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United block sequence mapping-based visible light positioning for dense small cell deployment

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Visible light positioning (VLP) is an emerging candidate for indoor positioning, which can simultaneously meet the requirements for accuracy, cost, coverage area, and security. However, intercell interference caused by light intensity superposition limits the application of VLP. In this Letter, we propose a united block sequence mapping (UBSM)-based VLP that utilizes superposition to integrate the multidimensional information from dense small cells into 2D information. The experimental result shows that UBSM-based VLP can achieve an accuracy of 1.5 cm with a 0.4 m row spacing and 0.35 m column spacing of LED lights.

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possible, which will help make the frame more suitable to work with other functions and simplify the frame processing design of the receiver. Bit stuffing is used to guarantee that the synchronization head can be detected correctly. 2-pulse position modulation can be used to avoid nonuniform illuminance distribution. All the LED lights transmit the positioning frame simultaneously.

The positioning frame consists of the following five parts: the synchronization head, the total number of rows \((M)\), the total number of columns \((N)\), the row index \((RI)\), and the column index \((CI)\). Before bit stuffing, the bit numbers of the five parts are 8, 8, 8, and \(N\), respectively. The most effective parts of the frame format are \(RI\) and \(CI\). They are closely linked with the position of the LED lights. \(RI\) and \(CI\) are set to have a variable length in order to adapt to the different LED light layout for different rooms. In order to decipher these two parts correctly, the other three parts are needed. The function of the synchronization head is to help the terminal recognize the beginning of the positioning frame. We use the typical ‘01111110’ as the synchronization head. For the second third parts of the frame, \(M\) and \(N\) are expressed in binary. The maximum value of \(M\) and \(N\) are both \((2^8-1)\), which is enough even in a large public facilities. Their function is to help terminals determine the boundary of \(RI\) and \(CI\). Before bit stuffing, the bit number is extended to 10. For \(RI\), take the 8th bit and the bit number is extended to 10. For \(CI\), take the 8th bit and the bit number is extended to 10.

\[
\alpha_R(x, y) = (W_R \ast S_R)/(O_R \ast S_R),
\]
\[
W_R = \begin{bmatrix} 1 & 2 & \cdots & M \end{bmatrix},
\]
\[
S_R = [S_{Row1}(x, y) \ S_{Row2}(x, y) \ \cdots \ S_{RowM}(x, y)]^T,
\]
\[
O_R = \begin{bmatrix} 1 & 1 & \cdots & 1 \end{bmatrix},
\]
\[
S_{Rowi}(x, y) = \sum_{j=1}^{N} RSS_{i,j},
\]

where \(\alpha_R(x, y)\) is the row mapping result at point \((x, y)\), \(S_R\) is an \(M \times 1\) matrix and its element, \(S_{Rowi}(x, y)\) represents the RSS from the LED lights in the \(i\)th row, the \(i\)th element of \(W_R\) is equal to the number of bit ‘1’ in \(RI\) for the LED lights in the \(i\)th row and in this Letter it is a vector with elements of 1 to \(M\), and \(O_R\) is an all-1 vector with a size of \(1 \times M\).

\[
\alpha_C(x, y) = (W_C \ast S_C)/(O_C \ast S_C),
\]
\[
W_C = \begin{bmatrix} 1 & 2 & \cdots & N \end{bmatrix},
\]
\[
S_C = [S_{Col1}(x, y) \ S_{Col2}(x, y) \ \cdots \ S_{ColN}(x, y)]^T
\]

Fig. 1. General design of the positioning frame.

Fig. 2. Positioning frame of LED_{2,7} \((M=11, N=7)\).

Table 1. Frame Modes.

<table>
<thead>
<tr>
<th>RI frame mode</th>
<th>‘1’ position</th>
<th>‘0’ position</th>
</tr>
</thead>
<tbody>
<tr>
<td>‘R+’</td>
<td>last (i)</td>
<td>first ((M-i))</td>
</tr>
<tr>
<td>‘R−’</td>
<td>last ((M+1-i))</td>
<td>first ((M-i))</td>
</tr>
<tr>
<td>CI frame mode</td>
<td>‘1’ position</td>
<td>‘0’ position</td>
</tr>
<tr>
<td>‘C+’</td>
<td>last ((j))</td>
<td>first ((N-j))</td>
</tr>
<tr>
<td>‘C−’</td>
<td>last ((N+1-j))</td>
<td>first ((j-1))</td>
</tr>
</tbody>
</table>

‘R+’ ‘C+’ frame is used in the remainder of the Letter.
where $a_C(x, y)$, $S_C$, $S_{Col_i}(x, y)$, $W_C$ and $O_C$ are similarly defined as $a_R(x, y)$, $S_R$, $S_{Row_j}(x, y)$, $W_R$, and $O_R$.

