OptiTrack-aided Supervised Learning for Neural Network Based Ultra-wideband Ranging Bias Correction

Changwei Chen  Solmaz S. Kia, senior member, IEEE
University of California Irvine

Abstract—This paper proposes a learning-based bias correction method to improve the measurement accuracy of the ultra-wideband (UWB) ranging sensors. Our approach uses multiple artificial neural networks (ANNs) for the UWB line-of-sight (LoS) and non-line-of-sight (NLoS) measurements scenarios discrimination and bias-free range prediction for each scenario respectively. The innovation in our work includes a novel set of features that are readily available on low-cost UWB ranging sensors to train the ANNs and collecting the training data via the OptiTrack motion capture camera system. OptiTrack system allows us to collect measurements between an UWB sensor mounted on a moving pedestrian and a set of stationary UWB sensors, resulting in collecting a diverse set of training data at various relative poses between the UWB transceivers. The effectiveness of our OptiTrack-aided supervised learning-based UWB bias correction (OLUC) method is demonstrated via a set of pedestrian localization experiments, which show our method results in significantly improved localization accuracy.

Index Terms—UWB ranging, OptiTrack, machine learning, bias correction, neural network, localization

I. INTRODUCTION

Radio frequency (RF) communication-based localization techniques that use Time-of-Flight (ToF) ranging [1] between a transceiver on a mobile agent (e.g., pedestrians, unmanned aerial vehicles, and mobile robots) and a set of pre-installed beacon transceivers with known locations have been proposed as a practical solution for some applications such as asset tracking indoors where the Global Navigation Satellite System (GNSS) fails to provide accurate location. Among various RF signals for ranging, the Ultra-wideband (UWB) signal has received considerable attention for indoor localization applications [2], [3]. The short impulse of the UWB signals makes them less susceptible to interfering with each other and with other coexisting radio signals such as WiFi and Bluetooth [4]. The low power emission of the UWB signals also makes them energy-efficient [4]. Comparing to radar-based techniques, UWB has better accuracy ratios and higher signal-to-noise ratios [5]–[7]. Other favorable attributes include low cost, high time-resolution, and obstacle-penetrating ranging [5], [8]–[10] that enables non-line-of-sight (NLoS) ranging. Nevertheless, a number of challenges should still be resolved to ensure high accuracy UWB ranging. NLoS and multi-path radio propagation can lead to biased measurements due to the time increment for the signals to penetrate through obstructions or travel a longer non-direct path [11], [12]. It is also observed that the line-of-sight (LoS) UWB range measurements exhibit spatially varying bias due to the relative pose and orientation between UWB sensors [13] and their antenna radiation patterns [14]. Therefore, to ensure UWB localization accuracy, it is critical to account for the bias in the UWB range measurements before using them. Bias correction/compensation in the UWB ranging is not fully resolved and is an active area of research.

NLoS UWB ranging bias is often significant. To deal with UWB NLoS bias, some localization approaches rely on identifying NLoS signals and avoid using them for ranging [15]–[18].

However, excluding NLoS range measurements means that in complex and cluttered indoor environments where most of the measurements are obtained in the NLoS cases, we should deploy a large number of beacon transceivers to increase the probability of taking LoS measurements if we want to implement the LoS-only UWB ranging. Still, NLoS scenarios may not be fully avoidable because of mobile obstacles in the environment, such as pedestrians.

There are mainly two approaches in the literature to handle

The authors are with the Mechanical and Aerospace Eng. Dept. of Univ. of California Irvine, CA 92697, USA, changwc3,solmaz@uci.edu. This work was supported by the U.S. Dept. of Commerce, National Institute of Standards and Technology award 70NANB17H192.
In this paper, we propose a novel bias correction framework for both LoS and NLoS UWB ranging via low-cost UWB transceivers. Our method, as depicted in Fig. 1, involves the following steps:

1. **Feature Extraction**: The first step involves extracting relevant features from the UWB measurements. These features include range, PM, FPPL, and RSS. Each of these features plays a crucial role in understanding the signal behavior in both LoS and NLoS conditions.

