Weighted Naïve Bayes Approach for Imbalanced Indoor Positioning System Using UWB

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***Abstract*—The accuracy and reliability of an Ultra-WideBand (UWB) Indoor Positioning System (IPS) are compromised owing to the positioning error caused by the Non-Line-of-Sight (NLoS) signals. To address this, Machine Learning (ML) has been employed to classify Line-of-Sight (LoS) and NLoS components. However, the performance of ML algorithms degrades due to the disproportion of the number of LoS and NLoS signal components. A Weighted Naïve Bayes (WNB) algorithm is proposed in this paper to mitigate this issue. The performance of the proposed algorithm is compared with conventional state-of-the-art ML algorithms such as K-Nearest Neighbor (KNN), Support Vector Machine (SVM), and Decision Tree (DT) using the Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC). The results prove that the WNB classifier can significantly reduce the impact of the limited number of NLoS components that are available for training the model. The proposed WNB algorithm also maintains a high classification accuracy and robustness in mixed LoS/NLoS conditions.**

***Index Terms*—Ultra-wideBand, Indoor Positioning System, Machine Learning, Non-Line-of-Sight Identification, Naïve Bayes, Weighted Naïve Bayes.**

I. Introduction

Target tracking and positioning in an indoor environment have emerged as a great challenge for future wireless networks [1]–[6]. Among several popular technologies available for IPS in the literature includes Visible Light Communication (VLC), Radio Signal Identification (RSSI), Wi-Fi, Bluetooth, Zigbee and Ultra-wideBand (UWB). UWB has gained significant attention in the community, because UWB can estimate the location of a tag with centimeter (cm)-level accuracy due to its wider bandwidth and very accurate timestamps [7]–[9]. However, one of the substantial challenges for UWB based IPS is the presence of Non-Line-of-Sight (NLoS) components that arise due to the reflection and refraction of the UWB signal [10]. These NLoS components adds a positive bias error in the estimated distance and thus, degrade the localisation accuracy [11], [12].

Several Machine Learning (ML) algorithms for NLoS identification have been proposed in the recent literature [13]–[16]. The authors in [14], [15] investigated ML-based NLoS identification and proposed the Support Vector Machine (SVM) algorithm as a classifier. The results indicated that the ML approach could improve the accuracy of UWB IPS by identifying the NLoS components. Consequently, in [16], the authors also applied SVM as a classifier, and used linear discriminant analysis to train the model. The authors proposed the K-mean clustering algorithm for NLoS classification in [17]. The signal features used in the paper were mean excess delay, kurtosis, and root mean squared delay spread of UWB signals [17]. Different ML techniques like Naïve Bayes (NB) based on the Bayesian sequential test [11], [18], [19], Boosted Decision Tree (BDT) [20], K-Nearest Neighbor (KNN) [21], etc., were also investigated. Deep-learning based approach was proposed for the identification of NLoS signal as well in [22].

The above-mentioned methods require a large number of balanced LoS and NLoS signals for training the ML model. However, in practice, the available dataset is not always class-balanced. This results in poor performance of the proposed model due to the limited availability of the NLoS components for training the model. Therefore, it further results in a low classification accuracy. To address this issue, we proposed a weighted Naïve Bayes (WNB) classifier for an imbalanced LoS and NLoS signals for UWB IPS.