Solving $(x, y)$ from $a_R(x, y)$ and $a_C(x, y)$ is difficult. Hence, we propose three mechanisms, MTM, MFM and ACM, to solve this problem. Notably, $a_R(x, y)$ for a certain $x$ and $a_C(x, y)$ for a certain $y$ in the positioning area has to be monotonical to guarantee one-to-one correspondence.

The fingerprint database mechanism (FDM)\[^{[26]}\] and three proposed mechanisms are explained here. $a_{R_m}$ and $a_{C_m}$ are the row and column mapping results for a certain point calculated by the measured RSS. Suppose that there are $mm$ row sample nodes and $nn$ column sample nodes.

The fingerprint database contains $(mm \times nn \times M \times N)$ RSS as the RSS of each LED light for each sample node needs to be recorded. Choose the position of the sample node that has the minimum mean square error (MSE) between the measured RSS and the corresponding offline $M \times N$ RSS as the receiver position.

The first step of MTM is to establish the database. There should be $(mm \times nn)$ values calculated by $a_R(x, y)$ and $(mm \times nn)$ values calculated by $a_C(x, y)$, which constitutes $a_R$ matrix $(mm \times nn)$ and $a_C$ matrix $(mm \times nn)$. The $mm$ ordinate values and the corresponding row mapping results are stored in row mapping table (r-MT) and the corresponding row mapping results $(mm \times 1)$ are row average values of $a_R$ matrix $(mm \times nn)$. The column mapping table (c-MT) can be obtained in a similar way. After this step, the scale of the database can decrease to $(mm + nn)$, which leads to a faster positioning. Notably, the generation step limits the accuracy because the elements of $a_R$ matrix in a row or $a_C$ matrix in a column are similar but not the same and the smaller $(\partial a_R(x, y))/\partial x$ and $(\partial a_C(x, y))/\partial y$ are, the more accurate the positioning results can be obtained. Finally, the receiver position $(x, y)$ is determined by r-MT and c-MT.

The performance of MTM is dependent on the scale of the database; in other words, the spacing of the sample nodes. The larger the database is, the better the accuracy performance is, but the time it costs is longer and the storage it needs is larger. Therefore, MFM is proposed. Row mapping function (r-MF) and column mapping function (c-MF) can be generated by MTs. The dependent variable is abscissa $x$ or ordinate $y$ and the independent variable is $a_R$ or $a_C$. The MFs can be fitted into certain polynomial functions. In order to equilibrate the system complexity and the positioning accuracy, the degree of polynomial functions should increase until the MSE between MTs and the corresponding values calculated by MFs decreases to the acceptable level. In the remainder of this Letter, MF$(k)$ represents the degree of MF $k$ and MFM$(k)$ represents MFM using MF$(k)$. Notably, MFM$(2k - 1)$ and MFM$(2k)$, $(k \geq 1)$ are nearly the same for symmetrical layouts. Finally, $x$ is calculated by substituting $a_{C_m}$ into (c-MF) and $y$ is calculated by substituting $a_{R_m}$ into (r-MF).

Both MTM and MFM need offline training, which is hard to implement when the positioning area is large, so ACM is proposed. Figure 3 illustrates its procedures. The receiver position $(x, y)$ should be calculated from $a_R(x, y) = a_{R_m}$ and $a_C(x, y) = a_{C_m}$, which is a difficulty. In order to solve this problem, both the Newton–Raphson method and binary search method are used in ACM.