2. **Model Selection**: For classification and bias correction, we use two ANNs: LoS bias correction ANN (LBCANN) and NLoS bias correction ANN (NBCANN). Each ANN is designed to handle the specific characteristics of LoS and NLoS conditions.

3. **Bias Compensation**: The third step is to compensate for the bias in the UWB range measurements. This is achieved by using the trained ANNs to predict the bias-free range. The bias is modeled as a function of the channel impulse responses, energy of the received signal, and the mean excess delay. However, due to the limited availability of these features in low-cost UWB devices, we consider the antenna radiation patterns of UWB sensors as well.

4. **Training and Validation**: The ANNs are trained using a combination of state parameters and the true range (ground truth). The true range is obtained by measuring the distance between UWB sensors using a measurement unit (IMU)/UWB system, or by using a laser tracker and tape ruler. The training data is collected using the OptiTrack real-time motion capture system, as it is relatively easy to obtain accurate measurements.

5. **Performance Evaluation**: After training, the ANNs are evaluated using both LoS and NLoS conditions. The performance is assessed using metrics such as accuracy, precision, and recall. The results show that the proposed framework significantly improves the accuracy of UWB ranging in both LoS and NLoS conditions.

The rest of the paper is organized as follows. Section II introduces the UWB ranging model. Section III gives the...
detail account of our bias correction method depicted in Fig. 1. Finally, Section IV demonstrates the effectiveness of the proposed framework and compares it with the state-of-the-art techniques via a set of UWB pedestrian localization experiments.

II. PROBLEM SETTING

Consider a group of $N$ anchor UWB nodes located at known positions $\{A_1, A_2, \cdots, A_N\} \in \mathbb{R}^3$. There is one moving agent with an UWB tag, whose location is denoted by $P_{\text{tag}} \in \mathbb{R}^3$. This agent can communicate with each of the $N$ anchors and compute the corresponding ToF ranges. The measured range with respect to each anchor consists of the actual distance, the measurement noise, and a bias. Thus, the range measurement $z_n$ between the UWB tag and the $n$-th anchor is computed as follows

$$z_n = ||A_n - P_{\text{tag}}||_2 + \omega + b_n,$$

where $||\cdot||_2$ is the Euclidean distance, $\omega$ is the zero mean white Gaussian noise and

$$b_n = \begin{cases} b_n^{\text{LoS}}, & \text{LoS} \\ b_n^{\text{NLoS}}, & \text{NLoS} \end{cases}, \quad n = 1, 2, \cdots, N$$

is the measurement bias whose value differs in the LoS bias and NLoS ranging conditions. The LoS bias exhibits the joint impact of multi-path, relative orientation, and actual distance, while the NLoS bias corresponds to the LoS bias together with the range measurement increment due to the NLoS additional transmission time. The state estimation update rule in terms of the recursive least square (RLS) estimator [42] of the tag location $\hat{P}_{\text{tag}}$ when the range $z_n^k$ between the UWB tag and the $n$-th anchor is obtained at timestamp $k$ is shown as follow:

$$\hat{P}_{\text{tag}}^k = \hat{P}_{\text{tag}}^{k-1} + K^k(z_n^k - \hat{z}_n^k),$$

where $K^k$ is the estimator gain matrix, $\hat{z}_n = ||A_n - \hat{P}_{\text{tag}}^{k-1}||_2$ is the predicted range measurement. Given the biased range measurement model in (1), the estimation error $\epsilon^k$ of the RLS estimator at time $k$ is obtained as

$$\epsilon^k = P_{\text{tag}}^k - \hat{P}_{\text{tag}}^k = (I - K^k H^k)\epsilon^{k-1} - K^k(b_n + \omega),$$

where $I$ is the identity matrix and $H^k = \frac{\partial ||A_n - \hat{P}_{\text{tag}}^{k-1}||_2}{\partial \hat{P}_{\text{tag}}^{k-1}}|_{\hat{P}_{\text{tag}}^{k-1} = \hat{P}_{\text{tag}}^{k-1}}$. And the location estimation covariance matrix $\Sigma^k$ at time $k$ is

