Received March 14, 2019, accepted April 2, 2019, date of publication April 9, 2019, date of current version April 19, 2019.

Digital Object Identifier 10.1109/ACCESS.2019.2909761

Robust 3D Indoor VLP System Based on ANN Using Hybrid RSS/PDOA

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This work was conducted within the Delta-NTU Corporate Lab for Cyber-Physical Systems with funding support from Delta Electronics Inc. and the National Research Foundation (NRF) Singapore under the Corp Lab@University Scheme.

ABSTRACT Indoor location-based services are becoming crucial parts of smart living, smart manufacturing, and all kinds of the Internet of Things. Visible light-based positioning (VLP) system is one of the cost-efficient and RF radiation-free solutions. However, conventional received signal strength (RSS)-based VLP system suffers inaccurate modeling and intensity variations, especially in 3-D positioning cases. Hence, we propose an artificial neural network (ANN)-based approach for accurate modeling and positioning with on-site data. Likewise, the proposed approach is also proved applicable to accurate modeling of initial time delay distribution of LED chips in VLP systems based on phase differences of arrival (PDOA). To improve the robustness by mitigating the impact of intensity variations, we introduce a selection strategy utilizing both PDOA and RSS measurements. Through simulations, we demonstrate the feasibility of ANN-based on-site modeling and present the robustness of the hybrid positioning system under various levels of intensity variations.

INDEX TERMS ANN, pre-training, PDOA, RSS, VLP.

I. INTRODUCTION

Nowadays, due to the development of the multi-functional robots for applications like housekeeping, cargo moving, medical caring etc., location based indoor services at decimeter-level accuracy are much desired in many circumstances. For outdoor positioning applications, the GPS with the positioning accuracy of meter level is achieved. However, due to the blockage and multi-path effects, GPS is relatively difficult to be applied to indoor environments to achieve high accuracy [1].

Techniques like Ultra-Wide-Band (UWB), Wi-Fi and Visible light based positioning are proposed to fill up the gap of indoor positioning applications [2]. The coverage of UWB and Wi-Fi based positioning techniques are relatively large, since RF transmitters are transmitting in all directions with the well developed receivers for high sensitivity signal detection. However, these radio based technologies, have a common issue of penetration and multi-path effects [3]. Signals from the same transmitter broadcasting through different indoor paths (with multiple positioning information (i.e. overlapped Time of Flight(TOF) or intensity)) are finally collected by the receiver hence causing interferences. Meanwhile high frequency RF radiations have potential effects on human health and electrical devices.

In the past few years, LED illuminations have been widely deployed in both public places (airports, hospitals, schools etc.) and private areas (factories, warehouses, homes). Visible light based communication (VLC) is then brought to the lights with considerable data rates [4], and the visible light positioning (VLP) system as one type of VLC systems is gradually developed as one of the promising ways to fill up the gap of indoor positioning systems [5]. While the coverage of the LED chips are much constrained to a cone space by the irradiation angle. This also helps to avoid interference between adjacent positioning units. The VLP based positioning system has limited bandwidth since commercially available LEDs have a bandwidth of only a few Megahertz even with blue filtering. Fortunately, for positioning cases, high bandwidth is not necessary for providing decimeter-level accuracy. Also the light cannot penetrate through walls nor can visible light diffract significantly in indoor

The associate editor coordinating the review of this manuscript and approving it for publication was Di He.

TABLE 1. Comparison between positioning techniques in VLP systems.

Techniques	Complexity	Tilting Tolerance	Intensity sensitivity
RSS [7], [8]	Low	Low	High
AOA [9], [10]	Moderate	High	Moderate
TDOA [11], [12]	High	Moderate	Low
PDOA [13], [14]	Moderate	Moderate	Low

environments, hence the multi-path influences are not manifest in indoor VLP systems [6]. In a word, VLP is a promising RF radiation free solution to high accuracy indoor positioning applications.

VLP systems are generally based on Received Signal Strength (RSS), Angle of Arrival (AOA), Time Difference of Arrival (TDOA) and Phase Difference of Arrival (PDOA) approaches. As listed in Table.1, RSS is the most cost efficient way using intensity information to estimate distances between transmitters and receivers with good SNR performances [7], [8]. However, achieving high accuracy requires precise channel modeling and also constrained by receiver tilting, stable channel gain as well as a constant transmitting power. AOA is a good approach which can not only solve positions via calculating incident angles, but also obtain the status of receivers' rotation [9], [10]. The drawback of AOA method is the good performance relying on Photo Detector (PD) array or image sensors with high resolution and proper signal processing algorithms which in turns increased the hardware and software complexity. TDOA based method is to apply correlations to extract the differences of TOF through short pulses transmitted by multiple transmitters. To achieve decimeter level accuracy, TDOA systems require time resolution of 1ns level (1 Gsa/s sampling rate is normally used [11]) as well as high clock precision which demands highly in hardware. The PDOA is another type of TDOA system using periodic signal sequences, the time resolution requirement of TDOA is hence transferred to the length of signal sequences. PDOA systems requires relatively long signal length which is relatively hard to overcome multi-path effects. However, PDOA can work at lower sampling rate of 100 Msa/s or even less and remain stable when the channel intensity gain varies [13], [14].

In commercial applications, robustness and system complexity are much concerned. Generally, in our on-site observations the RSS measurements have better SNR performance than PDOA, since phase information are more sensitive to the ambient noises. However, in circumstances with dimming, tilting and other intensity variations PDOA measurements present better stabilities. Hence, a system using hybrid PDOA/RSS is supposed to be a preferred scheme, in which PDOA measurements are selected as the main source due to its robustness against intensity variations, and the RSS measurements can be exploited to improve the accuracy of PDOA based techniques when the signal intensity is stable. Besides, the RSS information is inherently available in PDOA signals which reduces the complexity of the hybrid system. However, there is rarely literature reporting such hybrid system to our best knowledge.

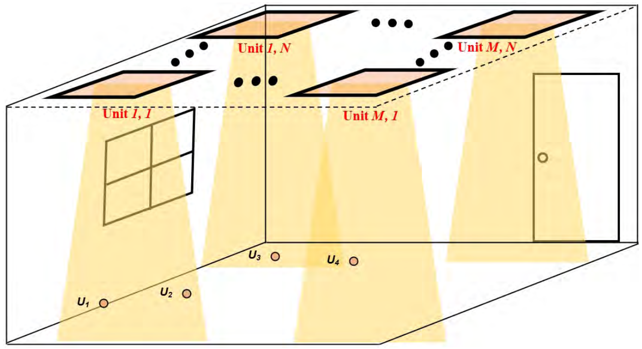

FIGURE 1. Indoor VLP system with multiple VLP units.

