Three-Dimensional Indoor Visible Light Localization: A Learning-Based Approach

Danping Su
Xiamen University
Xiamen, China
sudanping@stu.xmu.edu.cn

Xianbin Liu
Xiamen University
Xiamen, China
liuxb2021@163.com

Sicong Liu*
Xiamen University
Xiamen, China
liusc@xmu.edu.cn

ABSTRACT

In this paper, a three-dimensional (3D) indoor visible light localization method based on machine learning and deep learning is presented, which is able to obtain accurate 3D spatial coordinates of the user, including the location on the plane and the height in a room. The machine learning approaches adopted for localization include two typical algorithms, i.e., support vector machine and random forest. For the deep learning based approach, deep neural networks composed of full connected layers are employed for training in different indoor visible light localization scenarios. In the formulated learning-based visible light localization framework, the received signal strength of light-emitting diodes are taken as the input of the learning algorithm, and the measured position coordinates are inferred as the output. Apart from obtaining the two-dimensional location on the plane accurately, we also take the height into account and accurate 3D coordinates with height are obtained. The experimental results show that centimeter-scale accuracy of 3D indoor localization can be achieved using the proposed learning-based visible light localization method. Moreover, the performance of the visible light localization methods with respect to the number and the spatial pattern of LEDs, and the number of neural network layers, are also investigated.

KEYWORDS

visible light localization, machine learning, deep learning, received signal strength

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*Corresponding author.

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1 INTRODUCTION

Nowadays, the acquisition of accurate indoor position information is the foundation of many applications while mature Global Positioning System (GPS) cannot provide sufficiently accurate indoor localization due to building obstructs etc. In order to deal with this dilemma, Ultra-Wide Band (UWB) [15], Wireless Local Area Networks (WLAN) [16], Bluetooth [6], radio frequency identification (RFID) [12] and many other technologies are widely studied for indoor localization. Visible light communication (VLC) as a promising wireless communication technology has been extensively researched [13, 20, 22], which has many advantages such as adjustable lighting, high security, rich spectrum resources, complete infrastructure deployment etc., and can be applied to indoor localization.

Many traditional radio frequency based positioning schemes might be applied for indoor visible light localization, including received signal strength (RSS), time of arrival (TOA), angle of arrival (AOA) etc. The position can be estimated from the RSS of the photoelectric receiver (PD) following the VLC channel model by measuring the power of the received signal. The TOA-based method measures the travel time of the signal from the light-emitting diode (LED) to the PD, which is a function of the distance as well. The AOA method measures the angle from which the signal arrives at the PD and such information can be also exploited in estimating the location of the PD [1]. An indoor visible light positioning scheme based on TDOA is proposed in [8], and the location accuracy of the proposed localization method is less than 1cm which is verified by simulation. In [18], an indoor visible light positioning scheme based on AOA is analyzed and the Cramer-Rao bound is derived. The simulation results show that the estimation error is less than 8 cm when the SNR is 80dB. In [3], fundamental limitations of RSS-based range estimation in visible light positioning system are studied.

The learning approach is the science of allowing computers to operate without being explicitly programmed. In the past decade, learning based technologies have been applied to self-driving cars, speech recognition and web search [19, 24]. Learning-based approaches are so pervasive today that we probably use it dozens of times a day without knowing it. Many researchers even think it is the best way to progress towards human-level AI. There are already many indoor localization schemes whose performance have been improved by using learning approach. For instance, a smart wireless indoor localization framework with machine learning (ML) is proposed in [10] and it outperforms the comparative methods. In [21], a new indoor localization algorithm based on ML using RSS measurements is proposed and it can increase the training ability of localization dramatically. In [7], a visible light localization scheme based on artificial neural networks is proposed, where the trained neural network is applied to the diffuse channel. The results show that the average positioning error is reduced about 13 times and the positioning time is reduced about 2 magnitudes compared with the traditional RSS-based positioning algorithm.

However, the learning-based approaches should be incorporated into indoor visible light localization more properly to achieve higher accuracy. Moreover, learning-based 3D visible light localization with both the horizontal and the vertical coordinates remains to be well investigated. Hence, in this paper we propose a three-dimensional (3D) visible light indoor localization method that combines the RSS with machine learning and deep learning algorithms for the training and inference of the 3D spatial coordinates. Since support vector machine (SVM) can deal with nonlinear problems effectively and random forest can process high-dimensional data efficiently, these machine learning based algorithms are adopted in the proposed visible light localization scheme.

