Analyzing the Data-Driven Approach of Dynamically Estimating Positioning Accuracy

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Abstract—The primary expectation from positioning systems is for them to provide the users with reliable estimates of their position. An additional information that can greatly help the users utilize the position estimate is the level of uncertainty that a positioning system assigns to the position estimate it produced. The concept of dynamically estimating the accuracy of position estimates of fingerprinting positioning systems has been sporadically discussed over the last decade in the literature of the field, where mainly handcrafted rules based on domain knowledge have been proposed. The emergence of IoT devices and the proliferation of data from Low Power Wide Area Networks (LPWANs) has facilitated the conceptualization of data-driven methods of determining the estimated certainty over position estimates. In this work, we analyze the data-driven based determination of the Dynamic Accuracy Estimation (DAE), considering it in the broader context of a positioning system. More specifically, with the use of a public LoRaWAN dataset, the current work analyses: the repartition of the available training set between the tasks of determining the location estimates and the DAE, the concept of selecting a subset of the most reliable estimates, and the impact that the spatial distribution of the data has to the accuracy of the DAE. The work provides a wide overview of the data-driven approach of DAE determination in the context of the overall design of a positioning system.

Keywords—IoT, Fingerprinting, Error Estimation, LoRaWAN, LPWAN, Localization, Positioning, Reproducibility, Machine Learning

I. INTRODUCTION

The interest over the utilization of IoT networks has been increasing over the recent years. Moreover, the massive amounts of data that the IoT connectivity produces, invite for intelligent ways of utilizing this massive volume of information. In this direction, the emergence of Low Power Wide Area Networks (LPWANs) has offered the grounds for energy efficient localization applications. The data-driven methods of localization, which are a common solution for indoor positioning systems, called fingerprinting methods, have been recently applied in outdoor IoT settings [1], [2], [3], [4], [5]. Apart from the production of location estimates, the positioning systems may also produce a Dynamic Accuracy Estimation (DAE), which quantifies the certainty of the system over its produced location estimate [6], [7].

In this work, we elaborate on the concept of Dynamic Accuracy Estimation, in a data-driven approach. DAE can be perceived as the claimed accuracy of a position estimate, according to the positioning system that produced said estimate. As the name states, DAE is produced dynamically, in an on-line manner, along with the production of the location estimates, without having access to the ground truth location.

In order to calculate the DAE in a data-driven manner, a model is trained, receiving the same feature set as the model that produces the position estimates, while the targets of the two models are different. Instead of training the model having as target the ground truth location, as the positioning model does, the target this time is the distance between the ground truth location and the location estimate produced by the positioning model. Thus, this second model learns to predict the amount of the localization error of the location estimates of the first model. In this way, when the system processes a new reception of signals at an unknown location, the two models will be able to produce: (i) a location estimate, provided by the first (positioning) model, and (ii) an estimate of the localization error, given by the second (DAE related) model.

The potential of the use of DAE depends on the particularities of the business case in which a positioning system is meant to be applied. The main idea behind the use of DAE is that it can be used either for offering to the user a confidence level along with each position estimate, or for facilitating a higher-level system in taking related decisions. Two examples of such decision making could be the use of DAE in hand-off algorithms which could use the DAE to switch among different technologies, or the option to present to the user only a percentage of the most accurate position estimates, should that suit a particular business case. For instance, in business cases where a very frequent update of the location estimates is not required, the system could select to return only a subset of the produced position estimates based on their accuracy as estimated by the DAE. This concept is exemplified in one of the tests presented in this work.

II. RELATED WORK

The concept of on-line error estimation of the location estimates that a positioning system produces has been sporadically studied in the literature of the field, through more than a decade. This concept of error prediction is far from constituting a usually advertised feature of indoor positioning systems and relevant publications, or a subject of comparison in the competitions of the field [8] which mainly compare the accuracy of the location predictions. Nevertheless, a framework of evaluating positioning systems, proposed in 2016 [9].
lists the DAE as one of the metrics that the framework can evaluate. Different approaches have been proposed regarding the way in which the certainty over a produced location estimate can be estimated. The categorical division of these approaches can be described by two main types of methods.

