Using Received-Signal-Strength (RSS) Pre-Processing and Convolutional Neural Network (CNN) to Enhance Position Accuracy in Visible Light Positioning (VLP)

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Abstract: We propose and demonstrate a received-signal-strength (RSS) pre-processing scheme to mitigate light-deficient-region occurred in visible-light-positioning (VLP) and convolutional-neural-network (CNN) to enhance VLP performance. The RSS pre-processing and CNN model are discussed. © 2022 Author(s)
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1. Introduction

Indoor positioning system (IPS) can locate persons or objects in indoor areas, where Global Positioning System (GPS) may fail to provide accurate positioning. IPS can be implemented using WiFi or Bluetooth; however, the positioning accuracy could be restricted by the electromagnetic interference (EMI). Visible light positioning (VLP), which studies the optical signals emitted by light emitting diodes (LEDs) for positioning can be a promising candidate for the IPS. Several VLP systems have been demonstrated, including proximity [1], time-of-arrival (TOA)/time-difference-of-arrival (TDOA) [2], angle-of-arrival (AOA) [3], and received-signal-strength (RSS) [4]. Among these technologies; VLP system using RSS technique is easy to implement and cost effective. This scheme relies on different received optical powers to predict the distance between optical transmitter (Tx) and receiver (Rx). To improve the RSS based VLP positioning accuracy, machine learning (ML) schemes, including regression [5], and residual neural network (RNN) [6] have been proposed. Due to the finite field-of-view (FOV) of the LED light sources, light deficient regions can be observed particularly in 3-dimentional (3-D) VLP system. High positioning errors will result since very week or even no optical signal is detected in these light deficient regions.

In this work, we propose and demonstrate for the first time a RSS pre-processing scheme to mitigate light deficient regions in VLP. Convolutional neural network (CNN) is used to enhance the VLP accuracy. The RSS pre-processing and the CNN model will be discussed. Experimental results show that the RSS pre-processing scheme can significantly reduce the average position error by > 40%. Traditional neural network (NN) model is also compared with the proposed CNN model, and results show that the CNN with RSS pre-processing performs the best.

2. RSS Pre-Processing, CNN Algorithm and Experiment

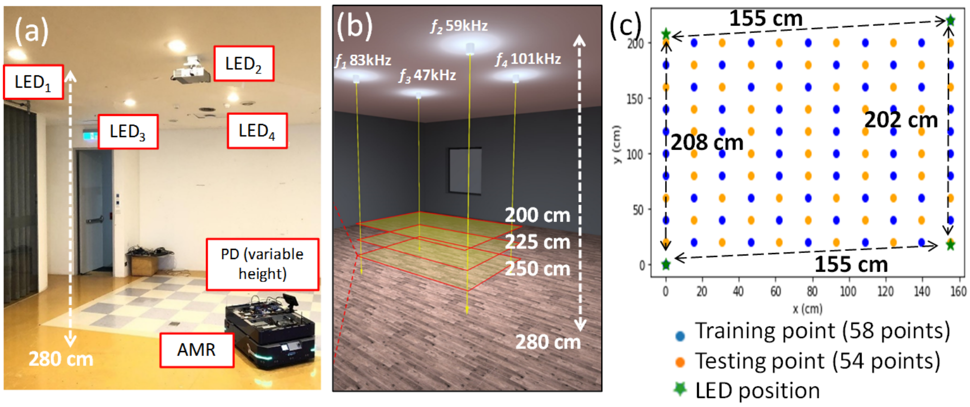

Fig. 1. (a) Photo of the experimental test-bed of the VLP system. (b) Architecture of the VLP system. (c) top-view of the VLP unit cell.

Fig. 1(a) shows the photo of the experimental VLP test-bed using RSS pre-processing and CNN to enhance the VLP performance. An autonomous mobile robot (AMR) is used as the mobile client. A photo-detector (PD) attached to a real-time-oscilloscope (RTO, PicoTechnology® ps5432d) to used to collect optical signal. The PD is mounted to an variable stand, so that the vertical distance between the LED Tx plane and the PD can be adjusted from 200 to 250 cm. Each VLP unit cell contains 4 LEDs (TOA® LDL030C), and each has an output power of 13 W. As shown in Fig. 1(b), each LED is modulated by a unique Manchester-coded identifier (ID) at data rate of 3.125 kbit/s, which is frequency upconverted to 47 kHz, 59 kHz, 83 kHz or 101 kHz, separately. The odd frequencies used here are to avoid harmonic spectra overlapping. The training and testing data are collected in 3 horizontal layers (or planes) at different distances of 200 cm, 225 cm and 250 cm away from the LED Tx plane respectively. Fig. 1(c) illustrates the top-view of the VLP unit cell. Because of the limitation of the actual room, the unit cell is not a perfect rectangle, and the size is about 155 cm × 200 cm. The training, testing and LED locations are illustrated in Fig. 1(c). The RSS values at each locations are measured 20 times. The PD receives 4 signal bands emitted by 4 LEDs at the corners of the unit cell for positioning. Analog-to-digital conversion (ADC) is performed by the RTO, then the 4 optical IDs and 4 RSS signal values can be retrieved. The details of the Tx and Rx architectures are shown in [6].