To further improve the localization performance, deep neural networks (DNNs) composed of fully connected layers (FCs) are adopted to better integrate local features, and are optimized by using gradient descent during the training process. In order to compare the localization performance of different configurations of system parameters, LED numbers, and LED spatial patterns, different experiments are conducted accordingly where a corresponding learning model is trained and applied for the visible light localization in each experimental configuration. The simulation results have verified the superior performance of the proposed learning-based method in different configurations and scenarios of indoor visible light localization.

2 SYSTEM MODEL

2.1 Indoor Localization Model

We depict the 3D indoor visible light localization model in a room with size 2m×2m×2m as shown in Figure 1, within which a Cartesian coordinate system is established. There are sixteen LEDs on top with fixed coordinates and a mobile user equipped with a PD with a variant coordinate in the room.

The LEDs are arranged symmetrically with equal intervals on the ceiling. The illumination radiation regions formed by different LEDs overlap with each other, so this layout can ensure that the PD can communicate with all LEDs in the radiation region [11].

In order to be able to evaluate the performance of 3D localization, the PD can be moving around in a 3D space of 2m×2m×1m, then its coordinates in this Cartesian coordinate system can be estimated using various localization methods.

2.2 Visible Light Channel Model

Because the intensity of the direct visible light signal is far greater than that of the reflected signal, we only consider line-of-sight (LOS) path [9]. We can get the channel gain H in the LOS environment represented by,

$$h = \frac{A(m+1)}{2\pi d^2} \cos^m(\varphi)\cos(\theta), \tag{1}$$

where d is the distance between the LED and the PD, and φ and θ are the angle of irradiance and the angle of incidence relative to the normal direction, respectively. A is the detector physical area. The order m can be given as $m = -\ln 2/\ln(\cos\varphi_{1/2})$, where $\varphi_{1/2}$

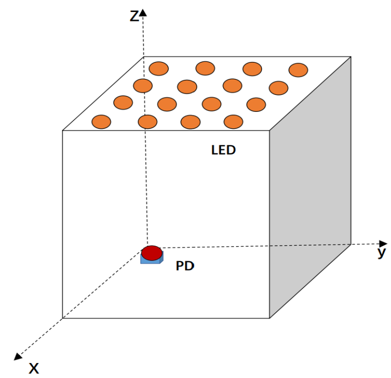

Figure 1: The visible light indoor localization model.

is defined as the half-power angle of the LED [23]. Therefore, the received optical signal y_r can be given by

$$y_r = x_t \cdot h + n, \tag{2}$$

where y_r and n denote the transmitted optical signal and the channel noise, respectively. For the sake of simplicity, the power of the transmitted optical signal is set to 1W and n is assumed to be additive white Gaussian noise with zero mean and variance of σ^2.

3 LEARNING-BASED 3D INDOOR VISIBLE LIGHT LOCALIZATION SCHEME

3.1 Machine Learning Based Localization Scheme with SVM and Random Forest

SVM is a typical classifier which can handle both linear and nonlinear problems. The basic idea of SVM is to find the optimal hyperplane of two types of samples in the original space when they are linearly separable. While in the linearly inseparable case, slack variables are added for analysis, and the sample of the low-dimensional input space is imported by using nonlinear mapping to the high-dimensional attribute space to make it linear. Then the optimal classification hyperplane is constructed in the attribute space using the principle of structural risk minimization, so that the classifier is globally optimal and the expected risk in the entire sample space also satisfies a certain upper bound with a probability [17].

SVM has good generalization ability, that is, the test error on an independent test set can be small even if the model is trained in a small amount of training set. Maximizing the classification interval can also bring the SVM algorithm better robustness. Moreover, employing appropriate kernel functions can transform nonlinear problems into linear problems. As the indoor visible light positioning problem is a non-linear problem, SVM needs a kernel function during the learning process [14]. A Gaussian kernel function is chosen in this paper to train the SVM classifier that can fit the problem well.

Due to the large amount of data that need to be processed in the visible light localization scenario and considering that time complexity and space complexity will increase when processing large scale data [2], the random forest algorithm is applied in this paper. Random forest, as its name implies, is to build a forest in a random manner containing multiple decision trees, and the correlation between the decision trees needs to be as small as possible. For a new sample input to a forest, each decision tree in the forest judges which category the sample belongs to and vote. The category with the most votes is the predicted category of this sample [5]. A large number of theoretical and empirical studies have verified that random forest has a high prediction accuracy and is not prone to overfitting. Thus, we use random forest in the visible light localization problem as a competitive alternative.

