An Indoor Visible Light Positioning System Using Artificial Neural Network

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***Abstract*—We propose a visible light positioning system based on an artificial neural network (ANN) and optical camera communications. The receiver's position is approximately and precisely estimated based on the decoded block coordinate and a typical back propagation ANN, respectively. The experimental results show that the proposed scheme offers a mean positioning error of 1.49 cm, which is required in many indoor positioning scenarios where high accuracy is essential.**

Keywords—Visible light communications (VLC), artificial neural network (ANN), optical camera communications (OCC), indoor positioning.

I. INTRODUCTION

Indoor positioning systems (IPSs) have attracted a considerable amount of attentions in recent years in a range of applications including highly automated manufacturing, shopping stores, medical environments, underground etc. The radio frequency (RF) based techniques such as zigbee, ultra wideband (UWB), bluetooth and RF identification (RFID) have been widely studied to provide indoor positioning with accuracy from tens of centimeter to several meters [1-2]. However, these methods are prone to high signal attenuation and multipath effects. However, there is an alternative IPS for indoor environments, which is based on visible light communications (VLC) that uses the already installed light emitting diodes (LEDs) lighting fixtures [3]. The VLC based IPS, which offers advantages such as not affected by the RF electromagnetic interference, high positioning accuracy, and low cost front-ends have been widely investigated [4]. Since in VLC-IPS the transmission data rate is not an issue, therefore both cameras and photo-detectors (PDs) based receivers (Rxs) are used.

In the camera based VLC-IPS, the Rx's position is determined based on the coordinates of LEDs installed on the ceiling and in the captured image, thus offering higher positioning accuracy (i.e., lower PE). In [5], both the Rx's position and direction was measured using an image sensor (IS), whereas in [6] using an additional accelerometer sensor (AS) the Rx was allowed to have arbitrary orientation. In [7] we, for the first time, experimentally demonstrated an IPS based on optical camera communications (OCC) with low PE.

Machine learning as a powerful interdisciplinary tool has been widely used to solve a range of problems in different application such as data mining, pattern recognition, medical imaging, artificial intelligence, etc. [8] Recently, machine learning based techniques have been adopted in optical communications for optical signal-to-noise ratio (OSNR) monitoring, modulation formats identification, nonlinearity mitigation, etc. [8-10]. In this paper, we propose an intensity modulation and direct detection based VLC-IPS with an artificial neural network (ANN) and OCC, where the LEDs are grouped into blocks with the block coordinate encoded on a single LED per block. Based on this scheme, the Rx's position is roughly and precisely estimated based on the decoded block coordinate and using a typical back propagation (BP) ANN, respectively. The feasibility of the proposed scheme is experimentally verified in a room with a size of 85×85×185 cm. We show that the proposed IPS with a mean PE of 1.49 cm is a promising alternative scheme for indoor applications such manufacturing, stores, etc.

The rest of the paper is organized as follow: Section 2 describes the proposed indoor positioning scheme in detail. Section 3 presents the experiment setup and results for positioning system followed by the concluding remarks in Section 4.

II. PROPOSED SYSTEM FOR INDOOR POSITIONING

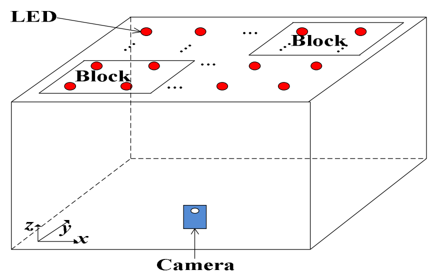

Fig. 1. System schematic.

Fig. 1 shows the system schematic of our proposed scheme, where LEDs are distributed evenly on ceiling. Every 4 LEDs is grouped as a block, and one LED per block is encoded with the coordinate information in order to acquire the Rx's position. The transmitted coordinate data is encoded with under-sampled based modulation and captured using a camera. The detail processing flow of the OCC can be found in [6]. The Rx's position can be roughly estimated based on the detected block coordinate. For more accurate positioning we use a typical BP ANN, which is composed of the input, the hidden and the output layers. The functional characteristics of the ANN are connected by the topology and the synaptic connection strength, which is decided by the connection weight. The total connection weight of the ANN can be represented by a matrix , see Fig. 2. The output of the ANN can be expressed as:

$$\begin{cases} v = \sum_{i=1}^{m} x_i \omega_i + b \\ y = \varphi(v) \end{cases}, \tag{1}$$

where m is the number of inputs, b is the bias, $\varphi(.)$ is the activation function, and x and y are inputs and output signal, respectively. The learning procedure of the ANN can be divided into training and trained stages. In the training steps, we evenly placed the camera on the plane with a grid to take a picture. Based on the sampled picture, we then determine the center point coordinate (i.e., (x', y')) of the block in the image. The center point coordinates and the Rx's coordinates in the real world are treated as the inputs and outputs, respectively, which are used to train the BP ANN until the sum of the mean squared error of the sampled points is minimized.