In this paper, we present a hybrid VLP system with modified PDOA method (Differential PDOA(DPDOA)) as preferred measurements, assisted with RSS method to enhance accuracy when intensity variations are not significant. The proposed positioning algo rithm is purely based on artificial neural network(ANN) instead of triangulation. The main contributions of our work are listed as follow:

- We propose a new approach using ANN addressing distortions induced by inaccurate modeling (phase, intensity model) in both PDOA and RSS based positioning systems.
- We for the first time apply pre-training techniques in the ANN based VLP system to reduce the off-line workload and enhance the system's robustness.
- We for the first time propose a selection based hybrid PDOA/RSS approach to achieve indoor localization.
- We design two selection strategies in the hybrid PDOA/RSS approach to switch between ANN-RSS estimations and ANN-PDOA estimations as the final outputs for sake of good accuracy and high environmental adaptivity under intensity variation situations.

The paper is organized as follow. In section 2 the principles of the hybrid system are introduced. Simulation results are given in sections 3, addressing the issues of inaccurate modeling in both PDOA and RSS based ANN schemes, and further demonstrating a robust scheme with our proposed hybrid approach under different levels of intensity variations. Conclusions are placed in section 4.

II. ARTIFICIAL NEURAL NETWORK BASED POSITIONING SCHEME USING HYBRID RSS AND PDOA

A. SYSTEM ARCHITECTURE

An indoor 3-D VLP system covers a large space consists of multiple VLP units arranged in hexagonal or square manner. As shown in Fig.1, each of the VLP unit covers a cone space forming a positioning network of M by N units with several users moving in side.

One of the VLP unit consists of four LED lamps as transmitters (without pre-known about their locations) placing on the ceiling to perform 3-D positioning is applied in this paper, similar to our previous work [15]. The Global coordinate is set with the origin on the floor around the center of the lamps'

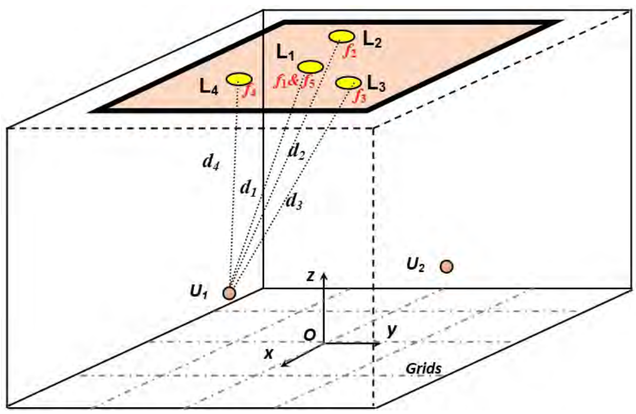

FIGURE 2. System architecture of one VLP unit.

layout, as shown in Fig.2. Sinusoidal signals with five comb frequencies (f_1 to f_5 in an arithmetical sequence) are modulated to four LED lamps in intensity. The central LED lamp is modulated with a mix of two sine-waves with frequencies f_1 and f_5. A common DC bias is given to maintain the normal operation of the lamps to ensure the illumination function and the linearity of intensity modulations. Receivers(U_1, U_2) are moving inside the illuminated space, the distance between a receiver and individual transmitters are defined as d_1 to d_4.

B. METHODS OVERVIEW

Conventional RSS systems require precise modeling of the LED's intensity irradiation pattern, similarly PDOA systems require a good phase model. However, the precisions of Lambertian irradiation model and sphere phase model are doubtable in real applications. Hence the ANN based approach is applied to model the system with on-site measurements. Meanwhile, the pre-training technique is also used for better system adaptivity and less off-line workload.

Moreover, PDOA approach has high robustness thanks to intensity irrelevant PDOA measurements (PDMs), however PDMs are sensitive to ambient noises. Meanwhile, the contained RSS measurements (RSSMs) are less sensitive to ambient noises but more sensitive to intensity variations. To make use of both the robustness of PDMs and the good performance of RSSMs under ambient noises, a selection based process is introduced to form a hybrid positioning system.

As shown in Fig.3, the proposed hybrid system has two processes: the pre-experimental preparation and the real-time position estimations. The pre-experimental process is called offline process, the ANN based positioning algorithm is trained with two steps: the ideal model based pre-training and the on-site data based training using RSSMs and PDMs. In the online positioning process, the trained ANNs are used to offer position estimations of ANN based RSS(ANN-RSS) and ANN based PDOA(ANN-PDOA) individually. Then a selection strategy is applied, to merge the estimations offering better position predictions.

C. RECEIVED SIGNAL STRENGTH METHOD WITH INDOOR INTENSITY CHANNEL MODEL

To study the indoor positioning environments, the Lambertian irradiation pattern is usually used to model the LED lamp intensity performance through indoor line of sight (LOS) channels. The intensity (H_i) at receiver side, for the carrier with frequency f_i, is expressed below:

$$H_i = \frac{(m+1)A}{2\pi d_i^2} cos^m(\varphi_i) cos(\Psi_i) P_i \tag{1}$$

where m is the order of Lambertian emission, we take $m = 1$ here in simulations, A is the physical area of the PD. d_i is the LOS path length between the LED transmitter carrying the f_i frequency and the PD, φ_i is the according irradiation angle, Ψ_i is the incident angle and P_i is the intensity of the transmitting signal. When the norm of PD plane is perpendicular to the LED plane, the relationship between φ_i and Ψ_i can be expressed as:

$$\varphi_i = \Psi_i = arcsin(h/d_i) \tag{2}$$

where h is the height of the PD to the LED plane. Lambertian order m in the model can be affected by the reflector or diffuser mounted to the LED lamp.

From the received intensity we can extract the RSSM (H_i) after filtering. Conversationally, using the relationship constructed by the Lambertian model, we can estimate the distance d_i numerically. However, the Lambertian model is not a precise modeling of the indoor channel which requires calibration works in 2-D positioning cases [16]. In 3-D cases, the Lambertian model is not generally fit the actual intensity distribution due to nonlinearity of the LED chips and other device level factors(like the lamp shell, diffuser, reflector). Hence, 3-D RSS based positioning experiments are rare reported or only presented with small converges (about 1m by 1m in x-y plane, at around 2m height).

D. DIFFERENTIAL PHASE DIFFERENCE OF ARRIVAL MEASUREMENTS

PDOA is a well-known algorithm for positioning systems, used for high accuracy positioning with moderate system complexity. A DPDOA method is formerly proposed by us [15], using two differential processes to extract phase/distance difference information as well as enhance robustness. Sine-wave signals are modulated on the intensity of LEDs and transmitted through the indoor channel, finally received by a PD. The phase and intensity of the frequency components (R_i) of the received signal are related to the line-of-sight path and LED Lambertian irradiation model as:

$$R_i = H_i \times Sin(\omega_i t + \phi_i) \quad (i = 1 \text{to} 5) \tag{3}$$

where $\omega_i = 2\pi f_i$ is the angular frequency and the phase terms can be expressed as follow :

$$\phi_i = \frac{\omega_i d_i}{c}, \quad (i = 1 \text{ to } 4) \text{ and } \phi_5 = \frac{\omega_5 d_1}{c} \tag{4}$$