In the first category of the rule-based methods, which monopolized the literature of the field for a long time, the aim is to hand-craft analytic or heuristic methods of estimating the quality of location estimates. A variety of rule-based methods has been proposed, such as using: the average geographic distance between the nearest neighbors [10], improved by factoring in as a weight the proximity of the nearest neighbors and also introducing the location estimate [11], or by introducing a weighted average of likelihoods instead of a simple average of euclidean distances [12]; a mechanism to calculate a Dilution-of-Precision-like value [13]; the geographic distance from the furthest neighbor to the location estimate [14]; the spatial distribution of the latest position estimates [15], [16]; and an offline method based on the Cramer-Rao Lower Bound ratio [17].

On the other hand, the data-driven methods, which constitute the second category, that recently emerged, aim at learning to predict the quality of location estimates based on a dataset used to train a machine learning model. The current work focuses on this second, data-driven approach. A surprisingly early proposal of a data-driven method of DAE determination dates back in 2007, when Dearman et al. [15] proposed a multiple linear regression approach. That work uses designer-defined features based on the RSS fingerprints to train a model which predicts the localization error of a location estimate produced by a new signal reception.

A pair of recent works, by Lemic et al. [6] and Lemic and Famaey [7] has revived the data-driven approach. The availability of large datasets of IoT-based, LPWAN networks, such as the ones presented by Aernouts et al. [1], lays a proper ground for such approaches. In 2019, Lemic et al. [6] presented an extensive analysis of the performance of several well-known regression algorithms (linear regression with regularizers, kNN, SVN, Random Forests) on predicting the positioning error of location estimates. In a natural continuation of that work [6], Lemic and Famaey [7] investigated the capabilities of Neural Networks (NN) in addressing the same regression problem. By utilizing the LPWAN datasets of [1], the authors show that the NN approach outperforms kNN, which was the best performing method of [6].

In the current work, we further analyze the data-driven based determination of Dynamic Accuracy Estimation (DAE), considering it in the context of a broader positioning system. In this context, we focus on points such as the repartition of the available training data between the models producing location estimates and DAE estimates, the location estimate selection based on the DAE, as well as the impact of the spatial distribution of the data to the DAE.

### III. The Dataset Used

Aernouts et al. [1] have made publicly available 3 fingerprinting datasets of Low Power Wide Area Networks. Two of these datasets were collected in the urban area of Antwerp, one using Sigfox and another using LoRaWAN. The third dataset was collected in the rural area between the towns of Antwerp and Ghent, using Sigfox. Since the initial publication, two major updates have been published. In this work, the latest version (1.3) of the LoRaWAN dataset has been utilized, which contains 130430 LoRaWAN messages in the urban area of Antwerp. The fingerprints are collected in an area of approximately 53 square kilometers, though the majority of them lay in the central area of Antwerp which is approximately half the size.

Fingerprinting techniques are often compared to their counterpart, the ranging techniques such as multilateration, which require a minimum of 3 receiving gateways to produce a unique position estimate. Even if satisfying results can be obtained with fingerprinting methods when using messages with fewer than 3 receiving gateways, in this work we limit the dataset to the messages containing at least 3 receiving gateways. A total of 75054 messages with fewer than 3 receiving gateways are dropped, while 55375 messages with at least 3 receiving gateways are kept to be used. A common train, validation, test set split will be used for the experiments of this work. We will use 70% of the dataset for training purposes, 15% for validation, and 15% as a test set for reporting the models’ performance. In the following sections we will elaborate on the way the training set is repartitioned among two distinct training tasks: the production of position estimates and the production of dynamic accuracy estimates.