$$\Sigma^k = (I - K^k H)\Sigma^{k-1}.$$ 

As we can infer from (4) and (5), even though the bias $b_n$ does not directly affect the covariance $\Sigma^k$, it aggravates the location estimation error $\epsilon^k$ instantly. In fact, the bias is ubiquitous in real data. Ignoring the bias mismatches the reality under both LoS and NLoS UWB ranging, which leads to inconsistent estimation results. Figure 2 shows the result of an experiment study that compares the raw UWB range measurements with the true distance between UWB sensors. As it can be inferred from Fig. 2 NLoS bias is more significant than the LoS bias in terms of magnitude, while LoS bias cannot be neglected for accurate ranging. A similar observation is reported in our previous work [13] for UWB foot-to-foot ranging where the magnitude of LoS bias is considerable, which motivates us to take LoS bias correction into account for UWB-aided pedestrian localization. The objective of this work is to improve the UWB localization accuracy by determining the LoS and NLoS scenarios and consequently correcting the corresponding bias to generate accurate UWB range measurements using ML techniques.

III. LEARNING-BASED UWB LoS AND NLoS CLASSIFICATION AND BIAS CORRECTION

This section gives a detailed account of our learning-based bias correction method depicted in Fig. 1.

A. Feature Analysis and Selection

We focus on designing a bias correction method that can be used with low-cost UWB transceivers. In this study, we use the popular UWB transceiver DWM1000 developed by DecaWave [32] whose data acquisition and ranging software runs on a Teensy 3.2 as shown in the right hand side of Fig. 3. The Teensy 3.2 microcontroller implements a serial peripheral interface protocol to communicate with the UWB and collect sensor measurements [43]. To pick the features for measurement classification and correction, we constrained the choice to the signals that are readily available on this UWB ranging sensor.

We guide our study by the existing results in the literature. To distinguish NLoS UWB measurements from LoS ones, [44] employs a PM-based ranging mode discriminator with a deterministic threshold. The motivation for this choice is that in the LoS condition, the received direct-path signal’s power takes a big proportion of the total received signal power. In contrast, in NLoS conditions, the direct path is significantly attenuated or even completely blocked. When the difference between total received power and the direct-path power is larger than a threshold value, [44] argues...
that the range measurement can be identified as NLoS. To investigate effectiveness of this feature, we carried out an experimental study at different distances between two UWB sensors under a controlled environment where we know the true measurement scenarios. The results shown in Fig. 4 however indicates that the deterministic threshold represented by the red line cannot completely separate LoS and NLoS measurements, and there is still significant overlapping PM values. By collecting experimental data under various NLoS and LoS ranging condition, in addition to the PM we also included the FPPL and RSS of UWB signals and the raw range measurements as features. For a fixed distance, e.g., 7 m, the 3-D visualization of the UWB measurements under controlled data collection is shown in Fig. 5. As it can be seen in this plot, using these features the LoS and NLoS measurements are more clearly separated from one another. As we discussed earlier, the relative pose of the transceivers can also affect the ranging bias and thus recent work like [31] considered relative bias as an input feature. However, since obtaining the relative pose is not straightforward and needs additional to the bias correction, because the relative pose is hard to obtain without additional sensors, we did not consider it as a direct feature. However, as our evaluation study for localizing a moving pedestrian in Section IV show our bias correction method delivers high accuracy results despite the varying relative of the transceivers due to the movement. This can be due to the use of a diverse training data that we collect at various relative poses, which provides the opportunity learning of the relative pose-dependent bias implicitly by using signal patterns that can be reflected in FPPL and RSS.

Figure 6 depicts the LaNANN component of our method that is used to classify measurement type. It uses 4 nodes in the input layer corresponding to the UWB measurements of range, RSS, FPPL, and PM while the output layer has 2 nodes for the LoS and NLoS probability, respectively. We use the same input for the two ANNs of LoS and NLoS bias correction in parallel, but their output layers only have 1 node of the bias-free UWB range. In general, the LoS and NLoS scenarios of the UWB measurement can be modeled as a random variable \( \theta \) with a Bernoulli distribution mathematically whose probability mass function is as follow

\[
f(\theta; p) = \begin{cases} 
    p, & \text{if } \theta = \text{LoS} \\
    1 - p, & \text{if } \theta = \text{NLoS}
\end{cases} \quad (6)
\]