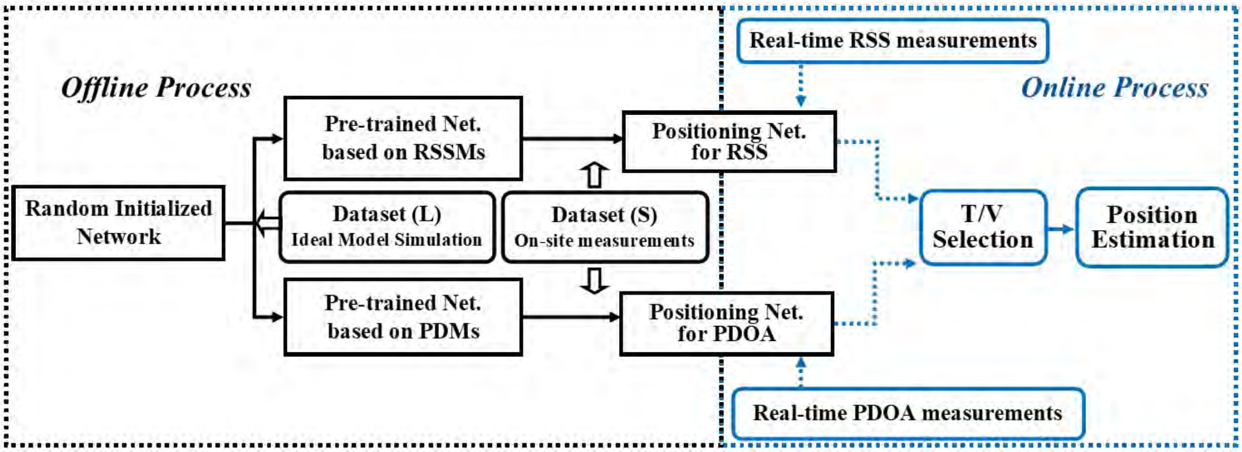

FIGURE 3. Flowchart of the selection based hybrid ANN-PDOA and ANN-RSS positioning system with pre-training.

where c is the speed of light. Noticing that $H_5 = H_1$, since these two signals with f_1 and $f_5$are transmitted from a same LED simultaneously. We then extract the phase related terms through two differential processes via cross multiplications [13]. And thus obtain the following equation:

$$\begin{bmatrix} \phi_1 + \phi_3 - 2\phi_2 \\ \phi_2 + \phi_4 - 2\phi_3 \\ \phi_3 + \phi_5 - 2\phi_4 \end{bmatrix} = \begin{bmatrix} Pd_1 \\ Pd_2 \\ Pd_3 \end{bmatrix} \tag{5}$$

where the terms Pd_i are the results of phase extraction. The phase differences between signals from transmitters are measured through in-phase and quadrature phase extraction method [14]. The left part of eq.5 is consist of differential of phase differences, where noises are much mitigated. Using the arithmetic relationship between ω_i and the relationship between d_i and ϕ_i in eq.4, we can express the eq.5 with distance differences as:

$$\begin{bmatrix} \omega_1 & -\omega_3 & 0 \\ 0 & \omega_2 & -\omega_4 \\ \omega_5 & \omega_5 & \omega_3 + \omega_5 \end{bmatrix} \begin{bmatrix} d_1 - d_2 \\ d_2 - d_3 \\ d_3 - d_4 \end{bmatrix} = c \begin{bmatrix} Pd_1 \\ Pd_2 \\ Pd_3 \end{bmatrix} \tag{6}$$

where the respective distance differences($d_i - d_{i+1}$ $i = 1, 2, 3$ as PDMs) can be obtained, as Pd_i is known from phase extractions.

As can be observed, intensity related terms H_i of the received signals are neutralized during the phase extraction processes which indicating robustness under environments with intensity variations. Likewise, eq.6 and eq.4contain no angle related terms, indicating PDMs are theoretically irrelevant to receivers' rotations.

Normally, when the PDMs are obtained, the numerical method is applied to calculate the position $Po(x, y, z)$ by solving a set of quadratic equations substituting eq.7 in to eq.6:

$$d_i = \sqrt{(x - x_i)^2 + (y - y_i)^2 + (z - z_i)^2} \tag{7}$$

where (x_i, y_i, z_i) are the i-th LEDs' positions.

Such approach poses high calculation complexities in function solving, requires good modeling on the lamps' initial time distribution [13] and centimeter level measurements on LEDs' positions.

E. ARTIFICIAL NEURAL NETWORK BASED POSITION ESTIMATIONS

1) ANN BASICS

A classical ANN is consist of three parts : an input layer, hidden layers and an output layer. The inputs represents measurements(RSSMs, PDMs), in our case, and the outputs are the estimations of position. ANN can be used to approximate functions or models forming the projection between the inputs and the outputs [17], in this way the RSSMs/PDMs are translate to positioning estimations through two individual ANNs. For complicated functions, multiple hidden layers can be applied to increase the degree of freedom (DOF). There are several neurons within each hidden layer, the number of neurons also influence the DOF of the ANN. A general propagation expression from the i-th layer to the n'-th neuron of the i+1 layer is given [18], [19]:

$$I_{i+1,n'} = f\left(\sum_{n=1}^{N} w_{i,n,n'} I_{i,n} + b_{i+1,n'}\right) \tag{8}$$

where, $w_{i,n,n'}$ is the weight of the n-th neuron in layer i to the n'-th neuron of the layer $i + 1$ and $I_{i,n}$ is the output value of the n-th neuron of the i-th layer. We take $Sigmoid()$ as activation function $f()$,which is commonly used is fitting applications.

The single hidden layer ANN applied here is trained with the back-propagation method, which follows gradient descent and back-propagates the RMS errors from the output layer to the input layer, to determine the weights through iterations (epochs).

2) LEVENBERG-MARQUARDT BACKPROPAGATION WITH BAYESIAN REGULARIZATION

In our application cases, the scale of the dataset is relatively small and the number of inputs and outputs are within five. Hence, all training data shall be involved in weights adjustments and Bayesian regularization shall be applied to minimize the over-fitting effect. The weights are updated through training in the manner of Levenberg-Marquardt Backpropagation with Bayesian Regularization [20]:

1) Initialize α,β and the wights. Set $\alpha = 0$ and $\beta = 0$.
2) Take one step of Levenberg-Marquardt algorithm to minimize objective function $F(\mathbf{w}) = \beta E_D + \alpha E_W$.
3) Compute $\gamma = N - 2\alpha tr(\mathbf{H})^{-1}$, where $\mathbf{H} = 2\beta \mathbf{J}^T \mathbf{J} + 2\alpha \mathbf{I}_N$ which is available in Levenberg-Marquardt algorithm.
4) Update the objective function parameters $\alpha = \frac{\gamma}{2E_W(\mathbf{W})}$ and $\beta = \frac{n-\gamma}{2E_D(\mathbf{W})}$.
5) Update weights with the Levenberg-Marquardt algorithm based gradient descent [21].
6) Iterate from step 2 to 5 every epoch.

In which, $F(\mathbf{w})$ is the objective function, E_D is the sum of squared errors, E_w is the sum of weights, N is the number of parameters. Hence through epochs, the objective function will be minimized and a projection between inputs and outputs of the network is then formed though the ANN.