### IV. Methodology and Terminology

In the setting used in the current work, each message reception obtained by the network of LoRa gateways will be utilized to produce a position estimate, accompanied with a degree of certainty that the system assigns to the position it produced. In this work, this second estimate will be referred to as the Dynamic Accuracy Estimation (DAE), since it concerns an estimation over the accuracy of produced location estimates, which is produced dynamically, as the system operates. The relevant literature refers to DAE either as an ‘accuracy’ [13], [14], [17] or as ‘error’ [18], [10], [11], [6], [12] estimation, or even as ‘confidence’ [15]. The actual, accurate measurement of the error/accuracy of a position estimate, can only become available when the ground truth location is known and its distance from the location estimate produced by the positioning system is measured.

For the positioning system to produce this twofold estimation, two data-driven models are trained. The first model, \( M_1 \), is trained to predict the locations from which the messages transmissions were made by the mobile device, based on the signals received by the LoRaWAN gateways. In training time, the received signals (in this case the RSS values received at each gateway) are the input features fed to the model, while the target variables are the latitude and longitude of the ground
truth location $\text{Loc}_{GT}$. In testing time, a set of previously unseen message receptions are fed to the trained model $M_1$ which produces location estimates $\text{Loc}_{est}$. The error of each produced estimate is defined as the geographic distance between $\text{Loc}_{GT}$ and $\text{Loc}_{est}$. In this work, the Haversine distance formula has been used to define this distance.

$$\text{Error}_{pos} = \text{Error}_{M_1} = D_{\text{haversine}}(\text{Loc}_{GT}, \text{Loc}_{est}) \quad (1)$$

The predictive performance of model $M_1$ is evaluated by calculating the errors of all produced location estimates, as by Equation [1] and drawing statistics such as the mean, the median or specific percentile values of the error distribution.

The second model, $M_2$, aims to predict the error $\text{Error}_{pos}$ that the location estimate $\text{Loc}_{est}$ produced by $M_1$ will have, given only the signals received by the gateways. Therefore, in training time, $M_2$ utilizes the same input features as $M_1$: the received signals of message transmissions (in this case the RSS values received at each gateway), while this time the target variable is the positioning error $\text{Error}_{pos}$ that $M_1$'s position estimates have for the same message reception.

In testing time, $M_2$ produces the Dynamic Accuracy Estimation, or $\text{DAE}$, that is a prediction regarding the value of $\text{Error}_{pos}$ that $M_1$ can achieve for a certain message reception.

In order to quantitatively characterize and evaluate the prediction of $M_2$, the absolute difference between the target variable $\text{Error}_{pos}$ and the predicted value $\text{DAE}$ is calculated for each prediction, and cumulative statistical metrics such as the mean or the median are produced. Thus, the following metric is commonly used:

$$\text{Error}_{\text{DAE}} = \text{Error}_{M_2} = |\text{Error}_{pos} - \text{DAE}| \quad (2)$$

V. EXPERIMENTATION AND RESULTS

In this section, the performance of model $M_2$, and more particularly, the repercussion that such a model can have on a positioning system as a whole, is studied. Firstly, since a finite set of fingerprints will be available for the training of the two models ($M_1$, $M_2$), we experiment with the effect that the proportion of training data which are assigned to each of the two models has on their performance (Subsection V-A).

Following, in Subsection V-B we exemplify the models’ capabilities in a use-case where a percentage of the most trustworthy position estimates are selected to be used. Lastly, in Subsection V-C we analyze the performance of $M_2$ in local spatial areas.

Throughout the experiments of this work, the ExtraTrees regression method has been used for the training of both $M_1$ and $M_2$ models. Based on the results of [3] and on preliminary tests performed for this work, the ExtraTrees was preferred from the KNN used in other relevant works. Nevertheless, a detailed comparison among regression methods is out of the scope of this work.

