Improving the Precision of Wireless Localization Algorithms: ML Techniques for Indoor Positioning

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***Abstract*—Due to the tremendous increase in the number of wearable devices and proximity-based services, the need for improved indoor localization techniques becomes more significant. The evolution of the positioning from a hardware perspective is pacing its way along with various software-based approaches also powered by Machine Learning (ML). In this paper, we apply ML algorithms to the real-life collected signal parameters in an indoor localization system based on Ultra-Wideband (UWB) technology to make an analysis of the signal and classify it accordingly. The contribution aims to answer the question of whether an indoor positioning system could benefit from utilizing ML for signal parameter analysis in order to increase its location accuracy, reliability, and robustness across various environments. To this end, we compare different applications of ML approaches and detail the trade-off between computational speed and accuracy.**

***Index Terms*—Indoor Positioning Systems, Ultra-Wideband, UWB, Machine Learning, Precision Improvement**

I. Introduction

Wireless location systems, and especially Indoor Position Systems (IPS), have attracted significant attention over the course of the last several years [1]. Historically, the first location technologies became available to the general public with the outdoor Global Navigation Satellite System (GNSS). Over time, the focus was slowly extending to indoor positioning applications. With the use of well-known wireless communication technologies, such as Bluetooth Low Energy (BLE) or Wi-Fi, it became possible to achieve a location accuracy at the level of several meters. Ultra-Wideband (UWB) technology was introduced to bring a centimeter-level of accuracy and to push the limits of indoor location precision further [2]. Worth noting, that typical indoor environment is much more challenging for any radio technology in comparison to an outdoor deployment due to smaller communication nodes, obstacles, moving objects in addition to human mobility that affects the radio propagation characteristics, not to mention the variety of materials present. These factors can all contribute to unstable measurements, which result in a higher localization error.

A. Technologies in Question

Today, there are several available wireless location technologies used for indoor localization. Besides wireless radio systems, there is also a possibility to use systems based on ultrasound or optical sensors, such as infrared radiation or Light Detection and Ranging (LiDAR) systems. Nevertheless, this work focuses mainly on wireless radio technologies since there is not much need to increase the location precision of optical-based location systems. Historically, one of the technologies most commonly used for indoor positioning is the IEEE 802.11 family. Location capability is a secondary feature of the technology due to broad adoption and mass deployments as a primary communication technology for high-rate data transfers. In the most simple scenario, fixed Access Points (APs) can make ranging estimates from a moving device based on Received Signal Strength Indication (RSSI) and make the positioning estimate, resulting in the several meters accuracy level [3].

Continuing with the IEEE-defined standards, in the IEEE 802.11-2016 standard, the committee aimed to improve the location accuracy of Wi-Fi-based systems by introducing a technique called Fine Time Measurement (FTM) [4]. This technique should enable a device to precisely measure the Round Trip Time (RTT) between the devices and make a ranging estimate based on Time-of-Flight (ToF) rather than conventional RSSI. According to the Wi-Fi Alliance, such an approach should bring a meter-level accuracy [5]. However, real measurements show a significant difference in obtained indoor versus outdoor deployment results [6]. Another conventional radio technology used for indoor localization is Bluetooth or Bluetooth Low Energy. Similarly to Wi-Fi, Bluetooth mainly relies on RSSI measurements for positioning estimations. However, mainly with the advent of the recent Bluetooth 5.1 standard introduced in January 2019, there are other capabilities to improve the precision. Besides the pure ranging estimates, the standard introduces the Angle of Arrival (AoA) and Angle of Departure (AoD) techniques for incorporating angle measurements, see Fig.1.

