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***Abstract*—With the rapid development of wireless communication technology and the emergence of the Industrial Internet of Things (IIoT)s applications, high-precision Indoor Positioning Services (IPS) are urgently required. While the Global Positioning System (GPS) has been a key technology for outdoor localization, its limitation for indoor environments is well known. Ultra-WideBand (UWB) can help provide a very accurate position or localization for indoor harsh propagation environments. This paper focuses on improving the accuracy of the UWB indoor localization system including the Line-of-Sight (LoS) and Non-Line-of-Sight (NLoS) conditions by developing a Machine Learning (ML) algorithm. In this paper, a Naive Bayes (NB) ML algorithm is developed for UWB IPS. The performance of the developed algorithm is evaluated by Receiving Operating Curves (ROC)s. The results indicate that by employing the NB based ML algorithm significantly improves the localization accuracy of the UWB system for both the LoS and NLoS environment.**

***Index Terms*—UWB, IPS, localization, ML, Naive Bayes.**

I. Introduction

The invention of the Global Navigation Satellite System (GNSS) was pinnacle in enabling accurate location information for many application and thus brought tremendous convenience to human life [1]. With the upgrading of new generation navigation systems such as the Cyclone Global Navigation System (CYGNSS) in the United States, Global Navigation Satellite System (GLONASS) in Russia, TechDemoSat-1 (TDS-1) in the UK, Galileo GNSS for the European Union, BuFeng-1A/B twin satellites for China and the application of these technologies makes positioning and navigation easier than ever especially for outdoor environments [1]. However, with this continuous expansion and increased uptake for Industrial Internet of Things (IIoT)s, the application of Indoor Positioning Services (IPS) including commercial applications such as logistics, tracking, localize and fetch in warehouses, navigation of Unmanned Ground Vehicles (UGVs) etc. have been widely recognized and greatly developed [2], [3]. However, the GNSS does not provide accurate positioning for indoor environment and therefore warrants development of alternative technologies for indoor localization [4]. GNSS is also not a cost-effective option for large scale networks which will be of paramount importance in IIoT scenarios [5]. Therefore, for such indoor IIoT environments another independent positioning system is required.

Ultra-WideBand (UWB) system have the capability to provide high accurate ranging accuracy as compared to other available low rate wireless personal area networks systems such as WiFi, Bluetooth, RFID, and other relevant technologies [6]. UWB impulse radio system employs an extremely short pulse which has a duration of the order of nanosecond, to provide time resolution and ranging accuracy to be within centimeters [7]. Furthermore, UWB capability of penetrating different materials, ability to combat multipath and causing less interference to other operating systems in the same band makes it an ideal and a potential candidate especially for harsh environments and applications [8]. However, in real-world IPS, there are still many challenges before deploying UWB as the positioning technology due to the complex dynamics of the indoor environment which includes the movement of objects or people, serious reflection, signal attenuation and multipath propagation.

In general, for the indoor environments when clear Line-of-Sight (LoS) exists between the anchors and tag, the UWB localization system has the ability to reach an accuracy of around 10 cm. However, similar accuracy is difficult to attain in Non-Line-of-Sight (NLoS) environments.The probability of reception is significantly reduced which in turn effects localization accuracy. In this paper, we focus on applying Machine Learning (ML) techniques to initially identify LoS/NLoS scenario and then improve the localization accuracy especially for NLoS situation in the IPS. The ML algorithm employed is based on Naive Bayes (NB) principles. This algorithm will help discriminate the LoS or NLoS environment. From our simulations, it can be observed that a significant improvement in localization accuracy is achieved by employing the above mentioned algorithms especially for NLoS environment.

The reminder of the paper is organized as follows. Section II focuses on the system model adopted for UWB system. In section III the problem exxperienced by UWB signal is visited. In section IV the proposed algorithms for NLoS identification are described. In section V, the performance of the algorithm will be evaluated. Finally, conclusions are summarised in section VI.

II. System Model

A. Transmitted Signal

In UWB system, a range of UWB pulses have been proposed [9]. However, in this paper we have adopted Gaussian pulse due to its maximum range-rate resolution [10]. The Gaussian pulse is represented by $\psi(t) = \exp\left(-\frac{t^2}{\tau_p^2}\right)$, where τ_p is the pulse width.