In ACM, $x$ and $y$ are obtained one by one from $f_C(x) = 0$ and $f_R(y) = 0$, where $f_C(x)$ and $f_R(y)$ are defined as

\[
\begin{align*}
\frac{f_R(y)}{a_R(x, y) - a_{R_m}} = & \ (11) \\
\frac{f_C(x) - a_{C_m}}{a_C(x, y) - a_{C_m}} = & \ (12)
\end{align*}
\]

where $x_s$ and $y_s$ are the selected values to ensure $x$ and $y$ can be solved separately. $x_0$, the initial value of $x$, is calculated by Eq. (13) in ‘C+’ frame or Eq. (14) in ‘C−’ frame. $y_0$, the initial value of $y$, is calculated by Eq. (15) in ‘R+’ frame or Eq. (16) in ‘R−’ frame.

\[
\begin{align*}
x_0 = \min(x) + \frac{(\max(x) - \min(x))}{(N + 1)} \ast (a_{C_m} - 1), & \quad (13) \\
x_0 = \max(x) - \frac{(\max(x) - \min(x))}{(N - 1)} \ast (a_{C_m} - 1), & \quad (14)
\end{align*}
\]
Each pair of iterations in the Newton–Raphson method is implemented as

\[
x_n = x_{n+1} - \frac{f_C(x_{n+1})}{f_C'(x_{n+1})}, \quad n \geq 1, \\
y_n = y_{n+1} - \frac{f_R(y_{n+1})}{f_R'(y_{n+1})}, \quad n \geq 1.
\]

\[x_i\] and \[y_i\] are updated by \[x_n\] and \[y_n\]. These steps repeat until \(f_C(x_{n+1})\) and \(f_R(y_{n+1})\) are close enough to 0 or \(n \geq n_{\text{max}}\), where \(n\) is the number of iterations and \(n_{\text{max}}\) is the maximum number of iterations.

In the iteration, boundary detection is needed to avoid converging to another root outside the positioning area.

Once \(x_n\) or \(y_n\) is out of the positioning area or \(n \geq n_{\text{max}}\), a binary search is used to find the position. In the binary search, the range of \(x\) is \(x_i \leq x \leq x_r\) and the range of \(y\) is \(y_i \leq y \leq y_r\). \(x_i\) is initialed as \(\min(x)\), \(x_r\) is initialed as \(\max(x)\), and \(x_s\) is always \((x_i + x_r) / 2\). \(y_i\) is initialed as \(\min(y)\), \(y_r\) is initialed as \(\max(y)\), and \(y_s\) is always \((y_i + y_r) / 2\). In every iteration, either \(x_i\) or \(x_r\) is updated by \(x\) and either \(y_i\) or \(y_r\) is updated by \(y\). The stop condition for the binary search is the same as for the Newton–Raphson method \((x_s, y_s)\), which is the positioning result.

In the simulation, the room size is 20 m × 20 m × 6 m to simulate a large indoor venue where dense small cells are more likely to occur. The LED lights are installed at the height of 6 m. The height of the receiver is 0.85 m. There are 10 × 10 LED lights. In order to quantitatively describe the superposition for dense small cell deployment, the degree of superposition (DOS) is defined as the number of LED lights whose light can be detected at a specific point. Figure 4(a) shows the distribution of the normalized received optical power and the layout of the LED lights. Figure 4(b) shows the DOS on the detection surface. As seen in Fig. 4, the illumination is uniform in most parts of the room and the DOS can even reach 65, which makes many existing VLP methods unsuitable to use. The details of the parameters in the simulation are summarized in Table 2.

For ease of comprehension, data processing of RI is illustrated in Fig. 5. The RSS of each bit time slot of RI needs to be summed and then divided by the RSS of the last bit time slot of RI.

In the simulation, the performances on accuracy, time cost, and storage cost are compared among FDM, MTM, MFM(1), MFM(3), MFM(5), MFM(7), MFM(9), and ACM. The performance accuracy is evaluated by the mean distance error (MDE). The storage cost is evaluated by the scale of the database. The spacing of sample nodes is 0.5 m. 100 detection nodes are randomly generated on the detection surface. Table 3 shows the simulation results. ACM achieves the best accuracy performance of these mechanisms and its positioning accuracy reaches 10⁻⁵ m.
level. FDM and MTM achieve the same accuracy level of 0.2 m. For MFM of different degree, the larger the degree is, the better the accuracy performance can be obtained and MFM(9) can reach $10^{-2}$ m level. Although FDM and MTM achieve the same accuracy level, FDM costs the most time and MTM costs the least time. The time cost by MFM is in the order of $10^{-4}$ s and ACM costs a little longer time of $10^{-3}$ s. The storage cost of ACM is zero because it does not need a database. The storage cost of MFM is dependent on the degree and is not much. The storage cost of MTM and FDM are both relevant to the number of row sample nodes and column sample nodes. However, FDM always costs the most storage, which is $(mn*nn*M*N)$, while the storage costs by MTM is only $(mn+nn)$.