A. Training set repartition between $M_1$ and $M_2$

In this first test, we study the performance of the two models for different repartitions of the training set between the two training tasks. The overall dataset has been divided into 70%, 15%, 15% for train, validation and test purposes respectively. At this point, the further repartition of the training set into the two training tasks is studied. The positioning task, served by model $M_1$, is the principal task of the positioning system, while the production of a DAE by a model $M_2$ is naturally a secondary task. Given this fact, it is reasonable for a designer of such a system to assign more data to the training of $M_1$. On the other hand, one may consider particular use-cases in which it might be requested to prioritize a very high certainty regarding the quality of position estimates over the average overall performance of position estimate production. The overview of the performance trade-off between $M_1$ and $M_2$ for different repartitions of the training data is a suitable way of facilitating the designer of such systems to take informed decisions. Figure 1 presents the performance of $M_1$ and $M_2$ on the validation set, for different portions of the training set assigned to the secondary task, dealt by $M_2$. 

![Fig. 1. Performance of models $M_1$ and $M_2$ on the validation set, for various portions of the training set assigned to the training of $M_2$. The performance of $M_1$ and $M_2$ corresponds to the mean values of the errors described in Equations [1] and [2], respectively, calculated on the validation set.](Image)

In Figure 1, it can be observed that the repercussion of the volume of training data is greater on the primary task of positioning dealt by $M_1$ than on the secondary task of DAE dealt by $M_2$. In model $M_1$, the difference in the mean validation error between the case of using 90% of the training data and the case of only using 10% is 53 meters, which constitutes a 20% increase of the error. On the other hand, regarding $M_2$, the reduction of the mean error between the cases of using 90% and 10% of the training data for its training is only 16 meters, or 11% of relative error increase. As discussed previously, the selection of the way that the training data will be allocated to the two tasks depends on the requirements of the application. For the rest of the tests of this work we will proceed with 50%-50% sharing of training data between $M_1$ and $M_2$, corresponding to 35%-35% of the overall dataset. With this repartition, the validation error of $M_1$ has a mean of 275 meters and a median of 171 meters, while $M_2$ has a 149-meter mean error and an 85-meter median error. The respective test set error for $M_1$ has a mean of 276...
meters and a median 176 meters, while $M_2$ has a 147-meter mean error and an 83-meter median error.

**B. Location estimate selection based on DAE**

Having trained the two models, we proceed to the exemplification of their combined usage in a process of selecting a subset of position estimates, based on the confidence that the system claims over them. To do so, the following procedure is undertaken. Initially, both models provide their predictions on the previously unseen validation set: $M_1$ provides the position estimates, and $M_2$ the corresponding DAE. The outcomes for all data points of the validation set are sorted with respect to the estimated DAE values, thus starting from the position estimates in which $M_2$ assigns high certainty and moving towards the position estimates which $M_2$ predicts as being very erroneous. Figure 2 offers an overview of the positioning system’s performance with respect to different portions of the validation set, selected based on the DAE.

![Graph showing mean and median positioning error of portions of the validation set](image)

Fig. 2. The mean and median positioning error of portions (subsets) of the validation set, selected according to their DAE value. The data points have been sorted based on the DAE estimated over them.

Depending on how selective a higher-level system needs to be regarding the accuracy that it requires from the positioning system, the threshold of acceptable DAE values can be set accordingly. The designer of the system may decide regarding the selection method to be used. One approach is to select a certain percentage of the most accurate position estimates, according to the DAE. Alternatively, a hard threshold of the acceptable DAE values can be set, irrespectively of the distribution of the DAE value in the studied dataset.

It is important to note that if it is assumed that the selection process is not done on-line for each message individually as the messages arrive sequentially, but cumulatively upon the collection of a dataset of a certain volume, then the distribution of the DAE values in this set can be considered available. Consequently, in that case, the median or any other percentile value of DAE of such an available set (as for instance, the test set of the current study) can be used as the threshold for selecting the required percentage of position estimates on which $M_2$ has assigned the highest certainty. On the other hand, if the use-case dictates an on-line decision, the corresponding distribution of the DAE values can be obtained by the validation set, which is known.