3) APPLY ANN TO DPDOA/RSS BASED INDOOR VLP

To address the problem of modeling in both conventional RSS and PDOA method, we propose an ANN based scheme to perform position estimations without knowing the LEDs' locations (x_i, y_i, z_i). ANN is applied for position estimations directly from PDMs (Dd_i and RSSMs. Take PDOA approach as an example (as in Fig.4), the projection between Dd and actual position Po:(x, y, z) is a continuously function as stated in the previous section, an ANN can be constructed with Dd measurements as inputs and the according global coordinates (Po as outputs. A single hidden layer ANN is then constructed for 3-D indoor positioning and trained though Levenberg-Marquardt Backpropogation with Bayesian Regularization based on on-side data. The ANN is capable of modeling the actual indoor channel to avoid distortions and estimate the receiver's position. Finally, two ANNs are constructed to form projections from PDMs to Po and RSSMs to Po separately, as shown in Figure.3.

It's crucial to define the structure of the ANN properly. Too many hidden layers or neurons, can lead to over-fitting issues [22], meaning the ANN only fit to training dataset and fails to predict additional data. Too few neurons may be lack of DOF and unable to achieve good training results (underfit). Hence, the number of neurons and hidden layers have to be determined according to the complexity of the projection.

In our case, the network inputs and outputs are small, hence the number of the neurons and hidden layers can be determined through try-outs. With large number of neurons the accuracy of training dataset will be far higher than the testing dataset, while both the testing and training accuracy are bad with small number of neurons. Only with around the proper number of neurons the network can accurately translate the inputs to the outputs.

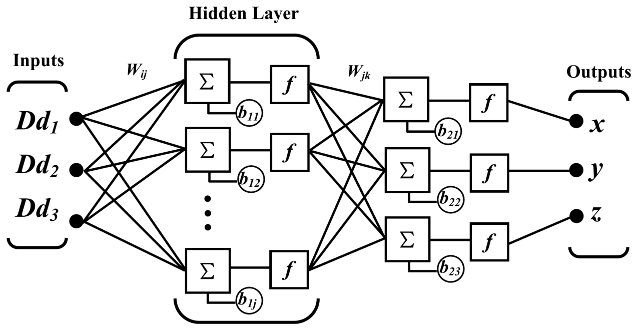

FIGURE 4. ANN with one hidden layer.

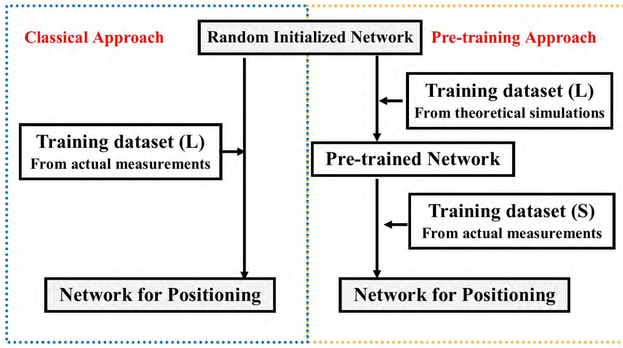

FIGURE 5. ANN flowchart w/wo pre-training.

4) POSITION ESTIMATIONS VIA ANN WITH PRE-TRAINING

In usual cases, the data used for training ANN is massive in order to form the projection accurately with high adaptivity. Via only experimental measurements, acquiring hundreds of samples for training is time consuming. However, training with small datasets compromises the convergence of the ANN, ending up with inefficient training process and causing over-fitting issues. Hence, we apply the pre-training technique into thes ANN training process [23].

As shown in Fig.5, to obtain the pre-trainied ANN model, simulations on the ideal model are conducted in the first place forming a large dataset (L) for pre-training. Noticing that the pre-trained ANN only fits well with the theoretical model, which can be highly different from the actual situations. However, datasets from simulations have large coverage and fine phase informations with easy control. Then the ANN is further trained using small dataset (S), acquired from experiments, to ensure the good fit under practical situations. Comparing with directly training with experimental data (in the left part of Fig.5), thanks to the proper initial weights from pre-training process, the network converges much faster and the on-site dataset required are smaller. Even with the same on-site dataset, the pre-training approach maintains generally better accuracy and larger coverage inherit from the pre-trained network.

TABLE 2. Simulation specifications.

Carrier frequency	Sample Rate	Scale of ANN	Regularization	Testing coverage
4MHz to 4.8MHz	100Msa/s	18 neurons	Bayesian	4m by 4m
Number of Carriers	**Signal Length**	**Activation Function**	**Training data collection**	**Height**
5 (0.2MHz gapped)	10000pts	Sigmoid	3m by 3m (0.5m gapped)	1m-2.5m

F. SELECTION STRATEGIES IN ANN BASED POSITIONING SYSTEM WITH HYBRID PDOA/RSS

1) T-SELECTION STRATEGY

Generally, PDOA based estimations offer results with small averaged error but higher variations in estimations, hence we can select the PDMs as the main source of positioning. In conditions where ANN-RSS estimations are near the estimations offered by ANN-PDOA, the ANN-RSS results are accepted as outputs to achieve better accuracy under lower intensity variations. Otherwise, estimations based on ANN-PDOA are taken to improve the robustness when variations are severe. The significance level of accepting the estimations from ANN-RSS can be determined with the t-test considering distance biases.

The index of conventional students' t-test can be expressed as below [24]:

$$t = \frac{|P_{PDOA} - P_{RSS}|}{s} \tag{9}$$

where P_{PDOA} and P_{RSS} are estimations of positions provided by ANN-PDOA and ANN-RSS approaches accordingly. And s is the estimated standard deviation of ANN-PDOA estimations. Noticing a crucial property in the positioning system that the signal quality is decreasing as distance grows, and the PDMs are more sensitive to the signal quality. A designed factor term $\frac{d_{lim}}{d}$, where d_{lim} is a pre-set constant in meter, is introduced to increase the biases on distances. As the distance grows the factor decreases, then less trust will be laid on the ANN-PDOA approach. Hence, we revise the index in eq.9 as follow:

$$t = \frac{|P_{PDOA} - P_{RSS}|}{s} \times \frac{d_{lim}}{d} \tag{10}$$

then a one-tailed t-test with a significance level of α is set to select ANN-RSS based estimations, such strategy is called T-selection.

2) V-SELECTION STRATEGY

V-selection strategy is to measure the variation of RSSMs by a few samples. When variations are less than $p\%$ the ANN-RSS estimation is selected, otherwise the ANN-PDOA is chosen as the output, which is formulated as:

$$V = \frac{\sqrt{\sum_{n=1}^{N}(H_{i,n} - \bar{H}_i)^2/N}}{\bar{H}_i} \tag{11}$$

$$P_{Outputs} = \begin{cases} P_{RSS} & V \leq p\% \\ P_{PDOA} & V > p\% \end{cases} \tag{12}$$

where N is the length of observation and $\bar{H}_i$ is the average of observations and $P_{Outputs}$ is the selected estimation. The slower the variation of intensity is the more samples shall be taken to determine the selection results and N will be grater.