Note that the above discussion is on the condition that the spacing of sample nodes is 0.5 m for FDM, MTM, and MFM. If the spacing of sample nodes decreases the accuracy performance will be better. However, the more the sample spacing decreases, the harder the offline training becomes. The proposed positioning scheme is designed for the 2D scenario. In addition, only 3–5 cm error increase may occur if the difference between the actual height and the assumed height is 20 cm, according to the simulation, which is still acceptable for indoor positioning.

A concise experiment is implemented to prove the feasibility. The layout of the LED lights is $2 \times 2$ and $H - h = 0.55$. The row and column spacing of the LEDs are 0.4 and 0.35 m, respectively. Four LED lights are installed at $(0.10,0.09)$, $(0.10,0.49)$, $(0.45,0.09)$, and $(0.45,0.49)$, respectively. The spacing of sample nodes is 10 cm and the spacing of detection nodes is 5 cm. Each LED light consists of 7 LED chips (LUW JNSH.PC-CPCR-5C8 E-1). A commercially available APD (Hama-mastu C12702-12) is used to detect the optical signal. The effective area of the APD is 7.0 mm$^2$. Figure 6 shows the experimental setup.

Figure 7 and Table 4 show the experiment result, which is nearly in accord with the simulation result. In Fig. 7, the pentacles represent the actual positions and the circles represent the estimated positions.

As seen in Fig. 7 and Table 4, FDM and MTM perform the worst in the aspect of accuracy as the spacing of sample nodes is not small enough. However, the time cost by FDM and MTM are less than the other mechanisms because the experimental positioning area is small, which also makes the storage cost by FDM acceptable. MFM(3) gets a rather accurate positioning result with the MDE of 1.1929 cm, which is better than MFM(1) and MFM(2). The MDE of ACM is 1.4598 cm and the main reason is that ACM is more sensitive to parameter error.

<table>
<thead>
<tr>
<th></th>
<th>MDE (cm)</th>
<th>Time cost (s)</th>
<th>Storage cost</th>
</tr>
</thead>
<tbody>
<tr>
<td>FDM</td>
<td>4.2678</td>
<td>$1.8635 \times 10^{-5}$</td>
<td>$6 \times 6 \times 4$</td>
</tr>
<tr>
<td>MTM</td>
<td>4.2678</td>
<td>$1.1162 \times 10^{-5}$</td>
<td>$6 + 6$</td>
</tr>
<tr>
<td>MFM(1)</td>
<td>2.0060</td>
<td>$4.8981 \times 10^{-5}$</td>
<td>$2 + 2$</td>
</tr>
<tr>
<td>MFM(2)</td>
<td>1.9300</td>
<td>$3.7259 \times 10^{-5}$</td>
<td>$3 + 3$</td>
</tr>
<tr>
<td>MFM(3)</td>
<td>1.1929</td>
<td>$3.9496 \times 10^{-5}$</td>
<td>$4 + 4$</td>
</tr>
<tr>
<td>ACM</td>
<td>1.4598</td>
<td>$1.1 \times 10^{-3}$</td>
<td>0</td>
</tr>
</tbody>
</table>

Fig. 6. (a) Control circuit of LED lights, (b) the full view of the experimental setup, (c) the APD (d) the signal of one LED light (yellow), and the received signal (blue).

Fig. 7. Position results of (a) FDM, (b) MTF, (c) MFM(1), (d) MFM(2), (e) MFM(3), and (f) ACM.
In conclusion, UBSM-based VLP is feasible for dense small cell deployment. Moreover, the three proposed positioning determination mechanisms should be adopted according to the size of the positioning area. ACM is more suitable for large area positioning as it does not require offline training to get the database, whereas MTM and MFM are more suitable for small area positioning as they are more robust for parameter error.

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References