The main contributions are as follows:

- We introduce a novel signal feature-based solution, i.e., WNB, to address the imbalanced NLoS classification. This approach will improve the classification of the UWB based IPS.
- We compare the proposed WNB classifier with the existing state-of-the-art ML algorithms that is KNN, SVM and DT in terms of the Receiver Operating Characteristic (ROC) and Area Under the Curve (AUC). Precision,

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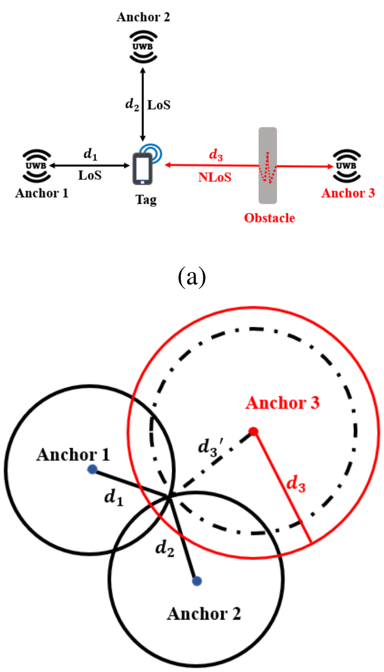
Recall, and Classification Accuracy is also compared.

This paper is organized as follows. Section II describes how the NLoS signal affect the UWB positioning accuracy. In Section III, we mainly discuss the principles of our proposed positioning algorithm. Section IV discusses the experimental setup employed for collecting the dataset including the hardware and signal features used for post processing. Section V presents the performance evaluation of the proposed algorithms with existing ML algorithms. The summary of the work is given in Section VI.



(a)

(b)

Fig. 1: (a) UWB scenario with three anchors and one tag in NLoS conditions, (b) positive bias error of range estimation caused due to the signal propagation.

II. NLoS Problem Formulation

A UWB positioning setup is depicted in Figure 1. From the figure, it can be observed that three fixed anchor nodes are placed at known locations. A tag will use the knowledge of anchors' location to estimate its position. We consider that the three-dimensional ($3D$) coordinates corresponding to the tag are (x, y, z). The $3D$ coordinates of the i-th anchor is represented as (x_i, y_i, z_i). The distance between each anchor and tag is estimated using a Time-of-Arrival (ToA) based method. In ToA, the estimated distance d_i between the ith anchor and the tag is computed as

$$d_i = \frac{c \times \tau_i}{2}, \tag{1}$$

where c represents the speed of light and τ_i represents the signal propagation time from the tag to the i-th anchor. Also the estimated distance d_i in terms of the coordinates of the i-th anchor and the tag is given as

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2}. \tag{2}$$

The position of tag (x, y, z) can be determined through equation (2) by using least-squares solution [19]. It is important to note that at least (three) fours anchors are required to determine position of the tag in (two) three dimensions. Furthermore, as depicted in Figure 1, the positioning accuracy degrades in the presence of NLoS condition. Let us consider Figure 1(a), where anchor 1 and anchor 2 have LoS link and anchor 3 has NLoS link due to the presence of an obstacle. This NLoS condition results in a positive bias error in the computation of d_3. This is because the signal propagation time τ_3 will be longer, which results in a typical NLoS measurement error. Correspondingly, the NLoS error is depicted Figure 1(b). Circles will overlap due to the positive bias error of d_3, and this significantly degrades the performance of the localization system. Now considering the NLoS condition, the estimated distance d_i^{NLoS} can be calculated by

$$d_i^{NLoS} \quad = \quad d_i + \epsilon_i + b_i, \tag{3}$$

where ϵ_i denotes the measurement noise which follows the Gaussian distribution with mean zero and variance σ_ϵ^2 and b_i is the NLoS measurement error. Finally, the corresponding ranging error δ_i can be expressed as:

$$\delta_i = \begin{cases} \epsilon_i, & \text{LoS}, \\ \epsilon_i + b_i, & \text{NLoS}. \end{cases} \tag{4}$$

The NLoS condition is common in the indoor environment due to a variety of physical obstcles such as walls, humans, and machines that can block the direct path between the transmitter and the receiver [23], [24]. Therefore, classification of NLoS components is crucial to develop an accurate IPS. In the next section, we will discuss the classification algorithm to distinguish between LoS and NLoS scenario.