It's important to notice that, in scenarios with rotations in receivers, T-selection is superior to V-selection. When the receiver tilting to certain angle, the RSSMs may be stable however different from actual values (with no rotations) while PDMs are not influenced. Hence, T-selection strategy is more likely to take P_{PDOA} outputs which outperforms the P_{RSS} taken by V-selection strategy.

III. SIMULATIONS

A. SIMULATION SETUP

The testing space is 4m by 4m in x-y plane with the height from 1m to 2.5m from the LED plane. The space is constrained by the filed of view (FOV) of LED lamps. The receiver modeled as an Avalanche Photo-diode (APD), detecting light intensity and converting to analog signals with white Gaussian noises, then sampled to digital signals through a data acquisition device (DAQ). The digital signal is then processed by a digital signal processor (DSP) (computer, Raspberry Pi, FPGA etc.) to extract measurements and update positioning estimations. The parameters of our simulations are listed in Table.2.

An example of the waveform is shown as in Fig.6 (a), as presented the waveform suffering nonlinear distortions (modeled by LED data-sheet) and the noises from APD as well as the ambient environment. The received waveform is then filtered and processed with the DPDOA algorithm to extract Dd information as mentioned in the previous section. An example of the measured Dds are shown in Fig.6 (b) the PDMs fluctuate due to the in-band noises. At the mean time, the RSSMs are also extracted from the filtered signal as shown in Fig.6 (c), which are less affected by ambient noises.

B. PRE-TRAINING THE ANN WITH THE IDEAL SYSTEM MODEL

The pre-training is a crucial step of the proposed scheme. Without pre-training, the trained network from on-site data will be much limited to the space acquiring the training dataset and also hard to converge to optimal weights. The pre-traning process providing proper initial positioning model assisting the training substantially, also such training method requires no extra off-line experimental efforts and provides better predictions.

To perform pre-training, an ideal theoretical system model(as described in the principle part) is build to generate

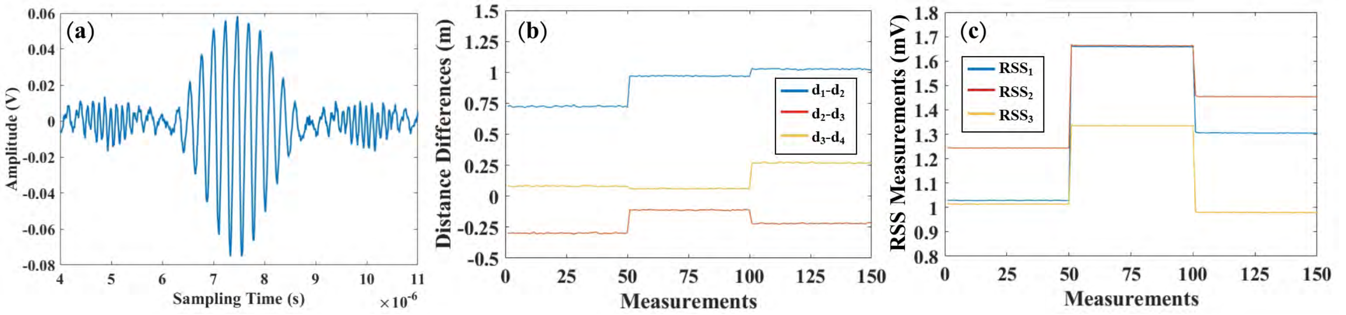

FIGURE 6. Received Waveform and measurements a) Waveform example; b) PDMs of distance differences; c) Intensity based RSSMs.

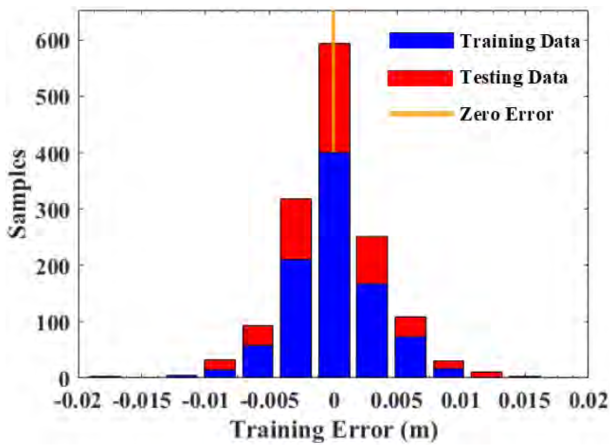

FIGURE 7. Pre-training ANN training performances.

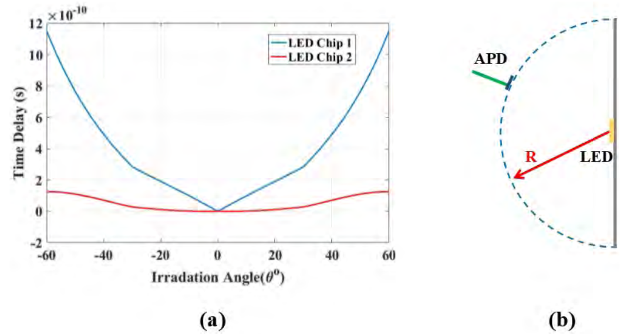

FIGURE 8. Initial time delay distribution of different types of LED chips a) Relationship between irradiation angle and signal time delay; b) illustration of ITD measurements' setup, dashed semicircle have the same distance to the LED.

a large dataset of Dd measurements inside a 4m by 4m space from 1m to 2.5m heights equally divided into 11 by 11 by 4 grids (484 measurements in all). Training with an ANN with random initial weights and 18 neurons in a single hidden layer, with Bayesian regularization to avoid over-fitting. 35% of the data are used for training, another 35% for testing the rest 30% is used for validation. These training datasets are randomly shuffled and divided to ensure trust worthy results. The training performance of the pre-trained ANN model is shown in Fig.7, training the network requires around 3 seconds and the RMS error of the pre-trained network is less than 2cm. The obtained pre-trained network is then stored for further training to be compatible with various practical situations.

C. SIMULATIONS AGAINST INITIAL TIME DELAY DISTRIBUTION

1) INITIAL TIME/PHASE DELAY DISTRIBUTION MEASUREMENT

The PDOA algorithm is based on the fundamental assumption that the signal from the LED chips have phase delays (ϕ_i) only relevant with the TOF as implied in eq.4, meaning the phase distribution is uniform in all directions. However, experimental measurements indicate that the modulated signal's initial time delay(ITD) is dependent on the irradiation angle, hence causing distortions and shifting.

Fig.8 (a) presents the ITD distribution measured experimentally. As shown in Fig.8 (b), the ITD distribution is measured with a single LED chip placed on the center, and a rope is used to make sure the receiver move on the same distance(R) circle from the center. Two synchronized signals are transmitted from a same generator, one modulated to the LED chip in intensity another is transmitted to the DAQ at the receiver side through cable as oscillator. By taking correlations between the received optical signal and the oscillator signal the time delay difference is then extracted in the way of TOA [25], also assuming the ITD at 0 degree irradiation angle to be $0s$.