Both of these approaches require one of the devices to be equipped with an antenna array. In the case of AoA, it is possible to calculate the angle by determining the phase difference on each antenna in the array from the received signal. In the case of AoD, the transmitting device also needs

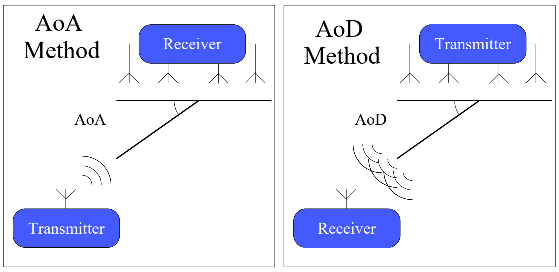


Fig. 1: Angle of Arrival (left) and Angle of Departure (right) techniques.

to send its absolute coordinates to the receiver. The receiver then processes the incoming signal from the antenna array with the use of IQ sampling and estimates its position. To summarize, these two techniques should bring a "direction-finding" capability into Bluetooth positioning systems to increase the overall accuracy.

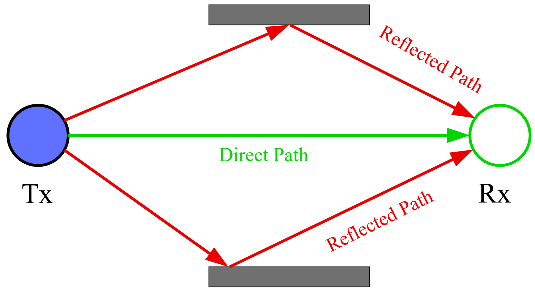
The last considered radio technology used in wireless Indoor Positioning Systems mentioned in this text is UWB. The fundamental difference compared with the already mentioned technologies lies in the fact that UWB technology is primarily based on the Time of Flight (ToF) estimates to bring location capabilities. The result of this is a greater location accuracy by default compared to other mentioned technologies, reaching a centimeter-level in ideal scenarios.

Currently, additional amendments are being made to the last standard of IEEE 802.15.4-2015, which incorporates the UWB physical layer. The new standard brings along new capabilities for the physical layer, including the increase of the radio range, increase in battery lifetime, increasing location accuracy, and other improvements [7]. The future generation of UWB chips could also incorporate the use of AoA techniques to increase the positioning accuracy, also with the use of a lesser number of receivers [8].

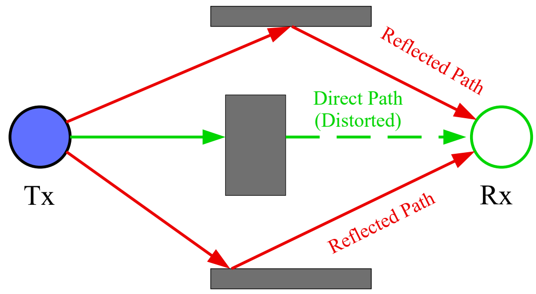
B. *Related Work*

In terms of UWB based localization systems, there is no need to make use of fingerprinting or RSSI radio maps, since the technology is based purely on ToF to make location estimates. For this technology, it is more crucial to detect whether the received signal component comes from a Line-of-Sight (LoS) or a Non-Line-of-Sight (NLoS) environment. Some experiments have already been done in this area, such as in [9], where the authors use a threshold based on the signal power readings obtained from the radio module. Similarly, authors in [10] also use thresholds based on first path signal power and received signal power. These threshold-based methods have a significant advantage of being very simple to implement. Therefore, they can be directly used in a real-time scenario. Due to simplicity, they may not be as robust as more sophisticated approaches.

Today, some experiments have also been conducted with more advanced approaches by using ML techniques, such as



(a)



(b)

Fig. 2: Examples of different signal propagation: (a) LoS environment (top) and (b) NLoS environment (bottom).

in [11], where the authors use one UWB Anchor (static location sensor in UWB terminology.) and one UWB Tag (moving device, a locator). The authors use a supervised ML method based on a multi-class support vector machine (MC-SVM) technique to detect walls and obstacles between the two devices and to determine whether the received signal is either LoS or NLoS. Authors in [12] also apply the SVM algorithm to determine whether the signal's direct path is present within the signal, even if an obstacle delays it.

