, smartphone-based systems are developed to be used in a real scenario. Thus a crucial aspect is the system's ability to generalize different aspects of the human's posture in terms of height, stride length, step length and pedestrian speed. During the calibration phase, besides these aspects mainly related to the step dynamics, a data fusion algorithm requires to also set-up other parameters. As an example, the dimension of the particle's cloud should be investigated. Basically, the model calibration for smartphone-based system should lead to finding an optimal combination of several factors. The goal of the proposed *Run-Once* tool is reaching an optimal parameter set in model calibration by following the process shown in Fig. 1. We suggest the use of a closed-loop scheme. The process starts by recording all the data available from the built-in sensors during a run, namely the raw-data. Successively, the raw-data are pre-processed and new events are evaluated (e.g. a new step detected, a new Wi-Fi scan). Data and events are given in input to the emulation controller which contains a parameters configurator. By combining parameters, configuration and data, the run generator is able to provide position estimation as input of the run evaluator module. Finally, by comparing ground-truth and estimated position, the run evaluator module allows to save the performance obtained applying the chosen parameters and, finally, to modify the configuration starting new emulated runs.

As an example, in this paper, we refer to an indoor localization system based on a particle filter, but the same concept could be applied to every data fusion algorithm developed for indoor positioning purposes.

The system shown in this paper is an example for describing best practices in model calibration relies upon particle filter. In our implementation, smartphone records mainly two different events: new steps detected and radio signals scans. The step detector algorithm relies on the step detector as implemented in modern OS, such as Android and iOS.

The flow to determine the best practices starts from a common point among all the smartphone-based solutions for indoor positioning. These systems collect data from the sensors available. In literature, systems have several similarities [13]: (a) collecting information from all the available sensors, (b) implementing a strategy for data processing, and (c) predicting positions using a data fusion technique (e.g., Kalman filter, extended kalman filter, particle filter). Typically, pedestrian dynamics and their trajectories are estimated through a pedestrian dead reckoning approach (PDR). PDR is a process for evaluating users' current position by using the knowledge of a previous position and updating the position by estimating speeds over elapsed time and course. For this purpose, data from gyroscope, accelerometers, magnetometer and compass are processed together for estimating a new step, step length, attitude, and heading. Although these evaluations generally suffer from noise and drift, mainly due to cheap sensors and weak calibration, they are generally combined with map information and radio signals.

III. Run-Once: A Tool for calibration and evaluation in a closed-loop

This section describes the idea behind the proposed tool. Furthermore, we will show the data collection phase detailing challenges and problems in designing an experimental campaign. The process we show in this paper could be easily adapted to every model calibration and experimental setting drawn for smartphone-based indoor positioning.

An experimental campaign starts by defining a path that contains a number of key-points. This path ideally will cover all the indoor maps crossing all the areas of interest. As meaningful an example, the evaluation could be performed by adopting the EvAAL framework, which requires ground-truth positions and estimated positions and is able to produce performances statistics following the suggestions in [11]. Basically, the evaluation is performed on different key points displaced into the environment. During a trial, the user walks at a natural pace along a loosely-defined reference path. The path connects some key-points on the floor. The list of time marks, together with the ID and positions of the key-points, will be the ground truth used by the measurement app to compute the localisation errors. In our implementation, the positioning system estimates the user's location as WGS84 coordinates `x,y` with a sampling frequency of 2Hz and the timestamp expressed in milliseconds. The accuracy of the system is evaluated considering the third quartile of the localisation errors at the key-points. The localisation error is the distance between the position estimation and the real position of a key-point.

Estimated positions strongly rely on several parameters of the chosen data fusion algorithm, the quality of the built-in sensors and other environmental parameters which could influence radio signal propagation. In the testing phase, if the algorithm only saves estimated positions, a small variation of a single parameter would result in executing a new experiment. Experiments are particularly time and effort consuming in this field; every trial requires walking along a predefined path, involving different users to enhance system robustness and, moreover, trying to reproduce in an identical manner walking speed, body position when the user cross a key-point and environmental characteristics. For example, if the target scenario is a public building or a hospital, people's presence in the environment and their behaviour could strongly influence the radio signal propagation. Similarly, doors and fire doors are expected to remain in the same configuration (i.e., closed or opened) for each experiment.

