Improving UWB Based Indoor Positioning in Industrial Environments through Machine Learning*

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***Abstract*—The detection and mitigation of Non-Line-of-Sight (NLOS) signals are crucial for achieving the full potential of UWB-based indoor positioning. In dense multipath industrial environments, it was seen that using the power characteristics of the received signal to identify NLOS conditions is effective when tracking stationary objects but is insufficient for mobile object tracking. Hence, machine learning classifiers utilizing Multi-Layer Perceptron (MLP) and Boosted Decision Trees (BDT) were developed to improve NLOS detection. Through experimental results from tests in a factory scenario, it is shown that BDT yields a higher accuracy of 87% as compared to the 79% obtained by the received power based method.**

I. Introduction

Ultra-wideband (UWB) has the potential to give centimeter-level positioning accuracy even in highly cluttered industrial environments [1]. Hence UWB can be used for positioning solutions in places like factories, manufacturing plants, and warehouses for tracking mobile assets and personnel. These positioning solutions are used for various purposes to improve productivity. They include cutting down time wastage in searching for items, identifying bottlenecks in process flows, and optimizing routes.

The performance of UWB, however, deteriorates significantly when the direct path from the mobile transceiver (tag) to the reference transceiver (anchor) is obstructed, resulting in additional ranging bias and less accurate positioning estimates. Various methods have proposed to use machine learning models to overcome the problems caused by these NLOS (Non-Line-of-Sight) conditions. Some have used regression to estimate and mitigate the ranging error due to NLOS [2] , [3]. Others detect NLOS conditions so that they can be mitigated by either eliminating those ranges or using a lower weightage for them in the position estimation [4] , [5].

The works reported in the literature have tested the machine learning methods and found them to be effective for stationary tag scenarios [2-5]. When the tag is mobile, the number of samples available at each position will be much fewer than the stationary case. Thus, the performance of machine learning algorithms that have been proven to be effective for the stationary scenario cannot be assumed to as effective for the mobile scenario. Also, the methods must be tested in a realistic environment, similar that of the actual application. For example, if proposed for a factory application, the solution must be tested in a similarly cluttered industry-like environment. The results can be rather over-optimistic if the solution is only tested in more benign environments such as laboratories and offices.

It is also necessary to take note that any methodology for improving UWB positioning has to be practically applicable and supported by the particular UWB chipset being used. The various parameters used must be available from the chipset under normal operation. Hence in this paper, we formulate machine learning solutions for mobile tag positioning that make use of parameters provided by the UWB chip, DW1000, from DecaWave. The solutions are tested and verified in an actual industrial-like environment. The machine learning models are also compared with the performance of a non-machine learning and less computationally intensive rule-of-thumb approach suggested by DecaWave [6].

II. Positioning Algorithm

The two methodologies used for positioning with DW1000 are Time-Difference-of-Arrival (TDOA) and TWR (Two-Way Ranging) [6]. Each methodology has their advantages and disadvantages. The main advantage of TDOA is that it is able to support more tags operating at the same time, but it however requires the tag to be in communication with at least 4 anchors. In contrast, TWR requires more messages to be exchanged between the tag and anchors, taking up more airtime and consequently reducing the number of tags that can operate at the same time. The advantage however is that TWR can work with the tag being in communication with just 3 anchors (one less than TDOA). This paper assumes a TWR methodology of positioning (Fig. 1). Using two-way ranging, the anchors in the system estimate how far the tag is from their location and send this data to a central server. At the server, the ranges from each anchor are used to estimate the position of the tag through trilateration. As seen, the ranging estimate derived from the to-and-from messages between the tag and the anchor can be through LOS or NLOS.

While factory environments are often highly cluttered, the NLOS situations that arise due to stationary machinery can normally be avoided or mitigated by judiciously choosing the positions of the anchors. By taking into account the position of the anchors, future modifications of the factory layout can be done in a way that minimizes deterioration in the performance of the positioning system. Where unavoidable, the anchors may have to be shifted or new ones may have to be added. In contrast to machinery, the NLOS situations that arise due to blocking by the human body, is rather difficult to avoid. The human body may completely block the UWB