III. POSITIONING ALGORITHMS

A. Naïve Bayes Algorithm, (NB)

It is a supervised learning method based on Bayesian theory which predicts the label class with a corresponding maximum posterior probability [19]. The predicted class $\hat{l}^k$ at the k-th instance of data can be determined as

$$\hat{l}^k = \arg\max_l P(l) \prod_{i=1}^{n} P(X_i^k \mid l), \tag{5}$$

where l is the class label and $l \in \{0, 1\}$ which indicates LoS ($l = 0$) or NLoS ($l = 1$) and $P(X_i)$ is the probability of the i-th attribute. The current formulation is more suitable for balanced classes. However, to address the imbalanced NLoS and LoS case, we propose a weighted Naïve Bayes (WNB) based classifier which is discussed in detail in the next section.

B. Weighted Naïve Bayes, (WNB)

In practice, the underlying principle of employing the weighted Naïve Bayes (WNB) algorithm is that some attributes are not of the same importance as others [25], [26]. By using the attribute weighting scheme, the predicted class $\hat{l}^k$ is determined as

$$\hat{l}^k = \arg\max_{l} P(l) \prod_{i=1}^{n} P_{w(i)}(X_i^k \mid l), \tag{6}$$

where $P_{w(i)}(X_i^k \mid l)$ represents the likelihood of the attribute and is given as

$$P_{w(i)}(X_i^k \mid l) := P(X_i^k \mid l)^{w(i)}. \tag{7}$$

Now by substituting (7) in (6) and taking logarithm of (6), a linear function of the weights can be achieved, yielding

$$\hat{l}^k = P_o + \boldsymbol{w}\boldsymbol{P}_{X^k}, \tag{8}$$

where

$$P_o = \log_2\left(\frac{P(l=1)}{P(l=0)}\right), \tag{9}$$

$$\begin{aligned}\boldsymbol{P}_{X^k} \;=\; & \left[\log_2\left(\frac{P(X_1^k \mid l=1)}{P(X_1^k \mid l=0)}\right),\right.\\ & \log_2\left(\frac{P(X_2^k \mid l=1)}{P(X_2^k \mid l=0)}\right),\\ & \left.\cdots, \log_2\left(\frac{P(X_n^k \mid l=1)}{P(X_n^k \mid l=0)}\right)\right]^T,\end{aligned} \tag{10}$$

and the weight vector is defined as

$$\boldsymbol{w} = [w(1), w(2), \cdots, w(n)]\,. \tag{11}$$

Finally, we can classify data as

$$X^k \text{ is classified as} = \begin{cases} 1, & \text{if } \hat{l}^k > \alpha,\\ 0, & \text{if } \hat{l}^k \leq \alpha. \end{cases} \tag{12}$$

where α represents the threshold and its value depends on the available data set.

IV. Measurement Scenarios and Data Collection

This section provides the details regarding the considered measurement scenario and as well as the data preparation method. The particular focus is on the data collection process, followed by extraction of the key features of UWB IPS.

TABLE I: MDEK-1001 Configuration

Properties	Values
Chip	DW 1000
Data rate	6.8 Mbps
Frequency	3993.6 MHz
Channel	2
Pulse-reception frequency (PRF)	16 MHz
Bandwidth	499.2 MHz

A. Data Collection Process

In this section, we describe the experimental setup for the evaluations and the data collection process for the UWB IPS. For labeling the data, we consider a binary classification i.e, either LoS or NLoS. For the LoS samples, there is a direct signal propagation path between all anchors and the tag. Although, in the NLoS scenario, an obstacle is placed between the anchor and the tag. The data collection environment was carried out in a room occupying of size 3.3×4.8 m^2. The MDEK1001 UWB kits that can be configured either as an anchor or a tag are used in our experiment. Table I provides the detailed MDEK1001 kit configurations used in our evaluation. Four anchors are placed in each corner of the room with same height. The tag was connected to a personal computer (PC) to collect the dataset with the help of MATLAB. As the focus of this work is to mitigate the imbalanced class issue, therefore, we randomly selected 1000 LoS and 100 NLoS components from the dataset.