The number of parameters for such complex systems is significant and lead to an n-dimensional problem. Consequently,

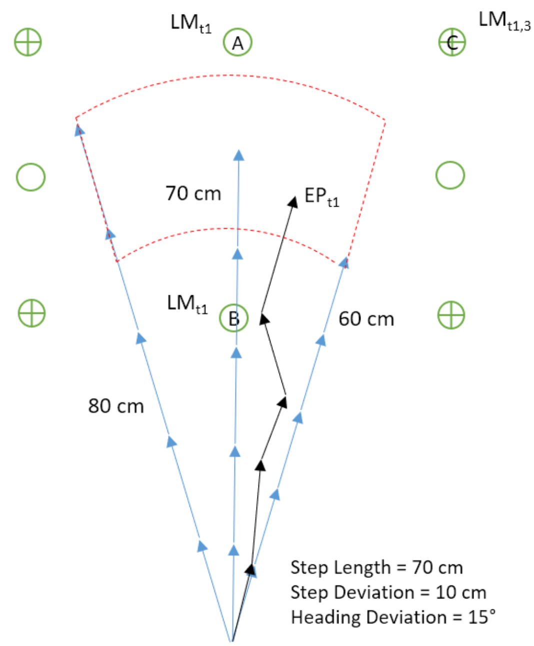


Fig. 2: deviation

in real-world scenario, finding an optimal solution would be burdensome.

In this paper, our data fusion algorithm is a particle filter. Fig. 2 shows an example of particle movements related to a set of parameters. In detail, setting step length (70 cm), step deviation (10 cm) and heading deviation (15°), after five steps performed along the line B, a particle will be moved into the area within the red dotted lines. The black segments connect all the five estimated positions evaluated from t0 to t1, and represent the likely movement of a single particle. Supposing one ground-truth key-point is the green circle A, it means the system is underestimating the distance walked by the user: all particles that fall into the red zone will never reach circle A unless the experiment is repeated, trying to understand if it is convenient to change the average length of the step or just its deviation (i.e. 75 cm or 15 cm). Similarly, if the ground-truth is placed on the green circle on the side of blue lines, it means the system is underestimating step length and heading.

The main suggestion for avoiding the need to perform a new experiment is to collect and save the time series (data sensors, timestamp) for all the events that helped to determine the estimate of the position along the chosen path. Saving all the occurred events, for example, Wi-Fi scan and the sequence of step detected, easily allow running the data fusion algorithm more times and evaluating several times errors, performances and statistics. Basically, following our guidelines, a positioning system benefits from experimental data retrieved by real users and an additional set of data obtained varying all the algorithm