Two different ITD patterns are presented in Fig.8 (a) of a white light LED chip (chip 1) and a blue light LED chip (chip 2). As shown, the LED chip 2 is generally following a uniform ITD in all directions, which should be a flat line with 0s time delay. While LED chip 1 has relatively larger ITD differences as the irradiation angle increases. The results support the idea that the phase/time measurements are also related to the irradiation angle of LEDs, and the ITD distribution is hardware dependent. Hence, distortions of the positioning space can be expected in conventional PDOA methods in experiments.

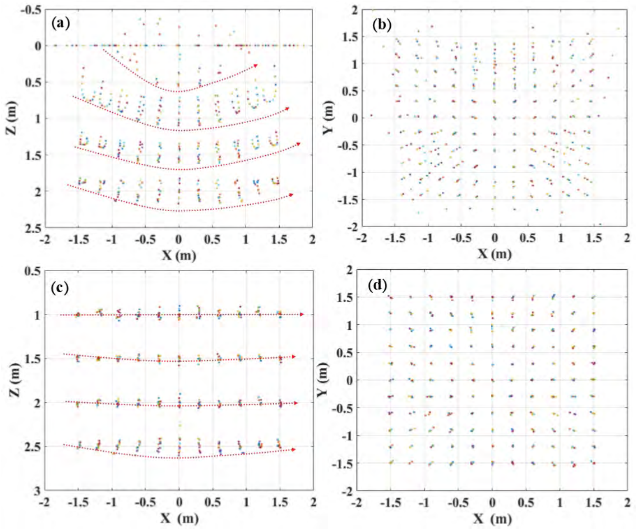

FIGURE 9. Simulation on ITD influences to PDOA measurements based positioning system (dashed arrows indicate the trend of distortions in X direction at different heights) a) conventional PDOA positioning results in X-Z view; b) conventional PDOA positioning results in X-Y view; c) ANN-PDOA positioning results in X-Z view d) ANN-PDOA positioning results in X-Y view.

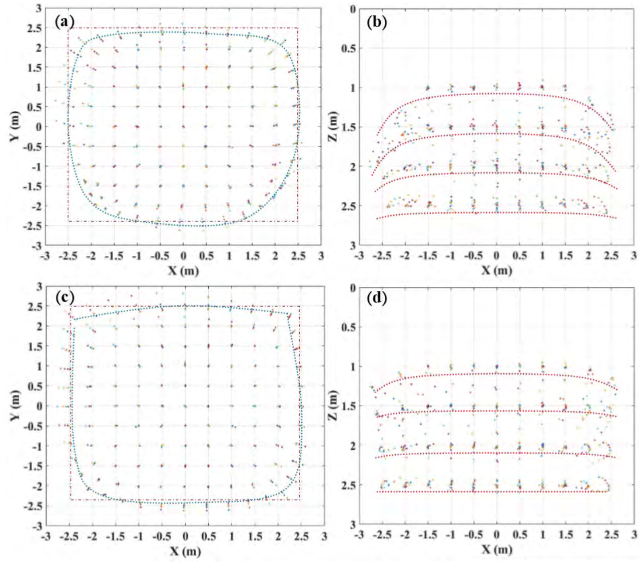

FIGURE 10. Estimation results of ANN-PDOA positioning w/wo the pre-training method at 5m by 5m coverage (in (a)&(c) squared boundaries are the ideal testing area, blue curves illustrate the bound of estimated positions; in (b)&(d) the red curves indicate the trend of distortions in X direction at different heights): a) X-Y view of ANN-PDOA wo pre-training; b) X-Z view of ANN-PDOA wo pre-training; c)X-Y view of ANN-PDOA w pre-training; d) X-Z view of ANN-PDOA w pre-training.

2) COMPARISONS ON CLASSICAL PDOA WITH ANN-PDOA ON ITD INDUCED DISTORTIONS

As we discussed that ITD is crucial to PDOA based method similar to the Lambertian model in RSS based methods. Here the ITD is taken into considerations on the PDOA based positioning system. We include the ITD model (chip 1 in Fig.8 (a)) in both conventional PDOA method and the ANN-PDOA positioning method and conduct simulations in the testing space. Fig.9 (a) presents the estimations through classical PDOA method in X-Z axis view without adding noises, the distortiosn and shifting in Z axis are evident and increasing when the receiver is far from the LED lamps, as shown by the dot lines. Shifts can also be observed in the X-Y view (Fig.9 (b)).

Then the ANN is applied to address the problem, datasets are collected within the testing space every 50cm apart in all axises. We train ANN without pre-trained network to testify the performance, estimation results are shown in Fig.9 (c) and (d). Comparing with conventional PDOA method, the distortion is much mitigated with estimation RMS error within 10cm range. This is mainly because the ANN training process takes the ITD model into consideration with the Dd measurements, which simplified the ITD modeling process (especially that the ITD distribution is hardware dependent).

3) ANN-PDOA WITH PRE-TRAINING

Without pre-training the performance are constrained by the collected training data (coverage, spacial resolution etc.) for ANN and consumes longer time in converging. Then we apply the pre-trained ANN as initial model and trains with the same on-site measurements, the positioning performance in area (x-y) of 5m by 5m with 0.5m gap are shown in Fig.10. It can be observed by comparing Fig.10 (a) and (c) that, within the space collecting the data, the performance are similar for both method. And the pre-training based ANN-PDOA estimations have less distortions(the blue doted are are closer to the red dashed square in (c) than (a)) in the space not covered by the collected data (beyond $\pm$1.5m in x, y axises). Such effects are more evident in X-Z view at 1m and 1.5m height from the LED plane (as in Fig.10 (b) and (d)). The improvements of the pre-training process are due to the a general pattern of PDOA is provided to the training process which makes up the insufficient of on-site dataset. Besides the coverage difference, as the training records shown in Table.3, the pre-trained ANN method is time saving in training with much less training epochs, also the accuracy of pre-training method is generally higher.

D. PERFORMANCE ANALYSIS ON HYBRID ANN-PDOA & ANN-RSS POSITIONING SYSTEM

1) ANN-RSS AND ANN-PDOA POSITIONING SCHEMES UNDER INTENSITY VARIATIONS

To further study the robustness of the proposed scheme, the influences of intensity variations is taken into consideration. Variations are possibly induced by dimming and power supply variations in the transmitter side, translucent blockages in indoor channel, or inclines in the receiver side. In simulations, intensity variations at different levels are induced, white Gaussian noises are also added to simulate the actual testbed. An example of waveform sequence with 15% intensity variations changing every 1ms is demoed

TABLE 3. Comparisons between ANN-PDOA w/wo pre-training model.