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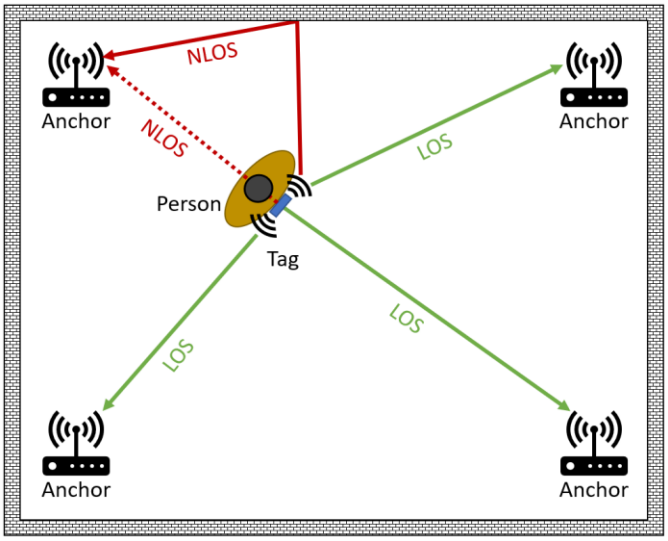

Fig. 1. Ranging Error Distributions of LOS and NLOS Signals

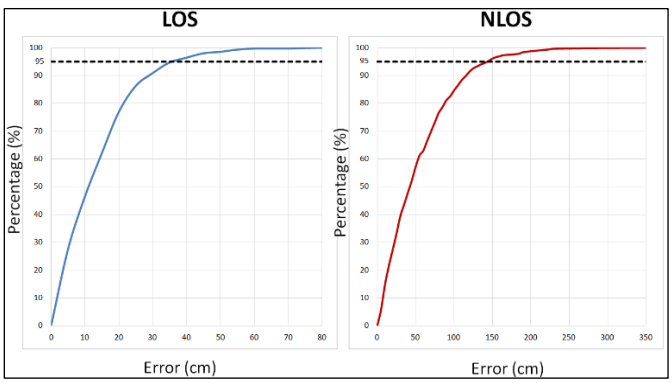

Fig. 2. Ranging Error Distributions of LOS and NLOS Signals

communication between the tag and the anchor or allow it to pass through after attenuation (Fig. 1).

The difference in the ranging errors under LOS and NLOS conditions were thus first studied using experimental data collected using a simple setup to measure the range between a tag and an anchor, along an office corridor. The NLOS condition was created by getting a person to block the LOS using his body. The results for the ranging errors based on 600 samples of LOS and NLOS are shown in Fig. 2. It can be seen that 95% of the LOS signals have range estimate errors less than 35cm whereas it is 140cm in the case of NLOS. Thus, the analysis of the experimental results confirms that ranging estimates obtained from NLOS signals can have a significant positive bias. Consequently, using these range estimates from NLOS signals in calculating the tag's position will lead to large errors if they are not eliminated or mitigated.

III. Power Distribution Metric Method for NLOS Detection

For the same received power of a signal, the power in the first path is expected to be higher for LOS signals than NLOS signals. This is due to the higher distribution of power to more multipath components in the case of NLOS. The DW1000 IC allows for the received power (RX_POWER) and the first path power (FP_POWER) to be estimated [6]. The estimated received signal power is given by:

$$RX\_POWER = 10\log\left(\frac{C\times 2^{17}}{N^2}\right) - A\ dBm \qquad (1)$$

where C is the CIR, A is a constant that is equal to 113.77 for a pulse repetition frequency (PRF) of 16 MHz or 121.74 for PRF of 64 MHz and N is the preamble accumulation count value reported in the RX Frame Information Register of DW1000.

And the first path power is estimated by:

$$FP\_POWER = 10 \times log_{10}\left(\frac{F_1^2+F_2^2+F_3^2}{N^2}\right) - A\ dBm \qquad (2)$$

where F1, F2 and F3 refers to the magnitude of the first path amplitude at points 1, 2 and 3 respectively. With A and N defined as in (1). A power distribution metric (PDM) can then be defined as:

$$\text{PDM} = \text{RX\_POWER} - \text{FP\_POWER} \qquad (3)$$

DecaWave [6] recommends a rule-of-thumb where PDM more than 10dB is taken to be NLOS. (For brevity sake, this method based on the power characteristics of the received signal will subsequently be referred to as the PDM method).

The PDM for LOS and NLOS scenarios were evaluated based on measurements taken with the tag worn on a lanyard by a person. For LOS, measurements were taken with the person facing the anchor and NLOS with the person facing away. This was done in a lab environment with minimal clutter. The measurements were done with the person both stationary (fixed range) and mobile (range changing). A total of 1879 and 1327 readings were taken for the stationary and mobile cases, respectively.