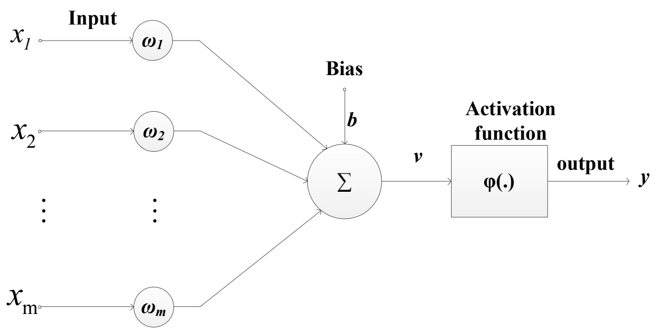

Fig. 2. The connection weight of the neural network.

III. Experiment Setup and Results

The feasibility of the proposed scheme is demonstrated experimentally as shown in Fig. 3. For the selected block, its coordinates are encoded and transmitted via the LED4. In the offline mode, we split the block into several cells with a size of (5×5×185) cm, and located the camera in each cell to capture an image of the light source. The captured image is processed in two parts in order to determine the position. I) The decoded output from the image is applied to the block coordinate module to determine the estimated position. II) The block center coordinates in the image are determined based on the sampled images, which are used to train BP ANN together with the coordinate of the Rx in the real world. The output of ANN provides the precise position compared to (I). The detailed position estimation process for the proposed scheme is shown in Fig. 4. To determine the position, the online processing time is 0.15s. All the key system parameters are provided in Table I.

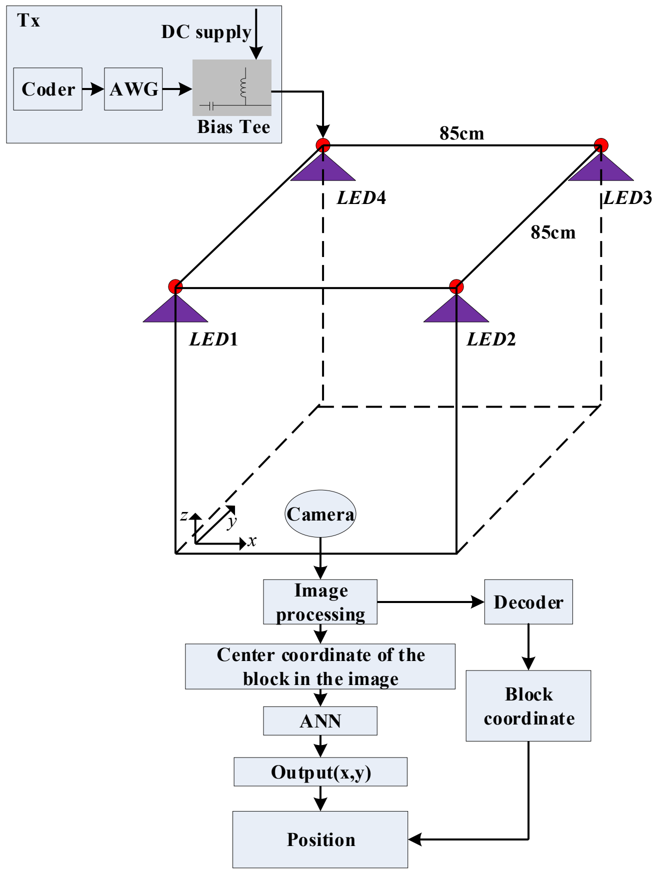

Fig. 3. Experiment setup for the proposed IPS based on OCC and ANN.