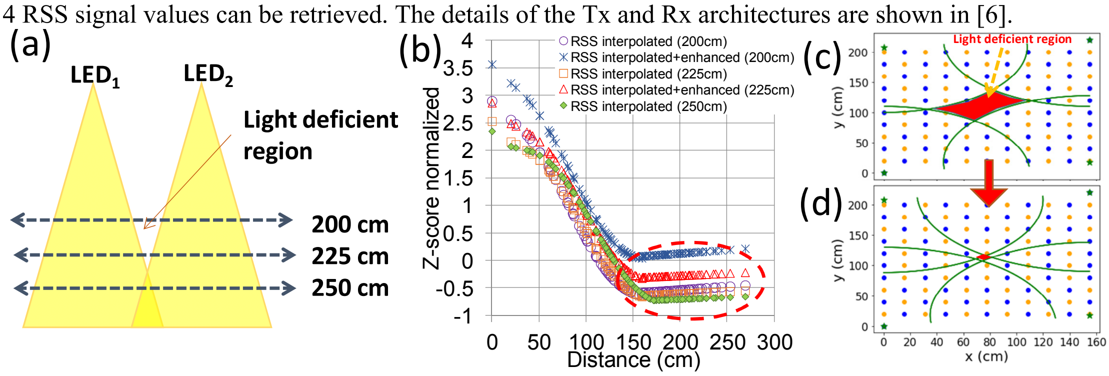

Fig. 2. (a) Schematics showing different VLP planes and the light deficient region. (b) LED light distribution profile in each plane after interpolation and signal enhancement. Top-view of the 200 cm planes (c) before and (d) after signal enhancement.

It is usually considered that the VLP performance will decrease when the transmission distance increases. This is true if the entire VLP horizontal plane is covered by light. Due to the finite FOV of LEDs, light deficient region can be observed particularly when performing 3-D VLP. As illustrated in Fig. 2(a), light deficient region can be observed in 200 cm and 225 cm planes when performing 3-D VLP. High positioning errors will result since week or even no optical signal is detected in these light deficient regions. Hence, we first propose the RSS pre-processing scheme, which contains data interpolation and signal strength enhancement. In the data interpolation, 32 RSS data are selected in each plane. Then, each LED light distribution profile at each horizontal plane can be up-sampled to 112 sample points based on polynomial curve fitting. Without the loss of generality, we use LED_1 as an example. Fig. 2(b) shows the RSS interpolated and Z-score normalized data in 200, 225 and 250 cm planes. 0 distance means directly under the LED. We can observe that when the horizontal distance > 150 cm, the Z-score normalized RSS value drop rapidly creating the issue of light deficient region. Hence, the RSS data at the light deficient region should be enhanced. This can be based on the trigonometric ratio as shown in Eq. (1), where h_{std} and h_{tar} are the vertical distances of the standard plane and target plane respectively. θ and α are FOV half angle and a scaling factor respectively. Since the 250 cm plane does not have the light deficient region, it is selected as the standard plane. The 200 and 225 cm planes are the target planes. Here, α of 3.3 is used to produce enough RSS signal enhancement. As illustrated in the top-view of the 200 cm plane as illustrated in Fig. 2(c), the light deficient region at the center of the unit cell (no light covered by the 4 LED lamps) will be significantly reduced after the RSS signal enhancement as shown in Fig. 2(d).

$$RSS_{Enhanced} = RSS_{Interpolated} + \frac{(h_{std} - h_{tar})\tan\theta}{h_{std}\tan\theta}\alpha \tag{1}$$

Fig. 3(a) shows the flow diagram of the RSS pre-processing and the NN/CNN models used for the VLP system. After the RSS pre-processing, the pre-processed data will be divided into training and testing sets depending on the location obtained. Here, we compare two kinds of models: the traditional NN and proposed CNN. The NN model has five layers (i.e. one input layer, three hidden layers, and one output layer). The loss function is mean-squared-error (MSE). Adam optimizer and three hundred epochs are used for training. Fig. 3(b) illustrates the structure of the proposed CNN model. It has nine layers (i.e. one input layer, two convolution layers, two max pooling layers, three fully-connected (FC) layers, and one output layer). The loss function, optimizer, and the training epochs are the same as traditional NN model. After the NN/CNN models are built, the pre-processed testing set will be launched to these trained NN/CNN models for VLP coordinate prediction.