The results depicted in Figure 2 suggest that $M_2$ manages to estimate the DAE values in a relatively reliable way. In the validation set, in which the positioning model achieves a 275-meter mean error and a 171-meter median error, it is possible to learn to select signal readings of good quality, which produce position estimates whose accuracy is significantly better that the rest. For instance, selecting 50% of the estimates (those with the lowest estimated error according to DAE), results in a mean positioning error of 108 meters with a median positioning of 35 meters. These values correspond to a 61% improvement of the mean error and an 80% improvement of the median error.

It is noteworthy that, for use-cases such as this one where the goal is the distinction between more accurate and less accurate location estimates, the absolute values of DAE, and consequently its absolute error values, as by Equation 2, are not as crucial as the relative ordering of the location estimates based on their DAE. In other words, assuming location estimates $i$ and $j$, with $\text{Error}_{M_1}^i < \text{Error}_{M_1}^j$, there are applications where the correct ordering of the $M_2$ estimates, that is $\text{DAE}^i < \text{DAE}^j$, may be more important than their absolute error values, $\text{Error}_{M_2}^i$ and $\text{Error}_{M_2}^j$.

![Spatial distribution of data points](image)

Fig. 3. The spatial distribution of the data points of the dataset, color coded into 20 clusters. The cluster ID is indicated in red at the cluster centres. Gateway locations are depicted in black.

**C. Location estimate selection in local clusters**

The spatial distribution of the location estimates and its relation to the DAE assigned to them by the $M_2$ model is a very interesting subject. The real-world dataset of Antwerp used in this work, as most relevant real-world datasets, does not have a regular, fixed density of collected data throughout different spatial areas. Using machine learning models implies that their performance is dependent on the quantity of available training data. Moreover, the particular setting of geo-localization further implies that the quantity of data at different areas (the spatial density of training data) determines the models’ performance at these areas. This is a consequence...
of the fact that fingerprinting techniques learn the local peculiarities of the environment through a mesh of fingerprints. A scarcity of data in a certain zone cannot be compensated by a profusion of data at a distant area, where most likely a distinct set of gateways will be involved in the signal reception, and thus other features will be of importance in that area.

To study the impact of locality in the two models discussed in this work, the dataset has been clustered into 20 areas, using the k-means algorithm, operated on the ground truth locations of the data. In Figure 3, the 20 clusters are presented in a color code, having their ID number indicated at the cluster centres.

It can be observed that the majority of data points has been collected at the central area of Antwerp, at the right-hand side of the map. On the other hand, clusters 5, 9 and 15 are characterized by a rather sparse collection of data. As mentioned previously, the density of data collection at different areas may affect the performance of the positioning system in those areas. Nevertheless, there are other factors that affect the performance of the positioning system as well. The complexity of the environment over which the signals are propagated is a major factor. Factors such as the presence of obstacles (high buildings, hills, etc.) as well as the density and the locations of the gateways may greatly affect a system’s performance. For instance, in the city center it is reasonable to expect to have a higher impact of the multipath effect, than in suburban or rural areas.

Figure 4 highlights in blue the mean positioning error, for each of the 20 clusters. Furthermore, as a metric indicating the spatial density of data within a cluster, the mean distance of all location pairs in a cluster is indicated in red. The correlation coefficient of the two metrics of Figure 4 is 0.72.

Figure 5 presents the distribution of positioning error of each cluster. Moreover, Figure 6 presents the distribution of positioning error after having selected the 50% most accurate location estimates of each cluster, based on their DAE, as discussed in Subsection V-B. In both Figures, the number of data points of each cluster contributing to the statistics is depicted in blue. The amount of points per cluster has an anticorrelation of coefficient $-0.63$ with the mean positioning error of the clusters in Figure 5 and of $-0.5$ in Figure 6. These figures provide an insight on how the location estimate selection process may perform when operated locally.