B. Channel Model

The UWB pulse experiences a multipath channel as given in IEEE 802.15.4a Task Group for wireless personal area networks (WPAN) [9]–[12], which is given as

$$h(t) = \sum_{l=1}^{L} \alpha_l \delta(t - \tau_l), \tag{1}$$

where $\delta(\cdot)$ is the Kronecker function, L indicates the total number of multipath taps, α_l and τ_l is the amplitude and the delay of the l-th multipath, respectively.

C. Received Signal

The received signal at a tag from the anchor can be expressed as

$$r(t) = \sqrt{E}_\psi \sum_{l=1}^{L} a_l \psi(t - \tau_l) + n(t), \tag{2}$$

where $n(t)$ is Additive White Gaussian Noise (AWGN) with zero mean and two-sided power spectral density $N_0/2$.

III. Problem Formulation

When employing time of arrival (ToA) algorithms the goal is to estimate the value of τ_1 which is the first multipath observed by the receiver [13]. This task is further complicated because of the AWGN noise and the other multipath components present in the received signal as mentioned in (2). Furthermore, in the NLoS environment the radio signal propagates across and through the obstruction of walls and other indoor materials present in surroundings. This results in

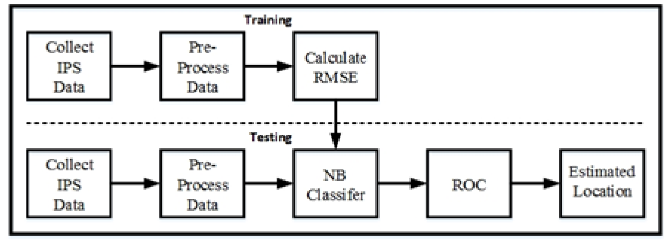

Fig. 1. Block Diagram of developed UWB IPS system

different propagation speed of the radio signal as the signals will be much slower than free space. Therefore, the transmitted information will be delayed at the receiver resulting in ranging error. Consequently, a simple way to mitigate the NLoS effects is to ignore it. However, ignoring such information may result in delayed or inaccurate localization for IPS. In this paper, the variance of the estimated distance and the power of the first path will be used to identity the NLoS environment.

The received power of the signal is evaluated in dBm and can be calculated as

$$P_r = 10\log_{10}\left(\frac{|h(t)|^2 \cdot 2^{17}}{N^2}\right) - A, \tag{3}$$

where A has a constant value of 113.77 when using a pulse repetition frequency of 16MHz as defined in IEEE 802.15.4 standard [14]. The received signal of first path power is estimated by

$$P_r^1 = 10\log_{10}\left(\frac{F_1^2 + F_2^2 + F_3^2}{N^2}\right) - A, \tag{4}$$

where F_i, $i = 1, 2$, and 3 represents the first path amplitude magnitude value at point i. N in (3) and (4) is the preamble accumulation count value defined in [14].

IV. Proposed Solution

In this paper, a Naive Bayesian (NB) algorithm is proposed to classify the NLoS environment and then used to further improve the accuracy of the UWB positioning system. NB algorithm is one of the most popular and widely used classification algorithms in ML [15]. This method is based on the Bayesian principle and uses the knowledge of probability statistics to classify the sample data set. Due to its solid mathematical foundation, the false positive rate of the Bayesian classification algorithm is very low. From the probability perspective, according to Bayes Rule, the given probability $P(l|x)$ can be calculated as

$$P(l|x) = \frac{P(x|l)P(l)}{P(x)} \tag{5}$$

where $P(l|x)$ is the probability of the localization of the tag given anchors. $P(l)$ is the prior probability of the location of the anchor, $P(x|l)$ is the probability of the anchor given location and the $P(x)$ is the prior probability of the distance of the anchor.