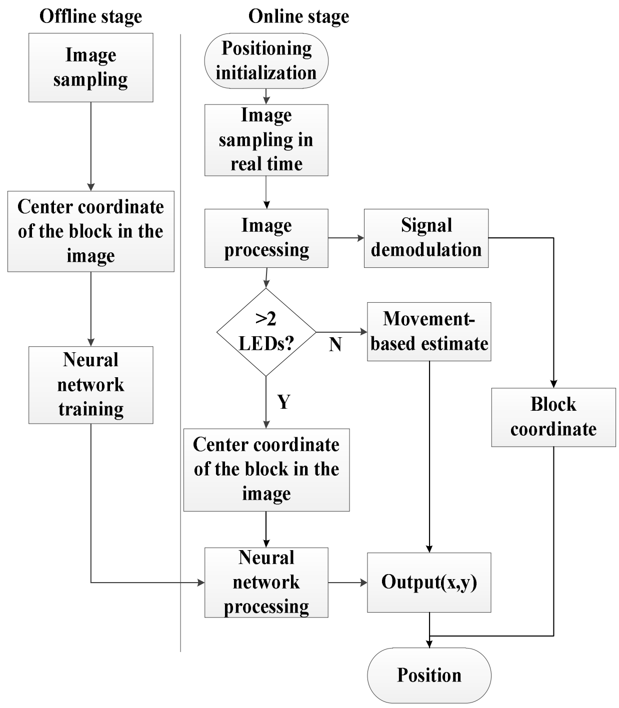

Fig. 4. The flow chart for determining the position in the proposed system.

The PE is given by:

$$D_{error} = \sqrt{(x - x_e)^2 + (y - y_e)^2} \tag{5}$$

where (x, y) and (x_e, y_e) are the coordinates of reference and estimated points, respectively. Fig. 5 illustrates 64 estimated as well as reference positions for the proposed system. Note that, the maximum and the average PEs are 3.72 cm and 1.49 cm, respectively. In the proposed system, the smartphone camera, used as a receiver, will not be influenced by received signal strength, and it is relatively straightforward to use it in larger size rooms by simply including more blocks without the need for additional training. Besides, each smartphone camera with the same resolution can be used as receiver. Note that, when the receiver moves from one block to another, the PE may not be the same.

TABLE I. KEY PARAMETERS OF EXPERIMENT

Parameter	Value
LED	
• Bandwidth	< 5 MHz
• Semi-angle of half power	~ 60°
• Transmit power	5 w
• DC bias	0.8 A
Camera	
• Frame rate f_c	50 fps
• Aperture	f/3.5
• Focal length	18-135 mm
• Shutter speed	1/4000 s
• Image sensor size	22.4×15 mm
ANN structure	
• Neuron number of input layer	2
• Hidden layer number and neuron number	1×15
• Neuron number of output layer	2
Room size	0.85×0.85×1.85 m

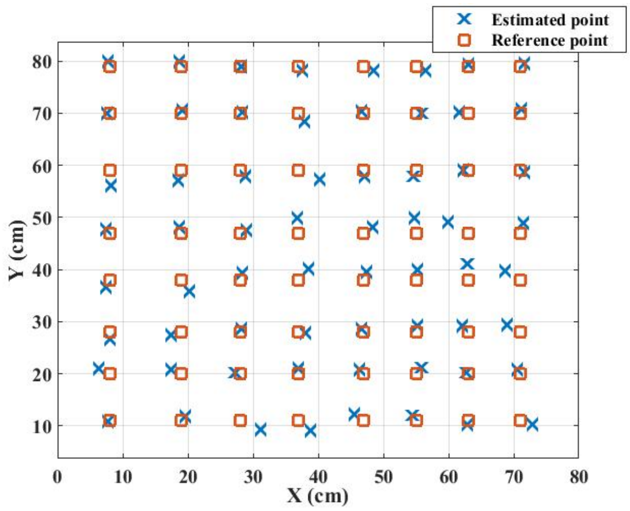

Fig. 5. The final estimated positions using our proposed scheme.

IV. CONCLUSION

In this paper, we proposed a visible light positioning system based on BP ANN and OCC, where LEDs were grouped into blocks and the block coordinate was encoded with the under-sampled modulation scheme. The position of a camera used as a receiver were roughly and precisely estimated based on the detected block coordinate and using the BP ANN, respectively. We also showed that the proposed scheme offers a mean positioning error of 1.49 cm, which was low compared with other RF-based positioning schemes, and its accuracy depended on the training samples and the convergence of the ANN.

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