This is of great interest, since a selection of estimates from the whole dataset may favour the overall error statistics, but under-represent certain regions of high error, and over-represent regions of low error. Specifically, when selecting the 50% of the most accurate (according to DAE) location estimates of each cluster, the mean positioning error of all selected locations is 186 meters and the median 111 meters, in comparison to the respective 108-meter mean and 35-meter median error reported previously for the case of selecting from the whole dataset. The significant difference, especially in terms of the median error, is related to the uneven selection of location estimates from different regions.

VI. CONCLUSIONS AND FUTURE WORK

In this work, we analyzed various aspects of the data-driven based determination of Dynamic Accuracy Estimation (DAE), in the context of its potential use in a broader system. In the previous interesting works that have only recently elaborated on the data-driven approach of DAE determination [6], [7],
the authors have utilized the great majority of the training set (87.6%) for training the DAE model. Though this option allows the presentation of the performance capabilities of the data-driven determination of the DAE in its full extend, we considered imperative to investigate the impact that the training data repartition between the two training tasks has to the overall system’s performance. In the general case, it is natural to prioritize the positioning task as the primary task of the system, assigning to it more training data, rather than the DAE determination task. Moreover, the experimentation of the current work indicated that when receiving more training data, the positioning model has a great gain in error reduction (both in absolute and percentage terms), than what the DAE determining model in the same case. This work has exemplified, in Subsection V-A the way to obtain an overview of this trade-off, which allows informed decisions to be taken.

In Subsection V-B we have elaborated on the fact that DAE, apart from its evident usefulness as an additional information to the user, can have other interesting applications when utilized by the overall system. A utilization of DAE for the selection of the most accurate location estimates has been exemplified, returning to the user a subset of estimates with a significantly increased location accuracy. Such a process may be used in use-cases where such an option would be appropriate. Moreover, Subsection V-C has studied the performance of the two models in local, spatial areas, via clustering. In the particular setting under study, it was observed that certain areas (cluster 3) may have a high concentration of data, yielding very accurate predictions from both models, in an unbalanced manner comparing to the rest of the dataset. Secondly, it was observed that the suburban areas (clusters 5, 9 and 15) had the highest error. These three clusters were also among the most sparsely collected areas. Overall, we identified that the mean positioning error per cluster had a significant correlation with the average distance among (or the density of) the data points per cluster, and a significant anticorrelation with the amount of data points per cluster. Lastly, we have highlighted the fact that in datasets with such diverse density of data collected among different spatial zones, it is interesting to look into performance statistics from spatial zones along with the statistics of the overall dataset.

In the spirit of repeatability, reproducibility, verifiability and comparability of results, it is important not only to report performance metrics over a public dataset, but to also provide the means for reproducing the same train/validation/test set split. Ideally, the code which unambiguously presents the exact way the reported results were produced may be published as well. In this way, the community is able to repeat, reproduce, verify and consistently compare results, and is eventually enabled to take informed decisions over the way positioning systems are designed, implemented and deployed. For these reasons, the full code implementation of the current work is openly available at the Zenodo repository.