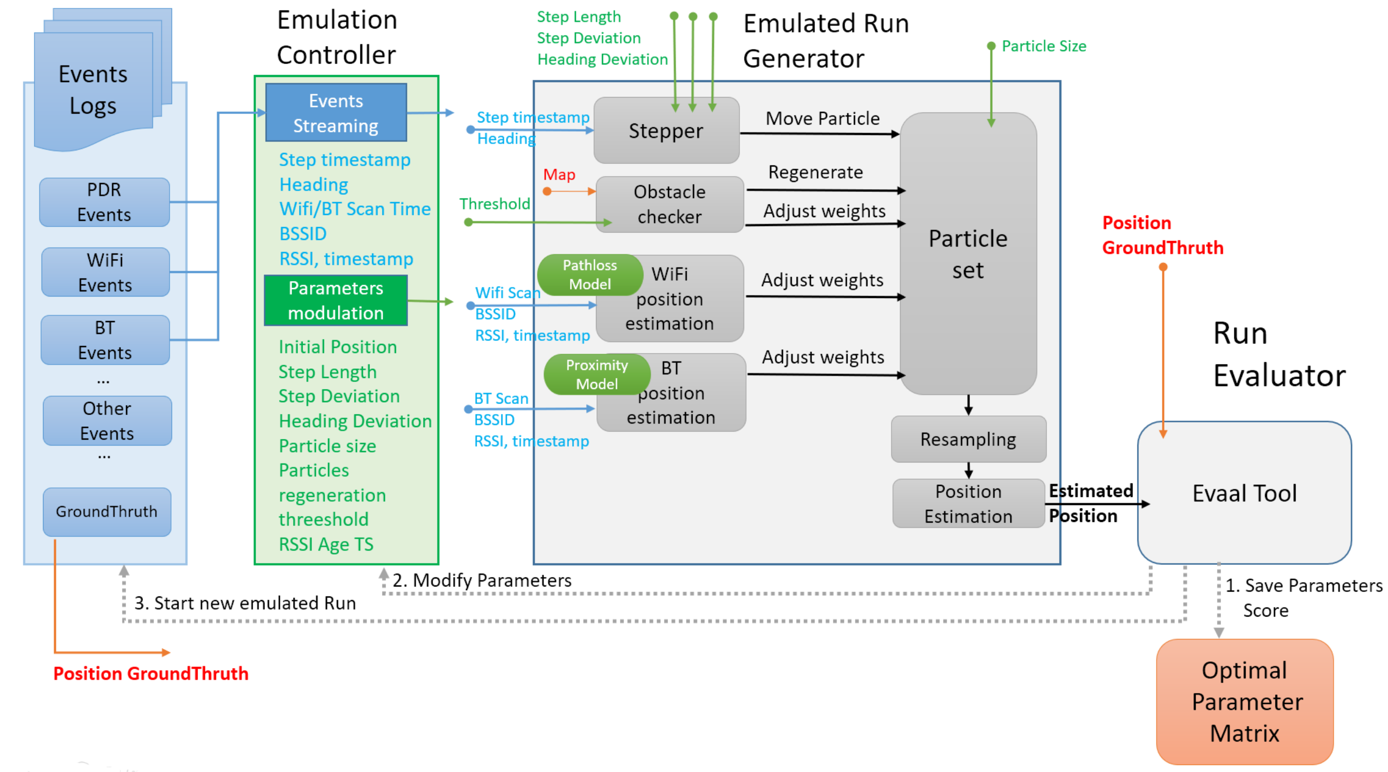


Fig. 3: The implemented solution consists of three main blocks: 1) Logs all the occurred events, 2) Control the emulation, 3) Run the emulation, 4) Evaluate the runs with the EvAAL framework.

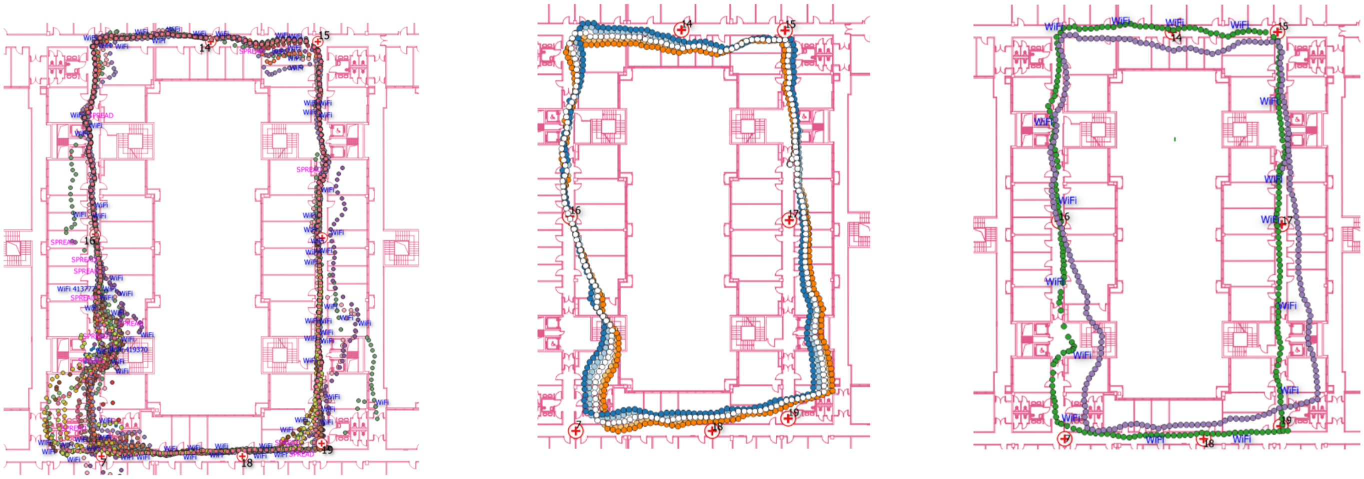
parameters. In fact, a new parameter configuration as input of the algorithm will produce new results as output, improving the overall robustness to stochastic variables and processes.