Figure 1 illustrates the block diagram of the developed UWB IPS system. The system operates by employing two

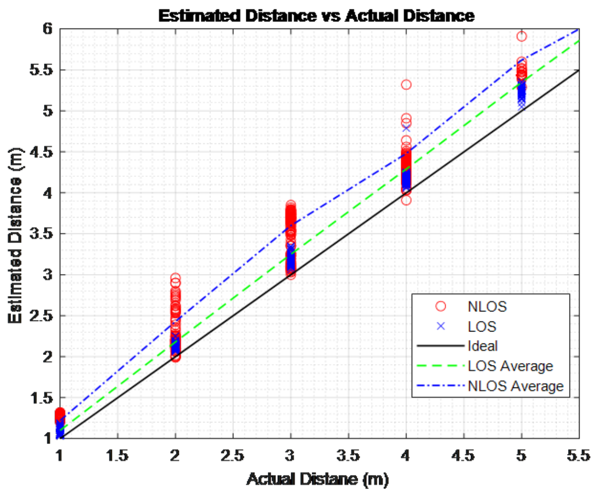

Fig. 2. Estimated versus Actual Distance in meters

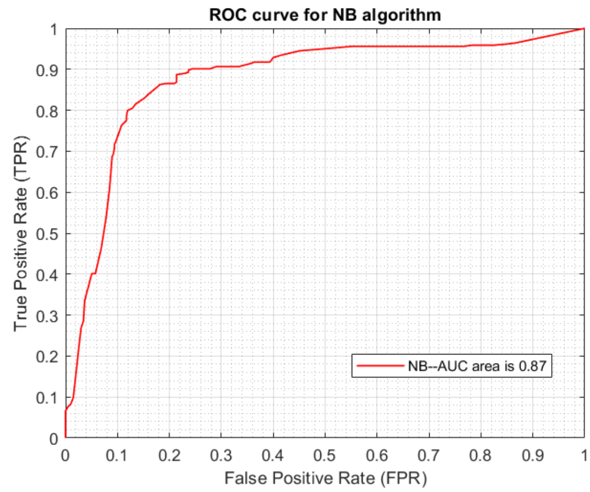

Fig. 3. Receiver operating curves for NB algorithms

phases: offline training and online testing. In the first phase, which is the training phase the UWB IPS data is collected from the tag and pre-processed. The distance between the anchors and tags is calculated, followed by the RMSE as given as

$$RMSE = \frac{1}{T}\sqrt{(d_1 - \hat{d}_1)^2 + \cdots + (d_T - \hat{d}_T)^2}, \tag{6}$$

where T represents the number of anchors present. It is further used to produce the fingerprint library. During the testing phase, the UWB IPS data are calculated and pre-processed. They are then compared with the database utilising an NB classifier as mentioned above. The ROC is then plotted and the confidence level is calculated which is utilised to improve the positioning results by deriving the final estimated location of the tag.

V. Simulation Results and Discussions

The experiment is set up in a room having area of $32m^2$, where four anchors are placed at the corners of the room and one tag will be tested to determine the location in this experiment. The tag is worn by the human. The data collection is collected over a complete day. The human orientation and stance remained unchanged during each data collection period. However, after the training is carried out, the human can move freely within this room.

In Figure 2 the estimated versus actual distance is plotted in meters for LoS and NLoS environment. Measurements are recorded after every meter using a meter ruler when the tag covers a total distance of 5m. One hundred samples of LoS and NLoS were collected and compared after every meter. From the figure, it can be observed that there is a certain error between the actual distance and the measured distance, and there is a tendency to increase slightly as the distance increases. In each measurement, the error of LoS is smaller than that of NLoS, which proves that NLoS will be greatly influenced by the ranging error and effect the accuracy of measurements. Therefore, classifying and processing NLoS is essential to improve the positioning accuracy of the overall system.

Figure 3 indicates the receiver operating characteristics (ROC) curve is plotted. In this figure, true positive rate (TPR) is plotted against the false positive rate (FPR). The accuracy of NB can be measured by determining area under the curve (AUC). From the figure it can be observed that AUC is around 87%, which suggest that the NB will be a able to easily separate the NLoS situation from the LoS situation. Furthermore, this will improve the overall positioning accuracy for NLoS environment.

VI. Conclusion

ML based algorithm which is based on NB principles have been designed for UWB IPS system. The proposed algorithms show considerable gain in termss of localization accuracy. The result indicates that the error between the actual distance and the measured distance increases as the distance between the anchors and tags increase. The result further shows that NB algorithm has good classification characteristics as the area under the curve is 87%, and the proposed algorithm will maintain good positioning accuracy in LoS as well as NLoS environment.

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