Pre-training	Training Epochs	Max. Training Error(cm)	Coverage
Yes	56	7	around 4m by 4m
No	120	10	around 3m by 3m

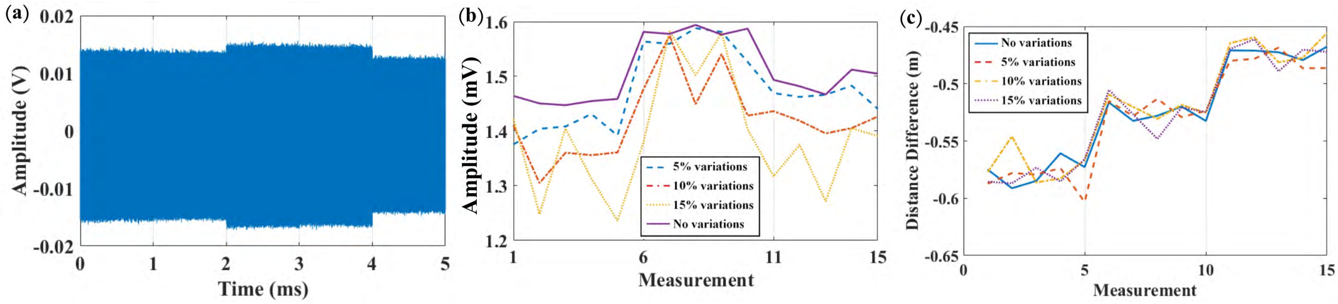

FIGURE 11. Waveforms of different intensity variations a) example of received signal under 15% intensity variations; b) RSSMs under different variation levels; c) PDMs under different variation levels.

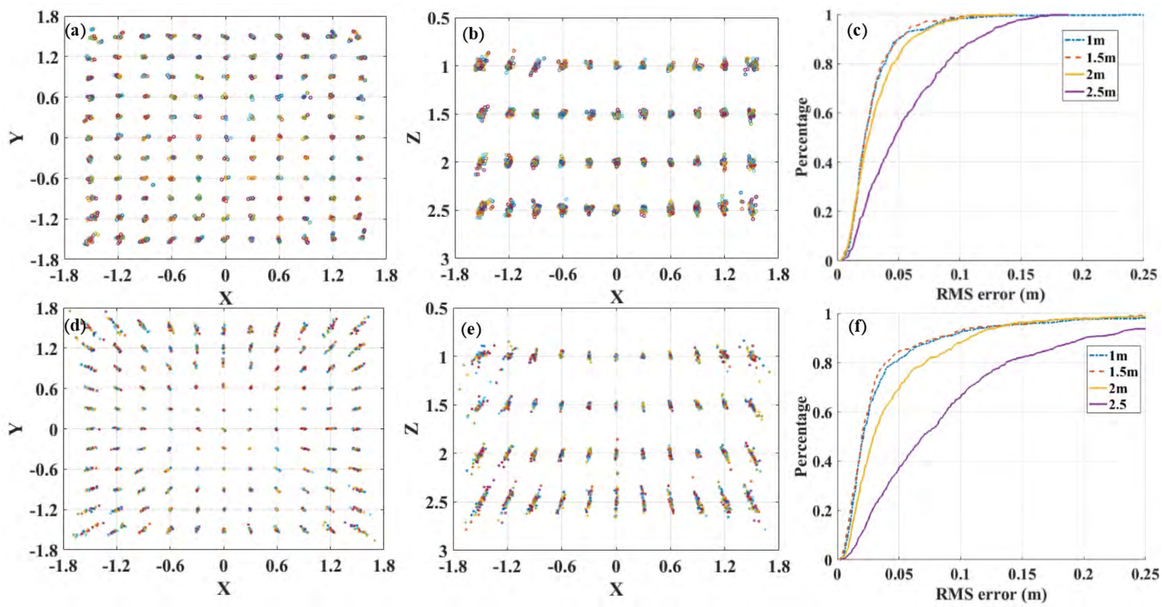

FIGURE 12. ANN-PDOA and ANN-RSS performances' comparisons with no intensity variations a) X-Y view of ANN-RSS positioning results; b) X-Z view of ANN-RSS positioning results; c) RMS error CDF of ANN-RSS positioning at different heights; d) X-Y view of ANN-PDOA positioning results; e) X-Z view of ANN-PDOA positioning results; f) RMS error CDF of ANN-PDOA positioning at different heights.

in Fig.11 (a). Three variation levels(5%, 10%, 15%) are simulated for comparisons as shown in Fig.11 (b) (c). The RSSMs and PDMs under different variation levels are given respectively, the receiver's position changes every 5 measurements. It can be observed that the fluctuations in RSSMs increase evidently as the variation level grows, while PDMs are less influenced. This is due to RSSMs are more sensitive to the intensity variations, while PDMs are sensitive to the in-band phase noises.

Applying the ANN to RSSMs and PDMs separately, positioning estimations and the RMS error distribution CDF of the system are then acquired. Fig.12 (a), (b) presents the RSS based positioning results in 3D and Fig.12 (d),(e) presents PDOA results. In X-Y view, both scheme have larger error at the edges, but PDOA estimations are more sensitive to noises. While in X-Z view, the error growing obviously as height increases since the SNR decreases as the distance to the LED plane grows, this can be confirmed with the CDF plot in Fig.12 (c), (f). Without intensity variations, the ANN-RSS scheme is generally more accurate than the proposed ANN-PDOA scheme at all heights(from LED plane).

To further research on the influences of intensity variations, we only observe the estimations at 2m with only

TABLE 4. Comparisons among state-of-the-art works.

Literature	Method	Intensity Model	Time delay model	2D/3D	Accuracy	off-line workload	Notice
[16]	RSS/WKNN	Fingerprinting	N.A.	2D	6cm	high(20cm grids)	Intensity Sensitive
[13]	PDOA	N.A.	ANN corrected	2D	5cm	medium(40cm grids)	Training required
[11]	TDOA	N.A.	No	2D	17cm	Low(1 or 2 points)	Calibration required
[26]	Imaging	N.A.	N.A	3D	6cm	No	Small coverage
This work	RSS+DPDOA	ANN fitted	ANN fitted	3D	12cm	medium(50cm grids)	Training required

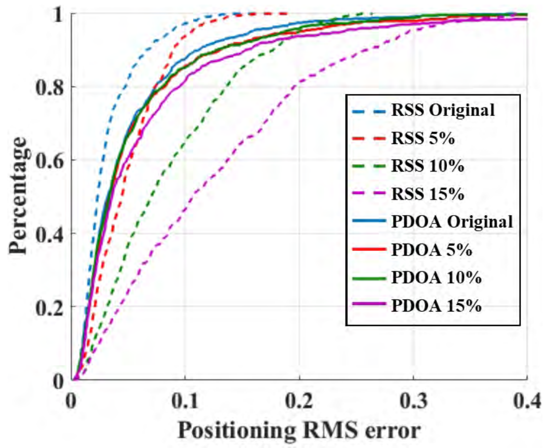

FIGURE 13. RMS error CDF of ANN-RSS and ANN-PDOA under intensity variations.

variation level changing. As shown in Fig.13, the solid curves representing the ANN-PDOA based estimations and dashed curves(different variation levels are distinguished by colors) are the ANN-RSS based estimations. Without variations, the PDOA method suffers more on the noises than ANN-RSS as curves in blue shows. As the variation increases to 5% in intensity the ANN-RSS based estimation error increase slightly with the error increased by 2cm at 80% confidence level, while ANN-PDOA are less influenced. Further raise the variation level to 10%, ANN-PDOA starts to perform better than ANN-RSS estimations, with 80% portions at 8cm versus 13cm. Such effect is even manifest at 15% variations, with 80% of the estimations in 10cm error comparing with 19cm in the ANN-RSS based scheme. These results illustrates a better robustness in intensity variations of ANN-PDOA based estimations.