The probability of LoS \( p \), as well as the bias-free range \( \tilde{z}_n = \| A_n - P_{Tag} \|_2 + \omega \), based on our selection of the features, are functions of range, RSS, FPPL and PM, respectively.

\[
p = f_{\text{LaN}}(\text{range}, \text{RSS}, \text{FPPL}, \text{PM}), \quad (7a)
\]

\[
\tilde{z}_n = f_{\text{BC}}(\text{range}, \text{RSS}, \text{FPPL}, \text{PM}). \quad (7b)
\]

Then our objective boils down to use ANNs to approximate these functions without explicitly know the exact mathematical
relations.

\[ \hat{p} = \hat{f}_{\text{LaNANN}}(\text{range, RSS, FPPL, PM}), \quad (8a) \]

\[ \hat{z}_n = \begin{cases} \hat{f}_{\text{LBCANN}}(\text{range, RSS, FPPL, PM}), & \text{if } \hat{p} \geq 0.5 \\ \hat{f}_{\text{NBCANN}}(\text{range, RSS, FPPL, PM}), & \text{if } \hat{p} < 0.5 \end{cases}, \quad (8b) \]

where \( \hat{f}_{\text{LaNANN}}, \hat{f}_{\text{LBCANN}} \) and \( \hat{f}_{\text{NBCANN}} \) denotes the generic functions of the feed-forward LaNANN, LBCANN and NBCANN respectively.

### B. OptiTrack-aided Training Data Generation

Generating the training data of ANNs for LoS and NLoS classification and the corresponding bias correction is not a trivial task. Traditionally, the UWB sensors are placed statically at known locations where the actual reference range between UWB sensors can be measured or calculated. The accuracy of the reference range highly depends on the precision of the location and the measurements. The success of ML-based methods depends on extensive and informative training data generation, otherwise, the out-of-sample performance cannot be guaranteed due to the distributional mismatch. UWB ranging is often used for moving target localization. Using data generated in stationary configurations lacks diversity of relative pose that is often the case when we track a moving object. As we mentioned in Section III-A we proposed to incorporate the relative pose implicitly in the measurements, therefore, we have to make our training data set contain as many relative-poses as possible. Collecting training data manually at various relative-poses is not feasible since there are infinite amount of relative-poses. Therefore, to obtain more abundant training data and reduce the difference between the training and the test data set, we use the OptiTrack motion capture camera system to obtain an accurate bias-free range in a dynamical manner.

The OptiTrack system is a precise motion capture and 3-D tracking system with a localization error of less than 0.2 mm via optical ranging and trilateration for numerous applications, e.g., video game design, virtual reality, and robotics. The OptiTrack system in our KCS lab is shown in Fig. 3. The cameras can precisely perceive the particular reflective markers’ location via visual-based ranging techniques. As such, we attach at least 3 reflective markers on the UWB sensors so that they form a rigid body that can be recognized and tracked by the OptiTrack system as shown in Fig. 3 which exhibits the track of a UWB sensor in the associated OptiTrack software called Motive.

The pivot point of the UWB rigid body defined by the reflective markers can be manually assigned and tracked. Consequently, we can obtain the accurate position of the UWB sensors by setting their antennas as the pivot points and then calculate explicitly the distances between the pivot points as the label values, i.e., bias-free ranges, for the ANN model. The advantage of this approach to measure the actual distances is that the UWB sensors are not necessarily fixed at certain locations. Instead, the UWB sensors can be attached or carried by any moving objects or agents, while the UWB sensors can provide their own measurements in the meantime as the input features go into the ANN. To generate a diverse and abundant training data set, in our study case, an agent holding a Tag UWB sensor that connects to three anchor UWB sensors randomly walks under the OptiTrack systems in the LoS condition in our KCS lab for 5 minutes. The agent also waves the Tag UWB in the air to make different relative poses and collects various measurements to the full extent that contains biased ones caused by other factors illustrated before. All collected data are labeled by LoS. For NLoS cases, we put various obstacles found in our lab space between the Tag and the anchors and repeat the same data collection procedure as in LoS. The OptiTrack-aided training data generation experiment is illustrated in Fig. 3. One assumption made here is that the effect of the UWB relative pose, NLoS and multi-path on the range bias is encoded intangibly in the power features of the UWB signals, i.e., PM, FPPL, and RSS, that can be learned by the ANN model. In conclusion, by collecting data in such a dynamical setting, we can enrich the training data set without collecting the relative pose data explicitly and reduce the distributional difference between the training data and the test data to a considerable extent.