From a Machine Learning perspective, an interesting approach is proposed in [13]. The authors seek to improve a location system based on a two-way ranging approach. In these systems, there can be a delay between two position updates within the location system if the number of users is too high. The authors seek to use Inertial Measurement Unit (IMU) sensors to count steps in between these updates and use ML to pick the right parameters. Such a method could be applied to a real-world people tracking system based on UWB two way ranging.

C. *Our Contribution*

The idea presented in this work proposes to utilize ML methods that are applied to the data set of signal measurement parameters gathered from a real installation of a UWB positioning system. The contribution of this work aims to answer the question of whether an indoor positioning system could benefit from utilizing Machine Learning for signal parameter analysis in order to increase its location accuracy, reliability, and robustness across various environments. The results are presented and discussed, along with an outlook of what could be improved in future work.

The remainder of this paper is structured as follows. In Section II, we discuss the motivation of using Machine Learning for indoor positioning. Going further, Section III describes the constructed environment, i.e., a research center for industrial machines. The obtained results for both scenarios, i.e., static and moving TAG are discussed in Section IV. Finally, concluding remarks together with the future steps are provided in Section V.

II. Motivation

Several new standards and techniques are being introduced into the world of indoor positioning that should increase the location accuracy (besides other improvements) of existing technologies. Some of these approaches also make use of several ML techniques. Considering a positioning system based on ToF measurements, the performance of such a system will be heavily influenced by its ability to detect the first path (FP) of an incoming signal and also to determine whether it is LoS or NLoS.

In an ideal scenario, there are no obstacles between the transmitter and the receiver. The direct path is accompanied by additional reflected paths whose number can vary depending on the environment. It is essential to reliably determine the direct path to calculate the signal ToF correctly. In a purely NLoS scenario, the direct path can be heavily distorted by an obstacle between the devices, and it can be hard to detect. If the device has to rely purely on NLoS signals, it will introduce an error to the ToF estimate and will affect the accuracy of the resulting estimate. In some cases, the FP may not be present at all in the signal.

Of course, these are two straightforward examples. In real scenarios, there can be any number of possible combinations between LoS and NLoS environments plus a varying number of reflected paths. This is also profoundly affected by the considered environment, such conditions will also change if we would consider an office space or an industrial facility with the presence of metallic objects. Under harsh conditions, the positioning system cannot rely purely on the ToF measurement performed by the device. However, it should also use other parameters made available by the equipment from the Channel Impulse Response (CIR) analysis, where a significant sample of measured data could be done by a suitable ML method, which could then determine whether the received signal was reflected or not and based on this assumption assign a level of confidence on the given measurement.

As demonstrated in a practical example, see Fig.3, such an approach could yield significant benefits in the signal classification and could serve as an improvement of the location accuracy. The future work should be then dedicated to finding such ML algorithms that would improve the indoor location systems based on these criteria and improving the following: (i) CIR analysis in various indoor environments; (ii) comparing the CIR results of such environments: ideal LoS environments, office spaces, industrial facilities; (iii) finding and testing ML algorithms onto the captured data, comparing supervised and unsupervised learning; (iv) selecting the most fitting algorithms for given types of environments to classify the signal with sufficient accuracy; (v) testing the discovered algorithms on a live positioning system to verify the results.

III. Indoor Positioning Use-Case

This section describes the preliminary results that were gained based on data from a real environment in a live positioning system constructed at the Brno University of Technology, Czech Republic. The used positioning technology is based on UWB chip DW1000 from DecaWave, which is compliant with the IEEE 802.15.4-2011 standard.

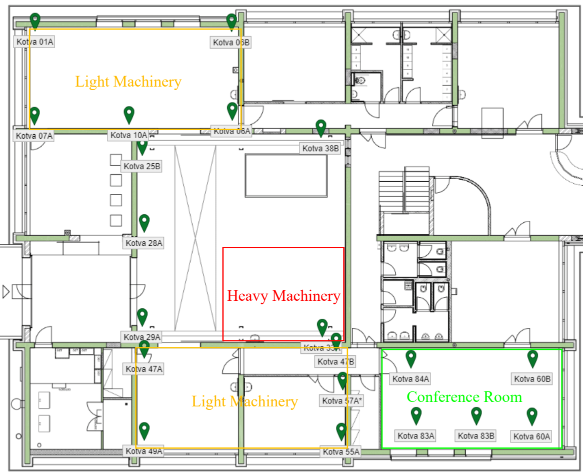


Fig. 3: The testing environment which consists of office space, a room with heavy machinery, and also a room with light machinery.