2) SELECTION BASED ANN-PDOA/RSS POSITIONING SYSTEM

As mentioned in the section 2, a selection method is applied here to achieve better position estimations under intensity variations. For the t-test based selection (T-selection), we take significance level $\alpha = 0.2$ and $d_{lim} = 1.5m$, and for the V-selection approach the variation level $p\% = 4\%$.

The RMS error CDFs of different selections in various intensity variations are given in Fig.14. V-selection and T-selection strategies achieve closely in performances under all variation levels and generally following the better estimations of either ANN-PDOA or ANN-RSS with better

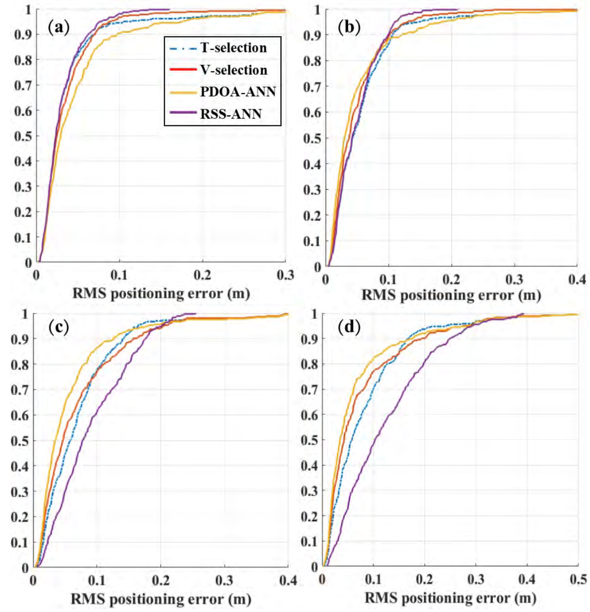

FIGURE 14. RMS error CDFs with selection strategies under intensity variations. a) no variation; b) 5% variation; c) 10% variation; d) 15% variation.

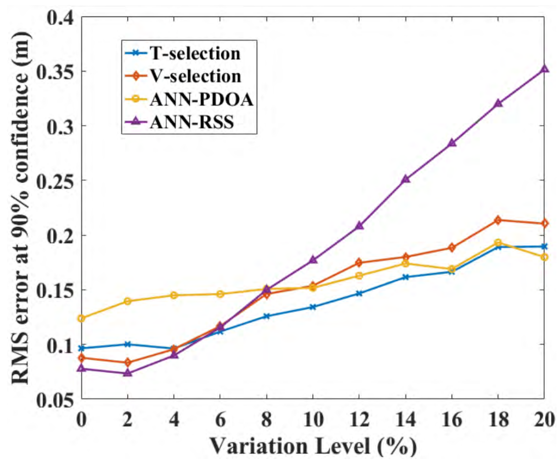

FIGURE 15. RMS error comparison of 90% CDF at different variation level.

CDF performances. Due to the selection based constrains, the highest accuracy is affected by the best estimations as well as the efficiency of the selection standards.

As shown in Fig.15, the tendency of RMS error at 90% confidence are given as intensity variation level increases from 0 to 20%. As observed, when variations below 8%

ANN-RSS have generally better accuracy, however, as variation level increases the performance drops sharply. Meanwhile, the ANN-PDOA is rare affected by the intensity variations regarding the positioning accuracy. The selection based strategies, as depicted in blue(T-selection) and red (V-selection) curve, generally achieves good accuracy at all variation levels. Especially for the T-selections, compensations from ANN-RSS estimations assisting the performances much better than ANN-PDOA alone, when variations are lower than 6%. As variation increases, the T-selection strategy is generally out-perform all other methods in accuracy.

Comparing the two selection strategies, the V-selection strategy judges the estimations with intensity variations in a short period. Therefore, when the intensity varies slowly the V-selection will be time consuming in selecting due to the process of obtaining the standard deviation, otherwise the estimations are inaccurate. While T-selection method uses only current estimations for judgments which is much efficient in real-time processes.

IV. CONCLUSION

In this paper, we propose a new hybrid 3-D VLP scheme of ANN-PDOA and ANN-RSS approaches with pre-training techniques, improving the robustness of conventional VLP systems under intensity variations as well as mitigating inaccurate modeling induced distortions. Moreover, the proposed hybrid positioning system requires no measurements on the LED lamps' layouts.

We elaborate the proposed scheme through simulations, addressing the issue of ITD induced distortions in conventional PDOA based positioning system. Our proposal is proved to mitigate the ITD induced distortions in 3D positioning environments with practical coverage.

To further reduce the complexity of the system, we propose the pre-training based method to assist the training process and release the data acquisition efforts. The pre-training technique is proved to improve the performance of the system with larger coverage and less off-line workloads.

We further validate the improvements and robustness of the ANN based hybrid positioning system using two different selection strategies. The hybrid positioning system using either selection strategy illustrates good positioning robustness and accuracy than the positioning system using only ANN-PDOA or ANN-RSS alone. V-selection strategy provides slightly better accuracy when variation is less than 6%, elsewhere T-selection outperforms V-selection strategy. Among the two selection strategies, T-selection is more suitable and adaptive in practical application environments considering it's real-time selecting mechanism.

Several state-of-the-art works are listed in Table.4. We can observe that works considering real system models perform generally better in accuracy like [13] and [16]. However, such modeling requires off-line workloads, with pre-training our work reduces the offline workload evidently. Comparing with work [16], the density off-line samples is saved over half, and off-line complexity is also reduced comparing with [13]. Moreover, different from [13], in this work triangulation and modeling are realized in the same single layer ANN which is around 50 times faster than solving quadratic equations. Comparing with image based positioning [26] (1m by 1m by 0.8m), our work is much larger in coverage.

Not many works considered the influences on light intensity variations (assuming a strictly stable LED power source). Under circumstances with intensity variations(5% to 20%), our proposal have less impacts on accuracy than RSS based methods. With stable intensity, the proposal is better in accuracy than the ANN-PDOA based system.

In conclusion, the proposed hybrid system has high adaptivity, high intensity robustness, better accuracy and lower complexity in off-line deployments and on-line calculations.

ACKNOWLEDGMENT

This work was conducted within the Delta-NTU Corporate Lab for Cyber-Physical Systems with funding support from Delta Electronics Inc. and the National Research Foundation (NRF) Singapore under the Corp Lab@University Scheme.

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