The results are shown in Fig. 3 and Fig. 4, and summarized in Table I. For the stationary case, it is seen that the PDM method is a simple and effective way of detecting NLOS. For the stationary case, using the PDM method garners an accuracy of 98%. However, for the mobile case, the accuracy drops significantly to 88%. Adjusting the threshold to other values may help in improving the accuracy of the detection but the results were still poorer than in the case of the stationary tag scenario.

As mentioned earlier, in order to fully make use of the potential of UWB to provide centimetre level positioning accuracy, NLOS detection and mitigation is necessary. And the greater the accuracy of NLOS detection, the more robust the solution. Hence for applications demanding a more robust mobile UWB tag positioning solution, a more complex machine learning based approach is thus justified.

TABLE I. ANALYSIS OF PDM METHOD FOR LAB DATA

	Stationary Case	Mobile Case
TP	533	536
FP	0	4
TN	1305	629
FN	41	158
Sensitivity = $\left(\frac{TP}{TP+FN}\right)$ %	93	77
Specificity = $\left(\frac{TN}{FP+TN}\right)$ %	100	99
Accuracy = $\left(\frac{TP+TN}{TP+FP+TN+FN}\right)$%	98	88

a) TP (True Positive) refers to actual NLOS detected as NLOS.
b) FP (False Positive) refers to actual LOS detected as NLOS.
c) TN (True Negative) refers to actual LOS detected as LOS.
d) FN (False Negative) refers to actual NLOS detected as LOS.

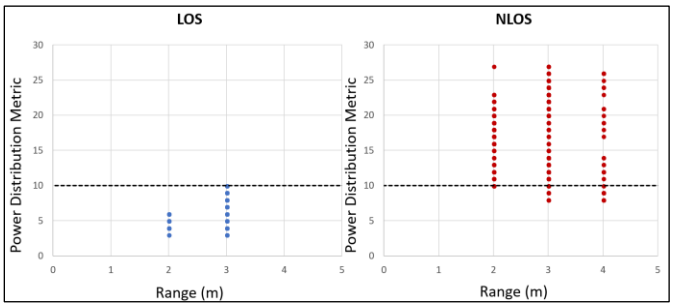

Fig. 3. Power Distribution Metric for LOS and NLOS Conditions under Stationary Tag Scenario in the Laboratory

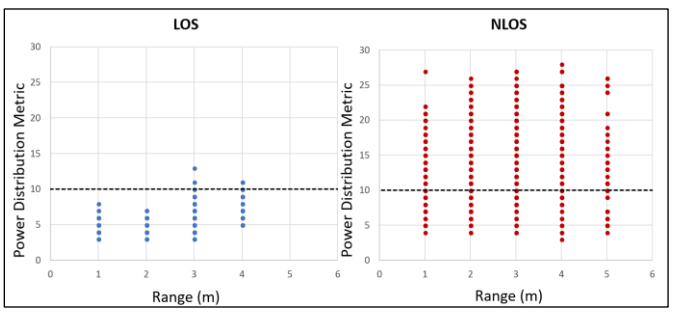

Fig. 4. Power Distribution Metric for LOS and NLOS Conditions under Mobile Tag Scenario in the Laboratory

IV. MACHINE LEARNING MODEL

A. Feature Selection

Using the functions of the DW1000 IC, three parameters were selected as features for machine learning: Range Estimate, First Path Amplitude and Standard Deviation of Channel Impulse Response Estimate Noise.

First Path Amplitude (FP_Amp): This value corresponds to the second point of the FP_Amp magnitude value obtained from DW1000 [6]. For the same range, NLOS signals generally have a lower FP_Amp value compared to LOS signals (Fig. 5).

Standard Deviation of Channel Impulse Response Estimate Noise (STD_NOISE): This parameter according the DW1000 manual [6] is a measure of the quality of the received frame's timestamp measurement. NLOS signals typically have a lower FP_Amp to STD_NOISE ratio compared to LOS signals (Fig. 6).