A. Scenario description

Generally, the UWB location systems consist of moving Tags and fixed Anchors. In the intended scenario, only one Tag was used, and the test has been performed in multiple rooms – the environment itself is described in more detail in the next section.

In total, there are twenty UWB Anchors installed in the whole testing area connected and powered via Ethernet to a local server where the location engine is running, see the Fig.3. From the communications perspective, there is no router on the way between the server and the Anchors, and all the components are connected directly to the L2 layer. Positioning data can then be visualized on a laptop, which is connected to the server either via Ethernet or a Wi-Fi connection.

The used positioning technique is based on Time Difference of Arrival (TDoA) – this means that the Tag sends a Blink message to the nearby Anchors. The Anchors then gather timestamps based on the received signal and send this information to the server along with CIR data and additional information. The server is then able to estimate the position of the Tags and also to capture the CIR data that were used for the analysis.

B. Testing Environment

For the practical evaluation, the testing environment used was a research center for industrial machines. The layout of the overall area can be seen in Fig. 3. The area partly consists of office space, a room with heavy machinery, and also a room with light machinery. There are also narrow corridors connecting the rooms. As can be seen, especially in the lower part, several Anchors do not have an LoS between them. Considering a moving Tag in that area, the radio channel will be challenging for the connection between Tag and surrounding Anchors as the walls between the Anchors are made from concrete.

As outlined in Fig. 3, the room with light machinery can be found in the top left part and also in the bottom part. In the center of the floorplan is a room with heavy machinery. The large machine itself is outlined in the floorplan with a red rectangle, and it is effectively blocking a direct Line of Sight (LoS) with the center of the room, making the environment more challenging. In the lower part, there are two smaller rooms with light machinery and a narrow corridor.

In all of the areas, the Anchors are mounted directly on the ceiling with wall mounts, creating a distance between the radio module and the ceiling in order not to impact the radio performance negatively. Only in the narrow corridor, the Anchor is placed directly in the false ceiling, which is made of polystyrene. The last room on the right side is a conference room where three of the Anchors are mounted with wall mounts, and two are installed in the ceiling the same way as in the hallway. Overall, this is an almost perfect testing area since it contains several different environments next to each other.

C. Evaluation Plan

In this work, two test runs were executed: (i) Tag in a static mode for the first and (ii) one in moving mode for the second. The Tag had a set refresh rate of 200 ms, yielding five positions each second.

In the static mode, the Tag was put into each room where the Anchors were installed and was left to Blink for several minutes. The Tag was always put on a table and had a clear LoS to the Anchors in the given room. The only major obstacle in the static mode was a heavy machine in the room in the center of the floorplan, marked in Fig. 3. All of these measurements were then chained together and split into two sets of data.

According to where the test was carried out, the data was then labeled by a mark, which meant that the given sample if either an LoS or NLoS signal. It is a significant step for the supervised ML process, and this is where it differs from unsupervised learning. The model needs to have the training data labeled or at least partially labeled for semi-supervised learning so it can learn and be trained on the given dataset.

In the second scenario, the mobile Tag was put on a tripod and held in hand. With the Tag mounted on the tripod, it was moved around the whole location area where the Anchors are installed. From this measurement, the second set of data was conducted.

IV. Data Processing

The captured data contained several parameters about the signals received by the Anchors that were then taken as inputs to the machine learning algorithms. The signal that is received by the Anchors can be described as

$$r(t) = \sum_{i=1}^{N} a_i p(t - \tau_i) + n(t), \tag{1}$$

where N is the total number of multipath components, a_i is the amplitude of each component, and τ_i is its delay, p is the pulse waveform transmitted by the Tags and $n(t)$ is the additive Gaussian noise. From this signal, we can then extract the parameters which are accessible directly from the radio module's registers.