In the case of a more complicated localization environment, a large area, or a more severe channel condition, machine learning algorithms might be limited. In order to further improve the positioning performance, deep learning methods with a larger learning capacity can be an excellent choice, which is described in detail in the following section.

3.2 Deep Learning Based Localization Scheme with DNN

The neural network introduced in artificial intelligence is a mathematical model simulating the mechanism of the human brain's nervous system based on the principle of biological neural networks. It is composed of an input layer, a number of hidden layers and an output layer, and each layer has a number of nodes that can be connected. Each node contains a specific output function called activation function. Each connection between two nodes has a weight that is imposed on the signal passing through the connection. The input of the neural network propagates forward through the hidden layers, and the results are obtained at the output layer [4]. DNN can be regarded as a kind of neural networks with a large number of hidden layers, so that the network is deep and has a greater capacity and better learning capability.

As shown in Figure 2, a DNN with n_h FC hidden layers is employed. Each node in an FC hidden layer is connected to all the nodes in its previous layer, which is utilized to synthesize the features extracted from the previous layer. The features are extracted and combined layer by layer to form high-level features. Gradient descent is adopted to optimize the DNN model during training, and the Adam optimizer is adopted, which is a commonly used optimizer. Gradient can be understood as a vector composed of partial derivatives of multivariate functions. The function increases fastest along the gradient direction, and in gradient descent, the direction opposite to the gradient should be followed. There are several points that can be tuned when using gradient descent as follows:

- `Step size`: the value of the step size depends on the data sample, so we can take a larger value and run the algorithm from large to small to observe the iterative effect. If the loss function is decreasing, the value is valid; otherwise, the step size should be increased. However, if the step size is too large, the iteration will be too fast, and even the optimal solution may be missed. On the other hand, if the step size is too small, the iteration speed is too slow, and the algorithm cannot converge for a long time.
- `Initial value selection for parameters`: different initial values may result in different minimum values, so gradient descent only results in local minimum values. Of course if the loss function is convex then it must be the optimal solution. Due to the risk of local optimal solution, the algorithm needs to be run multiple times with different initial values, to achieve the initial value that minimizes the loss function.
- `Nomalization`: due to the different value ranges of the different features, the iteration may be slow. In order to improve the dynamic range of the algorithm with respect to feature values, the feature data can be normalized. For each feature, its expectation and standard deviation can be found. In this way, the new expectation of the feature is zero and the new variance is one, and the iteration speed can be greatly accelerated.

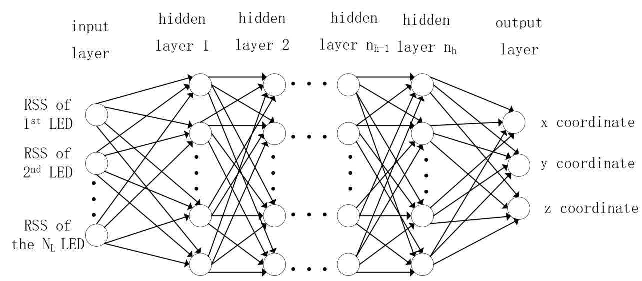

Figure 2: The DNN model adopted for visible light localization.

4 EXPERIMENTAL RESULTS

The initial parameters are set as follows: the number of LEDs $N_\mathrm{L} = 16$, the mode of LEDs $M = 1$, the number of features in each hidden layer $n_\mathrm{f} = 256$, the number of hidden layers $n_\mathrm{h} = 4$, batch size in training $n_\mathrm{B} = 32$, learning rate of the optimiser $\gamma = 10^{-4}$. The relevant descriptions of these parameters are shown in Table 1.