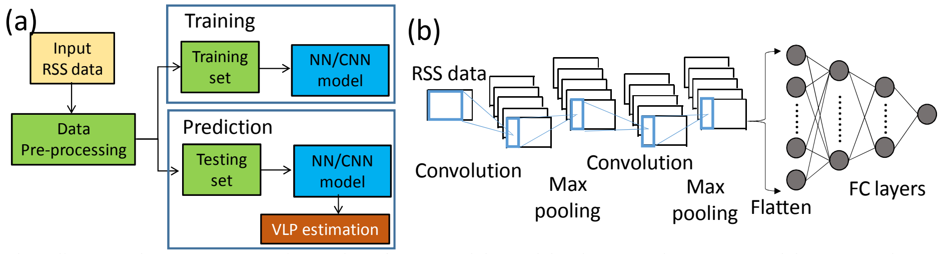

Fig. 3. (a) Flow diagram of RSS pre-processing and NN/CNN models used for the VLP. (b) Structure of the proposed CNN model.

3. Results and Discussion

Figs. 4(a) and (b) shows the experimental positioning error cumulative distribution functions (CDFs) using different kinds of VLP models at 225 cm and 200 cm planes respectively. We can observe that the RSS pre-processing scheme significantly reduce the positioning error. For example, at the 200 cm plane, 90% of the experimental data has positioning error within 17.7 cm when only CNN model is used. When the CNN with RSS pre-processing is used, the positioning error is reduced to within 9.8 cm (i.e. improvement of 44.6%). Figs. 4(c)-(f) reveal the experimental average error distributions at the 200 cm plane when using NN, NN with pre-processing, CNN, and CNN with pre-processing respectively. In Figs. 4(c) and (d), the average positioning error decreases from 12.5 cm to 5.7 cm (i.e. reduction by 54.4%) when the NN with pre-processing is used. In Figs. 4(e) and (f), the average positioning error decreases from 10.2 cm to 5.3 cm (reduction by 48.0%) when the CNN with pre-processing is used.

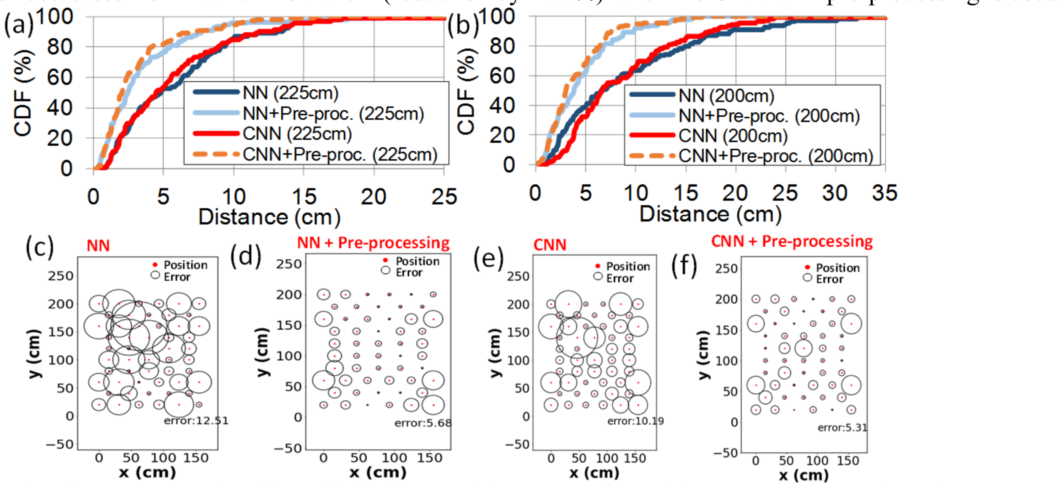

Fig. 4. Measured position error CDF using different kinds of VLP models at (a) 225 plane and (b) 200 cm plane. Experimental average error distributions at the 200 cm plane when using (c) NN, (d) NN with pre-processing, (e) CNN, and (f) CNN with pre-processing.

4. Conclusion

We proposed and demonstrated for the first time a RSS pre-processing scheme to mitigate light deficient regions in VLP. Convolutional neural network (CNN) to used to enhance the VLP accuracy. Experimental results show that the RSS pre-processing scheme can significantly reduce the average position error by > 40%. The average positioning error decreases from 10.2 cm to 5.3 cm (reduction by 48.0%) when the CNN with pre-processing is used.

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