The parameters that were processed are briefly described below, more detailed information can be found in [14] as well as they are given in Table I.

TABLE I: Main parameters

Parameter	Description
Label	The label that says whether the signal is direct or reflected.
FPindex	Position of the detected first path in CIR.
Peak Index	Index of the peak path in CIR.
RSSI	Received Signal Strength Indication.
FP_AMP1,2,3	First-third amplitudes around the First Path.
Peak Ampl	Amplitude of the peak path.
NoiseThr	Noise threshold.
C []	Array of complex CIR analysis.
RXPACC	Preamble Accumulation Count value.
Anchor name	ID of the Anchor that received the Blink.

Before actually feeding the data to the ML algorithms, it is crucial to select the valid parameters. At this point, it is not known which parameters will or will not affect the resulting decision, and thus, it is necessary to select the ones that will have the most significant impact on the model.

A. ML Techniques for Indoor Positioning

In machine learning, the following input parameters are called features – selecting only the essential features to train the model itself has several advantages: (i) Irrelevant features can negatively impact the model's performance; (ii) Improving the accuracy of the model; (iii) Reducing Training time; and (iv) Reducing Overfitting. The last one is of particular interest in this work. It means that the trained model performs very well with the given set of data and provides outstanding accuracy, but when the same model is applied to a different dataset, the performance drops significantly. It implies that the generated function is too tied to the training dataset. An opposite phenomenon is called underfitting. In order to avoid that phenomenon, Feature selection is advised to be done first, so it can search through the captured data and find a correlation between each feature and the desired output value. The remaining features are then considered as noise and are not used as the input to the model. Besides reducing the chances of Overfitting, feature selection can also improve the accuracy, and it reduces the necessary training time because the model has less features.

B. Feature Selection

The Feature Selection was performed by using a two-step selection. The feature set was the first subject to the Minimum Redundancy Maximum Relevance (mRMR) algorithm. Then, the selected features were subject to the Sequential Floating Forward Selection (SFFS) algorithm to pick the final features for the model. After that, the data were subject to both mentioned ML algorithms.

Various algorithms can be used for the Feature Selection, and some ML algorithms even contain feature selection capabilities within them. In general, Feature Selection approaches can be split into three categories: (i) filter-based methods, (ii) wrapper-based methods, and (iii) embedded methods [15]. In this paper, we used mRMR, which tends to select the subset of features that correlate the most with the output label and, at the same time, correlate the least among themselves [16]. The essential advantage of the mRMR algorithm is that it is very fast being based on statistics, and it is a form of a filter-based method.

In general, filter-based methods are swift. However, they are not as accurate as wrapper-based methods since these work iteratively and tune the model to the given set of features. One example if the wrapper-based methods are the SFFS algorithm used in this work. It starts with an empty feature set, and it keeps adding features in each iteration that offers the best possible results with the already selected features based on the criterion function. In each step forward, it can take several steps back by removing features that were already added in previous steps, if the new addition performs better without them [17]. The used implementation of the algorithm tries to maximize the Matthews correlation coefficient, which is described in detail below. Since this method is time-consuming, the features were roughly selected by using the fast mRMR first in the previous step.

Due to the binary nature of the result (the signal comes either from an LoS path or NLoS), we can use binary evaluation of the used classifying techniques. Overall, there can be four possible scenarios on the output, as shown in Table II.

TABLE II: A Confusion Matrix

	Positive	**Negative**
Predicted Positive	True Positive	False Positive
Predicted Negative	False Negative	True Negative

For example, if the signal was classified as LoS, and it indeed was, the result would be a True Positive. However, if the signal were NLoS in reality, the result would be classified as a False Positive. Similarly, we can classify the other two outcomes, as well.