Table 1: Key Parameters Used in Simulation

Parameter	Symbol
the number of LEDs	N_L
the mode of LEDs	M
the number of features in each hidden layer	n_f
the number of hidden layers	n_h
batch size in training	n_B
learning rate of the optimiser	γ

4.1 Data Set Preparation

Assuming that the PD can move in a 3D space of 2m×2m×1m with the step size of 10mm, the ground-truth distance and angle between each LED and the PD can be calculated. Substituting the distance and angle into equation (1) and (2), the RSS data subject to additive white Gaussian noise is obtained. Consequently, we obtain a four-dimensional (4D) tensor with the size of 16×200×200×100. The 4D tensor, the corresponding LED coordinates and the corresponding

PD coordinates are then gathered together to formulate the data set. After the data set is generated, it has to be preprocessed, that is, the 4D tensor in the data set and the corresponding PD coordinates are reshaped into a 2D array. Then the reshaped data set is divided into the training set, the validation set and the test set with a proportion of 16:4:5 for subsequent training, validating and testing procedures.

As the training parameters need to be adjusted continuously, different parameters can be conveyed in each training. In the training process, the training should be continued and the number of iterations should be continuously recorded, until 10 consecutive times of poor performance occur. Then the trained model with the best training performance are the final output model, whose performance indicates the training localization errors.

In addition, in order to process the data conveniently, the data are normalized before training. Finally, the unit is converted to centimeter when calculating the errors.

Table 2: Positioning errors with different spatial arrangement modes of the LEDs

M	Random Forest		DNN	
	error (2D)	error (3D)	error (2D)	error (3D)
1	1.85cm	2.79cm	1.01cm	2.16cm
2	11.80cm	17.08cm	8.70cm	12.61cm
3	4.15cm	6.33cm	2.77cm	4.533cm
4	4.97cm	8.51cm	3.94cm	7.56cm
5	3.56cm	5.60cm	1.88cm	2.80cm

4.2 Experiments and Results

We perform three kinds of experiments to investigate the performance of the learning-based visible light localization methods with respect to the number of available LEDs, the spatial arrangement modes of the LEDs, and the hyper-parameter, i.e., the number of features of each hidden layer, of the DNN. Experiment 1 investigates how much performance improvement can be achieved by using more received signals from more LEDs as input for the SVM, random forest and DNN. The experiment starts with a model that only uses one signal as input. This signal is the received signal with the highest RSS. Then more received signals from more LEDs are utilized in turn and the results are shown in Figure 3. The results show that the positioning errors of the proposed three approaches all tend to be stable when $N_{\mathrm{L}} \geq 4$, except for the 3D error of the SVM method. In general, DNN has the best performance, followed by the random forest method, while the performance of SVM is relatively poor. Moreover, it can be found that when the number of LEDs is greater than 3, both 2D and 3D positioning errors of the random forest and DNN methods fluctuate within a small range. The minimum 2D errors of SVM, random forest and DNN are 11.28cm, 1.81cm and 0.99cm, respectively, and the minimum 3D errors of SVM, random forest and DNN are 15.62cm, 2.79cm and 2.14cm, respectively. This implies that when the room size is fixed, the positioning accuracy will first increase with the number of LEDs but gradually saturate and no longer improve when the number of LEDs is sufficiently large.

The second experiment investigates the performance difference between different spatial arrangement modes of the LEDs. The spatial pattern of the five modes is shown in Figure 4. Mode 1 turns on all 16 LEDs as comparison, mode 2 turns on 4 LEDs in the corners, mode 3 turns on 4 LEDs in the middle, mode 4 turns on 8 LEDs except the 8 LEDs mentioned in modes 2, 3, and mode 5 is just the opposite of mode 4. For each of these modes, a model is trained and the localization performance is evaluated for evaluation. According to the results of experiment 1, we select random forest and DNN with better performance to train for these different modes. Table 2 presents the test error of localization accuracy for each model in different spatial modes of LEDs. The results show that except for mode 1 with all the 16 LEDs used, mode 5 using only half the total number of LEDs has the best performance. Specifically, for mode 5, the 2D errors of random forest and DNN are 3.56cm and 1.88cm, respectively, and the 3D errors of random forest and DNN are 5.60cm and 2.80cm, respectively. Furthermore, it can be observed that, when the number of LEDs is the same, the more concentrated the LEDs are distributed, the smaller the positioning errors are. We can get such a insightful conclusion that, when the number of LEDs is not enough in a harsh environment, maybe we can get compensation of localization accuracy from a better distribution of the available LEDs.