References

[1] M. Aernouts, R. Berkvens, K. Van Vlaenderen, and M. Weyn, “Sigfox and lorawan datasets for fingerprint localization in large urban and rural areas,” Data, vol. 3, no. 2, 2018. [Online]. Available: http://www.mdpi.com/2306-5729/3/2/13
[2] T. Janssen, M. Aernouts, R. Berkvens, and M. Weyn, “Outdoor fingerprinting localization using sigfox,” in 2018 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Sep. 2018, pp. 1–6.
[3] G. G. Anagnostopoulou and A. Kalousis, “A reproducible comparison of rssi fingerprinting localization methods using lorawan,” in 2019 16th Workshop on Positioning, Navigation and Communications (WPNC), 2019, pp. 1–6.
[4] A reproducible analysis of rssi fingerprinting for outdoor localization using sigfox: Preprocessing and hyperparameter tuning,” in 2019 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2019, pp. 1–8.
[5] T. Janssen, R. Berkvens, and M. Weyn, “Benchmarking rssi-based localization algorithms with lorawan,” Internet of Things, vol. 11, p. 100235, 2020. [Online]. Available: http://www.sciencedirect.com/science/article/pii/S2542660520300688
[6] F. Lemic, V. Handziski, M. Aernouts, T. Janssen, R. Berkvens, A. Wolisz, and J. Famaey, “Regression-based estimation of individual errors in fingerprinting localization,” IEEE Access, vol. 7, pp. 33652–33664, 2019.
[7] F. Lemic and J. Famaey, “Artificial neural network-based estimation of individual localization errors in fingerprinting,” in 2020 IEEE 17th Annual Consumer Communications Networking Conference (CCNC), 2020, pp. 1–6.
[8] J. Torres-Sospeda, A. Jiménez, A. Moreira, T. Lungenstrass, W.-C. Lu, S. Knaith, G. Mendoza-Silva, F. Seco, A. Pérez-Navarro, M. Nicolau, and et al., “Off-line evaluation of mobile-centric indoor positioning systems: The experiences from the 2017 ipin competition,” Sensors, vol. 18, no. 2, p. 487, Feb 2018. [Online]. Available: http://dx.doi.org/10.3390/s18020487
[9] C. M. de la Osa, G. G. Anagnostopoulou, M. Togneri, M. Deriaz, and D. Konstantas, “Positioning evaluation and ground truth definition for real life use cases,” in 2016 International Conference on Indoor Positioning and Indoor Navigation (IPIN), Oct 2016, pp. 1–7.
[10] H. Lemelson, M. B. Kjærgaard, R. Hansen, and T. King, “Error estimation for indoor 802.11 location fingerprinting,” in Location and Context Awareness, T. Choudhury, A. Quigley, T. Strang, and K. Suginuma, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2009, pp. 138–155.
[11] P. Marcus, M. Kessel, and M. Werner, “Dynamic nearest neighbors and online error estimation for smartpotos,” International Journal On Advances in Internet Technology, vol. 6, pp. 1–11, 01 2013.
[12] Y. Li, Z. He, Z. Gao, Y. Zhuang, C. Shi, and N. El-Sheimy, “Towards robust crowdsourcing-based localization: A fingerprinting accuracy indicator enhanced wireless/magnetic/inertial integration approach,” IEEE Internet of Things Journal, vol. 6, no. 2, pp. 3585–3600, April 2019.
[13] V. Moghtadeiae, A. G. Dempster, and B. Li, “Accuracy indicator for fingerprinting localization systems,” in Proceedings of the 2012 IEEE/ION Position, Location and Navigation Symposium, 2012, pp. 1204–1208.
[14] D. Zou, W. Meng, and S. Han, “An accuracy estimation algorithm for fingerprint positioning system,” in 2014 Fourth International Conference on Instrumentation and Measurement, Computer, Communication and Control, 2014, pp. 573–577.
[15] R. Elbakly and M. Youssef, “CONE: zero-calibration accurate confidence estimation for indoor localization systems,” CoRR, vol. abs/1610.02274, 2016. [Online]. Available: http://arxiv.org/abs/1610.02274
[16] S. Khandker, R. Mondal, and T. Ristaniemi, “Positioning error prediction and training data evaluation in rf fingerprinting method,” in 2019 International Conference on Indoor Positioning and Indoor Navigation (IPIN), 2019, pp. 1–7.
[17] A. Nikitin, C. Laoudias, G. Chatzimilioudis, P. Karras, and D. Zeinalipour-Yazti, “Indoor localization accuracy estimation from fingerprint data,” in 2019 IEEE/ION Position, Location and Navigation Symposium (PLANS), 2019, pp. 1–9.
[18] D. Dearman, A. Varshavsky, E. de Lara, and K. N. Truong, “An exploration of location error estimation,” in Ubicomp 2007: Ubiquitous Computing, J. Krumm, G. D. Abowd, A. Seneviratne, and T. Strang, Eds. Berlin, Heidelberg: Springer Berlin Heidelberg, 2007, pp. 181–198.