B. Signal Feature Extraction

There are several features mentioned in the literature that can be used for ML based classification for positioning systems [11], [27], [28]. The first-path power level (FPPL) can be calculated as

$$\text{FPPL} = 10\log_{10}\left(\frac{F_1^2 + F_2^2 + F_3^2}{N^2}\right) - A, \tag{13}$$

where F_1, F_2, F_3 represents the first path amplitude value at points 1, 2 and 3, respectively [29]. A is the constant and equal to 113.77 and 121.74 for a Pulse Repetition Factor (PRF) of 16 MHz and 64 MHz, respectively, and N represents the preamble accumulation count value [29].

The received power level (RXPL) is calculated by the following formula

$$\text{RXPL} = 10\log_{10}\left(\frac{C \times 2^{17}}{N^2}\right) - A, \tag{14}$$

where C is the channel impulse response power value [29]. The difference between RXPL and FPPL can be used to identify the LoS and NLoS by setting a threshold. The formula for the threshold computation is given as

$$\text{Threshold Power} = \text{RXPL} - \text{FPPL} \tag{15}$$

Finally, $n = 10$ features are extracted from the UWB IPS signal in our analysis. The details these figures are given as follows:

- X_1: The first path amplitude (F_1) of the UWB signal.
- X_2: The second path amplitude (F_2) of the UWB signal.
- X_3: The third path amplitude (F_3) of the UWB signal.
- X_4: The preamble accumulation count value.
- X_5: The power of the channel impulse response (C).
- X_6: The standard noise variance.
- X_7: The estimated FP power.
- X_8: The estimated RX power.
- X_9: The power difference between the FP and RX power.
- X_{10}: The reported estimated distance.

V. Performance Evaluation

In this section, we focus on examining the performance of the proposed algorithm. In order to verify the improvements of our proposed WNB algorithm, we compare the results with the existing state-of-the-art ML algorithms, i.e., KNN, SVM, and DT. Table II shows the classification accuracy of the mentioned algorithms. It can be observed that for the WNB algorithm, out of 100 NLoS samples, the True Negative (TN)= 98 samples were classified correctly, resulting in a classification accuracy of 98% for NLoS classification. The remaining False Negative (FN)= 2, i.e., 2% of NLoS samples were incorrectly classified as LoS samples. For the LoS samples, 991 out of 1000 samples were classified as True Positive (TP)= 991 out of 1000 were classified accurately resulting in an accuracy of 99.1% whereas the 9 False Positive (FP) cases resulted in 0.9% of inaccurate classification as NLoS samples. The overall classification accuracy for both classes is 98.8% which is higher than other state-of-the art ML algorithms.

TABLE II: Performance comparison of the proposed WNB with KNN, SVM and DT algorithm.

Algorithms	LoS Classification Accuracy	NLoS Classification Accuracy	TP	FP	FN	TN
KNN	96.6%	72%	966	34	28	72
SVM	96.9%	88%	969	31	12	88
DT	97.2%	87%	972	28	13	87
WNB	99.1%	98%	991	9	2	98

Figure 2 shows the plot for ROC curves and corresponding AUC areas obtained for the proposed WNB and baseline algorithms. The ROC curve is drawn for the true positive rate (TPR) versus the false positive rate (FPR). If one ROC curve is more closer to the upper left, the classifier performance better. For AUC area, it refers to the area under the ROC curve in a single number. Generally, the better classification performance, the higher the AUC value which corresponds to the ROC obtained. From the Figure 2, we can observe that our proposed WNB algorithm is the closet to the upper left corner which indicates it performance the best compare with KNN, SVM and DT. Furthermore, the AUC area can reach 0.988 which is the highest in the mentioned algorithms i.e., 0.214 higher than KNN, 0.192 higher than SVM, and 0.105 higher than DT. This implies that WNB outperforms other ML algorithms for the NLoS classification.