Fig. 3 shows in detail *Run-Once*. It is worth to notice that the goal of this paper is to show best practices for calibration and evaluation of indoor positioning systems. The idea behind the tool is widely applicable to design every experimental campaign of indoor positioning. The blue block, namely events logs, represent the module responsible for logging all the events regarding pedestrian dead reckoning, Wi-Fi scan, Bluetooth scan or other events detected. The emulation controller block is responsible to perform event streaming towards the run generator and to set parameters configuration. The run generator will be finally able to estimate new trajectories of each particle along the time, thus producing new estimated positions. The latter will be evaluated and compared with the ground-truth positions using the evaluation tool and the recommendations contained in EvAAL framework [11]. The EvAAL framework assigns a score to every set of parameters. Subsequently, the parameters can be adjusted manually or semi-automatically through scripts, and the process starts again in closed loop. An important feature of *Run-Once* is its modularity. In fact, to better understand underlying correlation between different modules, the run generator allows to enable/disable single modules. Analyzing the performances by combining different parameters, the system architect may easily choose the best set to improve the robustness without neglecting the accuracy.

IV. Best practice for improving the performances

In this section we shown some representative examples of enhancement using the proposed tool. Fig. 4 shows the estimated path obtained by a single data collection in our office building. The pink markers reported in Fig. 4a represent the estimated positions during a trial performed physically by a user walking along the corridors of the office and completing a rectangular path. Green markers (as well as the other markers) represent the same experiment emulated offline by the run generator module, that is disabling the module 'obstacle checker' that, in our implementation, is designed to detect any collision with an obstacle (e.g., walls, forbidden areas). By disabling such module, particles' weight is not correctly updated, as a result the estimated position is not correct. Fig. 4b shows the same experiment, by varying heading deviation and step length parameters. Fig. 4c shows the impact on the particle size enabling the obstacle checker and fixing the step length.

Parameters: The graphical interface of the emulator allows us to easily understand the impact of varying the parameters.



(a) disabling the obstacle checker

(b) changing person parameters: heading deviation and step length

(c) changing environment parameters: particle size

Fig. 4: Graphical representation of the estimated path super-imposed to a geo-referenced indoor map.

Generally, the admissible values for the parameters is n-dimensional, and it becomes difficult to understand the optimal setting. Parameters can refer to features of the *environment*, of the *person* performing the test, or of the *localization model* used to process the estimated position. In our reference implementation, the number of particles for the particle filter is influenced by the type of environment, e.g. walking along a corridor or in an open space. The length of the step depends on the person and sensor sensitivity used by the smartphone. Finally, by using the multilateration of radio signals detectable in the environment, there are several calibration parameters to consider, depending on the path-loss or proximity model used.