### C. Training Result

The UWB device we used to generate the training data is DecaWave DWM1000 and the sampling rate was set to 10 Hz. We generated 300000, 150000, and 150000 samples of the UWB range, PM, FPPL, RSS, and bias-free range for the LaNANN, LBCANN, and NBCANN, respectively, via agent random walks conducted in the KCS lab at UC, Irvine. The samples are split into a training set, a validation set and a test set for LBCANN and NBCANN is the bias-free range. We used the grid search method [45], [46] to tune the hyperparameters of all ANNs during the training process. The fine-tuned design of all three ANNs is shown in Table II.

In summary, the training results are shown in Table II where the best classification accuracy in test sets achieved by LaNANN is 92.73%. Also, the root mean square error (RMSE) for the test set for LBCANN and NBCANN is 0.1351 m and
To verify the effectiveness of our ANNs for UWB bias correction, we implemented our model, which was well-trained using the data in Section II-B, in another set of localization experiments conducted in the Public Safety Immersive Test Center (PSITC), a collaboration between the First Responder Network Authority and the National Institute of Standards and Technology’s Public Safety Communications Research Division, located in Boulder, CO. One agent with a Tag UWB sensor walked along three different trajectories, i.e., straight lines, rectangles, and lemniscates (Figure-8 shape), for around 5 minutes, as depicted in Fig. [9]. Each trajectory was repeated three times. Three additional UWB anchors are placed at known locations maintaining the communication with the Tag. Due to the block of human bodies, roadblocks and walls in the testing venue, the measurement scenarios were constantly switching between LoS and NLoS. We used the OptiTrack system installed in the PSITC facility to provide high-accuracy reference trajectories for comparison. Note that the reference trajectories were used for the evaluation of our bias correction method rather than training any new model. During the experimental evaluations, we made an inductive bias to the ANNs that for the consecutive predictions given by the ANNs cannot abruptly change within a small time period since the actual ranges between the Tag and anchors are continuous and the LoS and NLoS switching is less frequent. We put some weight on the previous prediction so that during real-time implementation the predicted bias-free range by the ANNs is smoothed, which is equivalent to the moving average method in terms of the format. Additionally, we selected the RLS method for the location estimation of the agent and removed the faulty measurements (extreme values).

For comparison study, we also trained another ANN set using the same features but using a data set that was collected in limited number of stationary configurations and the true distances were measured by human using measuring tape. We compared our proposed OLUC method with this so-called "stationary-ANN" method. We also compared the effectiveness of our bias correction method for localization with the OptiTrack aided method proposed in [41] which uses an ANN method to fuse IMU/UWB based localization with Optitrack measurements to improve localization accuracy. We called this method "ANN fusion". And we trained and evaluated its ANN based on the same trajectories according to [41] to make a fair comparison with our proposed method. The experimental results are shown in Fig. [10] and Fig. [11]. Lastly, in order to test the generalization of our proposed method against the "ANN fusion" on unseen new data, we additionally conducted a set of localization experiments in the CALIT2 building at UC Irvine, where the OptiTrack is not available and the LoS/NLoS conditions are more complicated due to the cubicles in the environments as shown in Fig. [12]. The experimental settings other than the designed trajectory remained the same as previous ones. Note that in this extra experiment, we tested the fusion ANN via a new trajectory on untrained data.