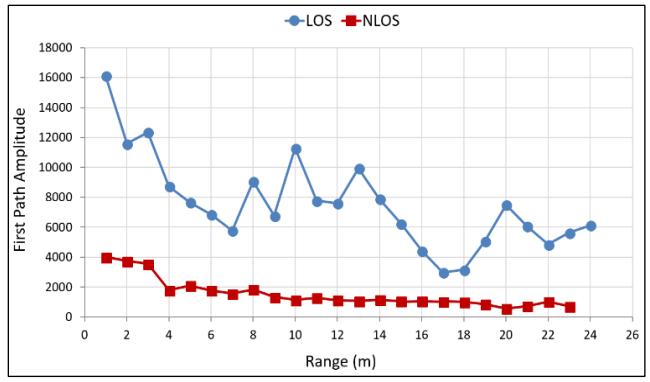

Fig. 5. Average FP_Amp over Range

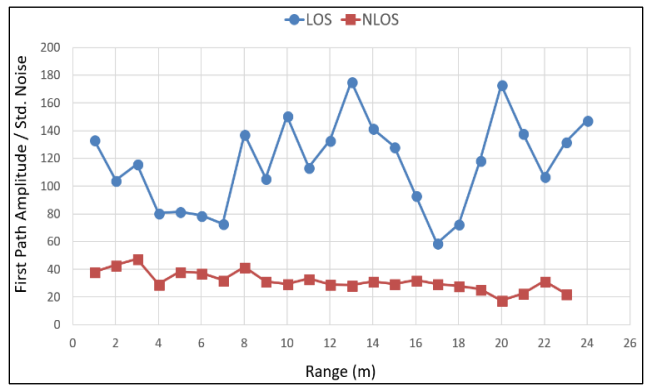

Fig. 6. FP_Amp/STD NOISE Ratio over Range

B. Algorithm Selection

The machine learning methods used for NLOS detection are the two classifiers: Multilayer Perceptron and Boosted Decision Trees. These models were developed using the Python programming language.

Multi-Layer Perceptron. Bregar, Hrovat and Mohorčič [5] proposed to use the neural network Multi-Layer Perceptron (MLP) in NLOS detection and mitigation. Despite yielding an overall accuracy of 90%, the proposed MLP was trained in a stationary mode and in a more benign environment than that faced in a factory. Hence, we use MLP to collect data under mobile tag conditions and test them.

MLP with three hidden layers consisting of 5, 12 and 3 neurons is used as a basis for the initial classifier. This model was trained using 75% of the data gathered and then tested with the remaining 25% to prevent overfitting. Later, it was fine-tuned using cross validation in order to further improve accuracy within the specific environment.

Boosted Decision Trees. In other fields such as particle physics [7] and financial risk management [8], ensemble learning methods have been shown to have higher prediction accuracies than neural networks. Hence, the potential of Boosted Decision Trees (BDT), an ensemble learning method, has been explored in this work. The BDT was developed using the AdaBoost algorithm [9].

The BDT model is more computationally intensive than the MLP model. It takes a relatively longer time to load and predict. However, this is not an issue for the current application as the positioning engine resides in the server-

side PC and not on the tags or anchors. Hence, the extra computational load has no noticeable effect on the real-time performance of the system in terms of response time.

A total of 3152 samples (1531 LOS and 1621 NLOS) were used for MLP and BDT model training. The LOS and NLOS measurements obtained in the lab earlier (Fig. 3 and Fig. 4) were then used to test the MLP and BDT models. The results were compared with the PDM method under various thresholds (besides the 10 dB suggested in [6]). The results for the stationary test are shown in Table II. It is seen that the MLP and BDT models are able to give the same level of accuracy (98%) as the PDM method with 10 dB threshold. Under mobile tag conditions however, the PDM method only yields 88% accuracy with the manufacturer recommended 10 dB threshold. The results shown in Table III do however improve a bit to 91% when the threshold is changed to 8 dB. The machine learning models are seen to perform better than the PDM, with MLP giving 92% and BDT giving 94%. Thus both the MLP and BDT were seen to show potential to perform better than the PDM method under mobile tag conditions. Hence the methods were put to test in a highly cluttered factory like environment as described in the next section.

TABLE II. STATIONARY TEST RESULTS IN LAB

	PDM Method Threshold (dB)					**MLP**	**BDT**
	4	***6***	***8***	***10***	***12***		
TP	574	574	532	533	456	542	547
FP	997	291	77	0	0	5	11
TN	308	1014	1228	1305	1305	1301	1295
FN	0	0	12	41	118	32	27
Sensitivity = $\left(\frac{TP}{TP+FN}\right)$ **%**	100	100	98	93	79	94	95
Specificity = $\left(\frac{TN}{FP+TN}\right)$ **%**	24	78	94	100	100	100	99
Accuracy = $\left(\frac{TP+TN}{TP+FP+TN+FN}\right)$**%**	47	85	95	98	94	98	98

a) TP (True Positive) refers to actual NLOS detected as NLOS.
b) FP (False Positive) refers to actual LOS detected as NLOS.
c) TN (True Negative) refers to actual LOS detected as LOS.
d) FN (False Negative) refers to actual NLOS detected as LOS.