These results can be then used to evaluate the model based on several ratios between them [18], calculated as

$$ACC = \frac{TP + TN}{TP + TN + FP + FN}, \tag{2}$$

$$SEN = \frac{TP}{TP + FN}, \tag{3}$$

$$SPE = \frac{TN}{TN + FP}, \tag{4}$$

where TP is a true positive, TN is a true negative, FP is a false positive, and FN is a false negative. The first equation calculates the accuracy of the result, which is the ratio of the correctly made predictions and all the predictions. The second classification is sensitivity, and the third is specificity.

Another measurement of quality in ML is the Matthews Correlation Coefficient (MCC), which is used to evaluate binary classification models. It can be calculated as follows

$$\begin{aligned} MCC = & \\ = & \frac{TP \cdot TN - FP \cdot FN}{\sqrt{(TP + FP)(TP + FN)(TN + FP)(TN + FN)}}. \end{aligned} \tag{5}$$

The coefficient returns a value between -1 and $+1$, where $+1$ indicated a complete classification, zero means no better than a random prediction, and -1 represents a lousy prediction of the trained model.

C. Cross-validation

In order to get the results, the model needs to be evaluated appropriately, which is ensured by using a technique called k-fold cross-validation. The data selected by the feature selection procedures are split into k different parts, and $k - 1$ parts are used as training data, and the k part is used to evaluate the performance of the model.

In this experiment, the 10-fold cross-validation was used, which means that the set was split into 10 parts, and 9 were used to train the model and the last one for the evaluation. This is a beneficial step which can suggest whether Overfitting has occurred and, of course, we can never know which subset of the data will prove to be best for the testing, that is why the whole set is split, and all of the parts are used.

D. Results Discussion

After the cross-validation was done, the results were processed, see Tables III and IV. Namely, the Accuracy, Specificity, and Sensitivity, together with the MCC, were calculated to evaluate both models. For the experiment, the Matlab environment was used along with machine learning toolboxes for the above-mentioned algorithms evaluation.

All of the values are taken as a mean from each of the 10-fold tests that were performed for each set of the data. As can be seen, the Random Forest algorithm generally provides much better results than GMM in all three scenarios. However, it took nearly three times more time for computation of the classification than the GMM. This a trade-off between two desired parameters, while the GMM provides good results at a relatively fast computation time, the Random Forest provides much better results, however, at the price of a more significant computation power or more computation time. Indeed, it is mainly a question for the end application, how accurate the results must be, and what kind of time efficiency is expected from the model.

In a global location system, a more light-weight implementation could be used directly on the location sensors themselves, and the filtered data could then be forwarded to the location engine. If we would consider using the module directly on a location server or a cloud, we could use a more computationally exhaustive method for the classification. However, this would also increase traffic over the wired or wireless network.

However, based on these obtained preliminary experimental results, we can state that ML has a strong potential in signal classification to improve location accuracy.

TABLE III: The obtained results with a static Tag (two experiments)

Used Algorithm	Accuracy	Specificity	Sensitivity	MCC
Gaussian Mixture Model	81.30 %	87.84 %	76.84 %	0.64
Random Forest	92.89 %	92.40 %	93.23 %	0.85

Used Algorithm	Accuracy	Specificity	Sensitivity	MCC
Gaussian Mixture Model	79.50 %	80.98 %	78.49 %	0.59
Random Forest	92.13 %	91.46 %	92,58 %	0.83

TABLE IV: The obtained results with a moving Tag

Used Algorithm	Accuracy	Specificity	Sensitivity	MCC
Gaussian Mixture Model	81.09 %	87.75 %	76.55 %	0.63
Random Forest	94.41 %	93.89 %	94.71 %	0.88

V. Conclusions

In this paper, we have approached the question of the localization based on Ultra-Wideband radio technology coupled with the Machine Learning approach. As these preliminary results suggest, an indoor positioning system could greatly benefit from utilizing Machine Learning for signal parameter analysis in order to increase its location accuracy, reliability, and robustness across various environments.

Current trends in Machine Learning lie in the so-called boosting algorithms, which provide great results in reasonable computing time. In this paper's experiment, only a supervised learning approach was considered. Future work could also compare the performance of supervised and unsupervised techniques.

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