Finally, Figure 3 shows the evaluation results of these algorithms in terms of precision, recall, and accuracy. It indicates that the accuracy of the KNN algorithm is equivalent to 94.8%, whereas for SVM and DT algorithm it is equal to 95.8% and 96.3%, respectively. On the other hand, the accuracy for WNB algorithm is equivalent to 98.9% which shows it is superior to the other state-of-the-art ML algorithms. Moreover, for precision and recall, WNB algorithm achieved 99.8% and 98.9%, and both are higher than other algorithms which show the WNB can provide better results for both NLoS and LoS classification. Therefore, we can summarize that the proposed WNB has shown very high accuracy for identifying the NLoS samples in case of the imbalanced data.

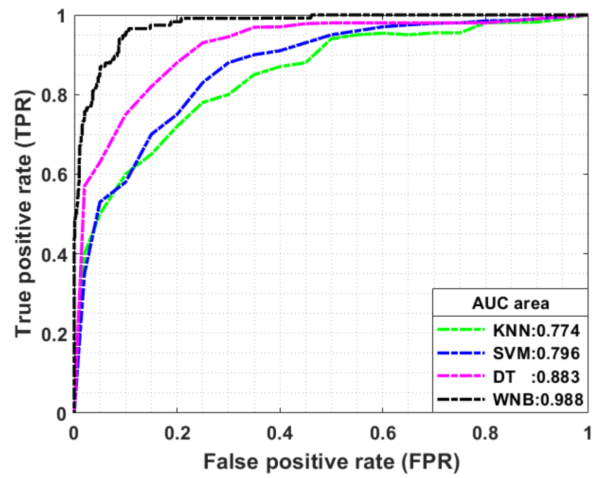


Fig. 2: Receiver Operating Characteristics (ROC) and Area Under the Curve (AUC) comparison of the four algorithms

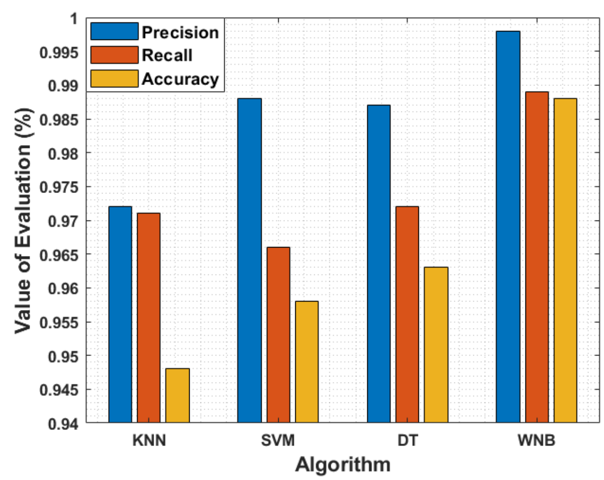


Fig. 3: Performance comparison in terms of Precision, Recall, and Accuracy for the KNN, SVM, DT and WNB algorithm.

VI. Conclusions

In the development of indoor localization applications, reliable and precise localization becomes significantly important owing to the presence of the NLoS components. This work proposed a signal featured-based method for imbalanced NLoS detection to improve the accuracy of the UWB positioning system in a harsh indoor environment. We compared the performance of the proposed WNB algorithm with the existing state-of-art ML techniques including KNN, SVM, and DT in terms of ROC curve and AUC area. Moreover, we also compared the precision, recall, and accuracy. Results showed that the proposed algorithm outperforms the state-of-art algorithms with an accuracy of 98.9% which indicates its robustness against the imbalanced data set. For future work, the proposed could be applied in different environments and different types of obstructions to experiment the robustness. Moreover, the data could be extended to a large dataset to evaluate the computational burden in terms of running time and classification accuracy.

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