TABLE III. MOBILE TEST RESULTS IN LAB

	PDM Method Threshold (dB)					**MLP**	**BDT**
	4	***6***	***8***	***10***	***12***		
TP	685	638	593	536	463	595	617
FP	465	79	16	4	1	2	9
TN	168	554	617	629	632	631	624
FN	9	56	101	158	231	99	77
Sensitivity = $\left(\frac{TP}{TP+FN}\right)$ **%**	99	92	85	77	67	86	89
Specificity = $\left(\frac{TN}{FP+TN}\right)$ **%**	27	88	97	99	100	100	99
Accuracy = $\left(\frac{TP+TN}{TP+FP+TN+FN}\right)$**%**	64	90	91	88	83	92	94

a) TP (True Positive) refers to actual NLOS detected as NLOS.
b) FP (False Positive) refers to actual LOS detected as NLOS.
c) TN (True Negative) refers to actual LOS detected as LOS.
d) FN (False Negative) refers to actual NLOS detected as LOS.

V. PERFORMANCE IN FACTORY-LIKE ENVIRONMENT

The positioning system was setup at the Model Factory facility of the Advanced Remanufacturing and Technology Centre, Singapore (ARTC). The Model Factory environment is representative of a typical industrial manufacturing facility. It consists of large machinery with many moving metallic parts. These objects cause more reflection and dispersion of the UWB signals, resulting in larger errors in the position estimates. Thus the environment is ideal for testing the potential of the machine learning models in improving the performance of the UWB positioning system.

The setup consisted of four anchors installed around an assembly line area. The anchors communicated with a mobile UWB tag and sent the four parameters (Range Estimate, STD NOISE, FP_Amp and PDM) to the server-side PC.

The tag was worn on a lanyard and carried along a route around the assembly line to obtain training data. The training data was classified as LOS or NLOS based on whether the body of the person carrying the tag was facing towards or away from the respective anchors.

After taking training data, test data was taken by going around the assembly line in a clockwise and anti-clockwise direction. The results of the test and their comparison with the PDM method are shown in Table IV.

From the results it is seen that using the PDM method, the best accuracy achievable was 79% at thresholds of 6, 8 or 10 dB. As in the case of the mobile tests done in the laboratory (Table III), the PDM method is not able to provide an accuracy comparable to the stationary tag case (Table II). The results are also significantly lower than that of the mobile tag tests done in the lab. This can be attributed to the fact that the test environment is a much harsher one, with a lot of metal and hence more multipath signals.

Both the machine learning methods have given better results than the PDM method. The MLP has given 82% while the BDT has given 87%. This is a significant improvement over the PDM method. The results thus support the use of BDT for mobile tag positioning in highly cluttered environments such as factories.

TABLE IV. MOBILE TEST RESULTS IN FACTORY

	PDM Method Threshold (dB)					**MLP**	**BDT**
	4	**6**	**8**	**10**	**12**		
TP	367	328	268	222	171	263	324
FP	316	173	106	63	32	73	75
TN	475	618	685	728	756	718	716
FN	43	82	142	188	239	147	86
Sensitivity = $\left(\frac{TP}{TP+FN}\right)$ **%**	90	80	65	54	42	64	79
Specificity = $\left(\frac{TN}{FP+TN}\right)$ **%**	60	78	87	92	96	91	91
Accuracy = $\left(\frac{TP+TN}{TP+FP+TN+FN}\right)$**%**	70	79	79	79	77	82	87

a) TP (True Positive) refers to actual NLOS detected as NLOS.
b) FP (False Positive) refers to actual LOS detected as NLOS.
c) TN (True Negative) refers to actual LOS detected as LOS.
d) FN (False Negative) refers to actual NLOS detected as LOS.

VI. CONCLUSION

UWB is a good technology for indoor localization if NLOS signals are properly detected and mitigated in the positioning engines that utilize it. While the PDM method utilizing First Path Power and Total Received Power was found to give very good results for stationary cases, its performance was seen to deteriorate when used for cases where the tag was mobile. This decline in performance was seen to be even more significant when tested in a factory-like environment. Hence machine learning models were used to explore the potential in improving NLOS detection.

Two machine learning models utilizing MLP and BDT were developed and tested in an actual factory-like environment. Both models yielded better results than the PDM method when applied to mobile tag positioning. The BDT model was found to give the highest accuracy of 87%.

This work has demonstrated the potential of BDT for positioning through application to NLOS detection of UWB signals.

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