Impact of parameters: The influence and the impact of the different types of parameters should be well defined, not only to achieve greater precision but also for greater robustness of the solutions. The experience we gained in systems evaluation described also in [10], shows us that systems appear complex enough to be deployed in every scenario but, nevertheless, models over-fit on specific characteristics of a limited group of users. Therefore, the performed calibration model is generally inadequate when the system is used by new users under new conditions.

Best practices: In summary, we claim the needs of reaching system robustness without neglecting the overall accuracy. To reach such an ambitious goal, the system calibration phase should be performed following the suggestion in Fig. 1. The best practices we propose are summarized as follows.

- The system should log every relevant event and also collect the raw-data from the sensor units used to estimate the position;
- Researchers should explicit consider all the parameters affecting the implemented algorithm, by avoiding hard-coded values;
- An experimental campaign should be designed so that to involve users following a non-trivial path in areas of interest. Users should also be un-aware of the internal design of the localization system, so that to avoid a bias during the experimental tests;
- A run generator should be developed in order to control and change every parameter previously identified. If it is not possible to exactly repeat a trial, new trials could be generated using a run generator;
- From a closed-loop perspective, parameters can be modified, and the system can be evaluated by observing the influence of one (or few) parameters at a time.

Optimal solutions: The last point concerns the complexity of the problem, which can generally offer multiple optimal solutions. How to move through the n-dimensional space of the parameters.

Run-Once can conceptually be represented as a P-Diagram (Fig. 5) for optimization of dynamic problems that can be faced with the Taguchi methodology [14].

The Taguchi methodology proposes to standardize the optimization process in eight steps, including identifying an objective function, the control factors and the range of values they assume, selecting a determined number of parameters from which to generate an orthogonal basis of control vectors with respect to conduct the experiments and evaluate the performance and optimal configurations.

Future directions: Reaching an overall robustness would open to a new scenario in this field. For example, it could enable more efficient and effective cooperation and interoperability among different localization systems. Applying the ideas described in [15] in a close future different indoor localization systems could cooperate, sharing the information about their working principles in a manifest and allowing, from a user per-

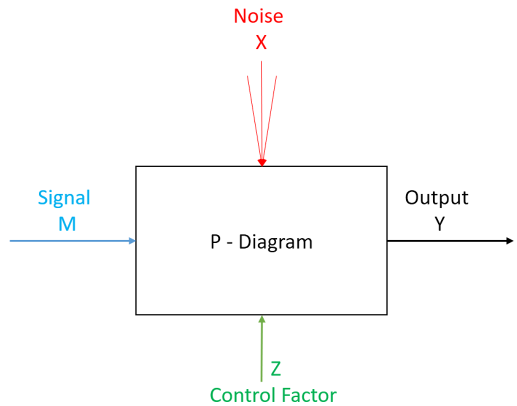


Fig. 5: Emulation Tool as Dynamic Problem Optimation

spective, to automatically discover and retrieve relevant features of the environment with suggested parameter settings to interact with the infrastructure available on the site [16]. Therefore the proposed tool is important not only to improve the accuracy of localization algorithms but also for administrative purposes, to easy configuration settings and realize transparent and seamless integration of localization systems.

V. Conclusions

Indoor localization systems are gaining increasing attention both from the industry and from the academia. Many technologies have been using and integrating with the goal of delivering to the community, a similar user experience for GNSS-based navigation systems commonly adopted on outdoor scenarios. In this paper, we focus on the configuration process for such systems, namely the process of identifying the optimal parameter settings for a specific scenario. In particular, we analyse in this work which best practices should be applied for model calibration in smartphone-based indoor positioning systems. We describe a reference system based on particle filtering of data collected from inertial sensors, and we show the most relevant parameters and the main factors that are generally determinant for increasing the performance. We also present a workflow for reaching optimal parameters, highlighting those best practices that should be applied to indoor positioning systems to maximize their performances and improve their robustness. In future work, it is our intention to investigate the applicability of Taguchi methodology to optimize and reduce the number of experiments to be conducted to find configurations of optimal parameters.

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