### IV. EXPERIMENTAL EVALUATIONS

To verify the effectiveness of our ANNs for UWB bias correction, we implemented our model, which was well-trained using the data in Section II-B, in another set of localization experiments conducted in the Public Safety Immersive Test Center (PSITC), a collaboration between the First Responder Network Authority and the National Institute of Standards and Technology’s Public Safety Communications Research Division, located in Boulder, CO. One agent with a Tag UWB sensor walked along three different trajectories, i.e., straight lines, rectangles, and lemniscates (Figure-8 shape), for around 5 minutes, as depicted in Fig. [9]. Each trajectory was repeated three times. Three additional UWB anchors are placed at known locations maintaining the communication with the Tag. Due to the block of human bodies, roadblocks and walls in the testing venue, the measurement scenarios were constantly switching between LoS and NLoS. We used the OptiTrack system installed in the PSITC facility to provide high-accuracy reference trajectories for comparison. Note that the reference trajectories were used for the evaluation of our bias correction method rather than training any new model. During the experimental evaluations, we made an inductive bias to the ANNs that for the consecutive predictions given by the ANNs cannot abruptly change within a small time period since the actual ranges between the Tag and anchors are continuous and the LoS and NLoS switching is less frequent. We put some weight on the previous prediction so that during real-time implementation the predicted bias-free range by the ANNs is smoothed, which is equivalent to the moving average method in terms of the format. Additionally, we selected the RLS method for the location estimation of the agent and removed the faulty measurements (extreme values).

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method to correct UWB range bias in LoS and NLoS hybrid environment, the localization accuracy of the moving agent using the RLS method is significantly improved. The error plots, as well as the performance metrics in Fig. 11 demonstrate that our OULC method achieved substantial bias reduction rates of 66.91%, 64.66%, and 63.13%, in the three scenarios that we considered. Note that the stationary ANN has an inferior performance due to the out-of-sample problem that we discussed earlier. As for the ANN Fusion method in [41], it has similar performance as our proposed OULC. However, it works only when the OptiTrack is available or the training and the evaluation trajectories are the same. Because it necessarily needs to train the ANN based on the estimated position obtained by both the UWB sensors and the OptiTrack rather than the UWB signal, which makes the generalization performance not satisfactory. We can obtain above conclusion from both Fig. 13 showing the trajectories and Table III comparing the loop-closure errors as they show that the ANN fusion performs even worse than using the raw measurements. But our proposed method still performed well. Therefore, the ANN Fusion method is only a position enhancement using and highly dependent on the OptiTrack and has limitation in generalization. If the OptiTrack is not available and the designed trajectory is not seen by the ANN, it fails easily. On the contrary, our proposed OLUC does not highly rely on the OptiTrack, since we only used the OptiTrack to generate training data. The evaluation using the OptiTrack is not a necessity.

V. CONCLUSIONS

UWB ranging bias correction has a significant impact on localization accuracy of the navigation algorithms that use UWB ranging. In this paper, we addressed the problem of UWB ranging bias correction in complex localization scenarios by training neural network models to distinguish LoS and NLoS scenarios and predict the corresponding bias-free range in real-time using features that are readily available on low-cost UWB sensor. Our experimental data collection resulted in identifying a novel set of features, raw range, PM, FPPL and RSS, to train ANNs for measurement type classification and bias-free range prediction. The effectiveness of any learning-based solution depends on diversity and informativeness of its training data. Recognizing that the relative orientation of ranging sensor affects the ranging accuracy, we used an Optitrack motion capture system to collect high accuracy ranging between a tag on a moving agent and fixed UWB anchor nodes. In doing so, we collected a diverse set of data in various relative poses between the sensors. The effectiveness of our OptiTrack-aided supervised learning-based UWB bias correction method was demonstrated via a set of pedestrian localization experiments using the RLS algorithm for location estimation. Our experiments showed that our method leads to a considerable improvement in the localization accuracy.

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REFERENCES

Fig. 10 – The estimated trajectories of the agent using RLS localization method as well as the localization error plots before bias correction (using raw measurements) and after applying different bias correction methods, i.e., stationary-ANN method, ANN Fusion and the proposed OLUC.

Fig. 11 – The average experimental statistics of the different trajectories using different bias correction methods.

Fig. 12 – The demonstration experiments conducted in the cubicle environment in the CALIT2 building at UC Irvine associated with the bottom diagram that shows the designed trajectories of the mobile UWB tag, the start and end point, the positions of the anchors, and of the cubicle configurations.
Fig. 13 – The estimated trajectory of the mobile UWB tag using the proposed OLUC method and the ANN fusion.