The purpose of experiment 3 is to find a good model architecture of the neural networks through hyperparameter search. In Figure 5, the performance of the DNN is evaluated with various number of hidden layers and different number of features in each hidden layer, and other system parameters remain invariant to focus on the main aspect of interest. It can be seen that when $n_{\mathrm{h}} = 1, 2, 5$, the positioning errors decrease with the increase of n_{f}. When $n_{\mathrm{h}} = 3, 4$, the positioning errors first decrease and then increase with the increase of n_{f}. When $n_{\mathrm{f}} = 32, 64$, the positioning errors decrease with the increase of n_{h}. When $n_{\mathrm{f}} = 128$, the positioning errors first decrease and then increase with the increase of n_{h}. When $n_{\mathrm{f}} = 256$, the positioning errors decrease first and then fluctuate with the increase of n_{h}. In a word, the 2D localization error reaches the best performance of 0.95cm, when there are 5 hidden layers and 256 feature numbers, while the 3D localization error reaches the best performance of 2.02cm when there are 3 hidden layers and 128 feature numbers. It indicates that the number of hidden layers and features needs to be appropriately tuned due to over-fitting and other related hyper-parameter influences of the DNN.

5 CONCLUSION AND FUTURE WORK

In this letter, we have presented a learning-based 3D indoor visible light localization scheme in a realistic room environment with multiple LEDs available for localization, and obtain the RSS data and other prior information based on the LOS visible light channel. In order to better exploit the data with the physical prior information from the analytical model of the visible light channel, we have applied three learning-based approaches and carry out different experiments. These experimental results show that the number and spatial distribution of LEDs, and the number of hidden layers and features of the neural networks, can all affect the learning-based localization performance. It is found that under a certain physical circumstance, the best 2D and 3D positioning errors can reach 0.95cm and 2.02cm, respectively. In future research, we can also take factors such as NLOS visible light path and the orientation of

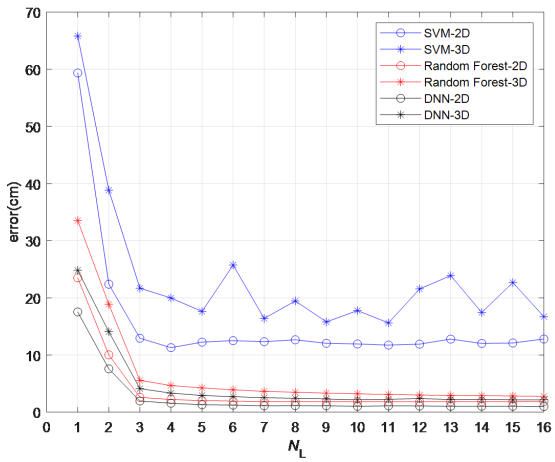

Figure 3: Positioning errors with incremental LEDs.

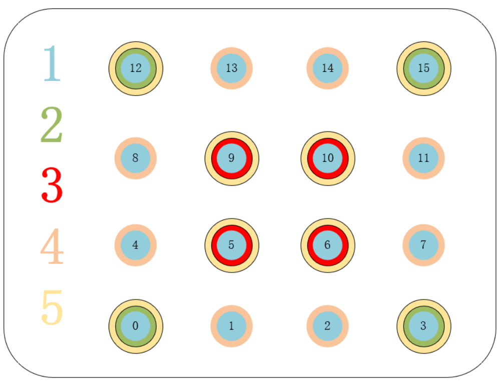

Figure 4: The spatial arrangement modes of LEDs.

the receiver or the PD into account, and formulate a more generalized learning model for visible light localization to achieve further performance improvement in different scenarios.

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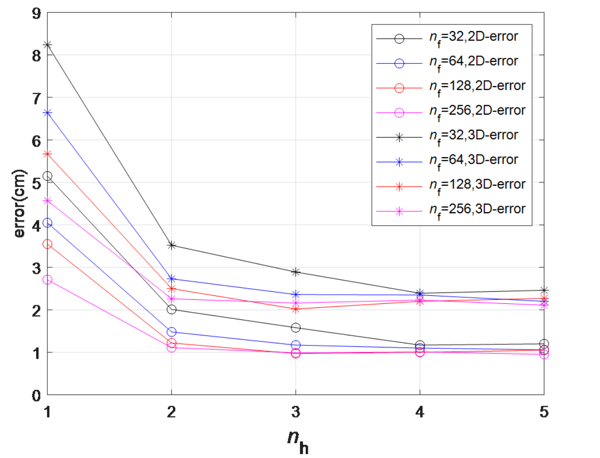

Figure 5: Positioning errors with different hyper-parameters of the DNN.

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