A Novel Geometry Method for LED Mapping

Junlin Huang, Shangsheng Wen and Weipeng Guan

Abstract—With inputs from RGB-D camera, industrial camera and wheel odometer, in this letter, we propose a geometry-based detecting method, by which the 3-D modulated LED map can be acquired with the aid of visual odometry (VO) algorithm from ORB-SLAM2 system when the decoding result of LED-ID is inaccurate. Subsequently, an enhanced cost function is proposed to optimize the mapping result of LEDs. The average 3-D mapping error (8.5cm) is evaluated with a real-world experiment. This work can be viewed as a preliminary work of Visible Light Positioning (VLP) systems, offering a novel way to prevent the labor-intensive manual site surveys of LEDs.

Index Terms—Camera, Geometry-based method, LED mapping, Wheel odometer.

I. INTRODUCTION

VISIBLE light positioning (VLP) systems have attracted a great research interest in recent decades [1]–[4], for its high transmission rate, pinpoint accuracy and no electromagnetic interference [5], [6]. They play a significant role in indoor positioning field. By utilizing light beam from light-emitting diode (LED), which carries unique identity code (LED-ID) and frequency, VLP systems can unscramble information related to LED location for further pose estimation of robot. To achieve this, most VLP systems [8]–[11] require a pre-built map composed of global LED locations and identifiers, for which there are a handful of works aiming to map LED locations. In [12], [13], the authors propose to exploit a mobile robot equipped with a 2-D LiDAR and a rolling-shutter camera for VLP calibration. The robot approaches each LED, takes images of overhead LED and decodes LED-ID. The LiDAR data processed by a Simultaneous Localization and Mapping (SLAM) algorithm give the 2-D LED position with an accuracy of centimeters, whereas the height of LED still need a manual survey. Recently, a LED mapping system, LedMapper, has been proposed [14]. The system is evaluated on a self-assembled handheld mapping device with visual-inertial sensors, including two rolling-shutter cameras and an inertial measurement unit. Extensive experiments verify its efficacy and performance in building 3-D LED map by posing a full-SLAM problem within a factor graph formulation. But the system still requires a few LEDs surveyed manually as control points.

Another difficulty which affects the performance of VLP systems is that the fragile transmission channel due to unpredictable environmental variation and the immanently asynchronous air conveying channel will impede the decoding of LED-ID [15]. Plenty of thresholding methods, e.g., quick adaptive threshold, polynomial threshold and iterative threshold, have been proposed to overcome this dilemmas, whereas fail in adapting different transmission channel [16].

Instead of forcing an absolutely precise and stable decoding of LED-ID, in this letter, we propose a geometry detecting method based on inputs from RGB-D camera, industrial camera and wheel odometer, by which the 3-D modulated LED map can be acquired with the aid of visual odometry (VO) algorithm from ORB-SLAM2 system [17], when the decoding result of LED-ID is inaccurate. The only usage of LED-IDs is classifying different LEDs for building LED map. By solving a least square problem with a proposed enhanced function, the detected position of LED can be optimized and the mapping accuracy (8.5cm error on average) is evaluated by an indoor experiment. As we use modulated LEDs, this work should be viewed as a pre-work for VLP systems.

II. PRINCIPLE

A robot equipped with RGB-D camera (Cam1), industrial camera (Cam2) and wheel odometer will execute the LED mapping task. In the following discussion, we use superscript $\text{obs}$, $\text{pos}$ to denote the parameter belonging to observation and posterior function respectively, and subscript $\cdot_k$ is exploited to denote the parameter belonging to $k_{th}$ observation. We highlight that all the LEDs are modulated and LED-IDs should be different but no correctly decoded LED-ID is necessary.

A data fusion scheme is proposed (Fig. 1(b)). From Cam2 image frame, the Region of Interest (ROI) and $d_{k_{th}}^{\text{obs}}$, which describes 2-D distance between Cam2 lens center and ROI center, can be obtained. Coupled with yaw angle $\theta_k^{\text{obs}}$ from wheel odometer, the observation is defined as

$$\text{Obs}_k = \left( \frac{\sqrt{(u_k^{\text{obs}} - c_x)^2 + (v_k^{\text{obs}} - c_y)^2}}{\arctan(u_k^{\text{obs}} - c_x, v_k^{\text{obs}} - c_y) - \theta_k^{\text{obs}}} \right)$$

(1)

where $(c_x, c_y)$ represents the coordinate of Cam2 lens center projected on pixel plane, which is an intrinsic parameter, and $(u_k^{\text{obs}}, v_k^{\text{obs}})$ is the ROI center coordinate on pixel plane. Fig. 1(a) and Fig. 2(a) illustrate the parameters defined in $\text{Obs}_k$.

Subsequently, a thresholding method is applied to LED position detection. The 2-D coordinate of Cam2 $X_k$ and 2-D coordinate of LED $P_k$ are defined as

$$X_k \doteq (x_k^{\text{cam}}, y_k^{\text{cam}})$$

$$P_k \doteq (x_k, y_k)$$

(2)

This work was supported by the National Undergraduate Innovative and Entrepreneurial Training Program under Grant 202110561162. (Corresponding author: Shangsheng Wen.)

Junlin Huang, Shangsheng Wen and Weipeng Guan are with the School of Materials Science and Engineering, South China University of Technology, Guangzhou 510641, China (e-mail: shshwen@scut.edu.cn).
Because the observed position of Cam1 can be obtained from VO algorithm of ORB-SLAM2 directly, the 2-D pre-estimated position of Cam2 denoted by

$$\hat{X}_k \triangleq (\hat{z}_{k}^{\text{cam}}, \hat{y}_{k}^{\text{cam}})$$ \hspace{1cm} (3)

can be acquired by a fixed coordinate transformation between Cam1 and Cam2 (green fixed transformation in Fig. 1c). Next, the Cam2 position from $k_{th}$ observation $\hat{X}_k = (\hat{z}_{k}^{\text{cam}}, \hat{y}_{k}^{\text{cam}})$ is considered to be an alternative estimated position of LED $P_{k}^{\text{alt}} = (x_{k}^{\text{alt}}, y_{k}^{\text{alt}})$ when $d_{k}^{obs}$ is smaller than an artificial threshold, i.e., $P_{k}^{\text{alt}} = \hat{X}_k$. By applying Pauta criterion\(^1\) to all the previously observed alternative positions of LED, we can acquire the roughly estimated position of LED $\hat{P}_{k} = (\hat{x}_k, \hat{y}_k)$.

Next, a geometry method is proposed in order to acquire a posterior function. Fig. 2(a) describes the parameters used in posterior function. The 2-D distance from LED center to Cam2 lens center is recorded as $D_{k}^{\text{pos}}$ and the vertical angle of $\varphi_{k}^{obs}$ is recorded as $\varphi_{k}^{\text{pos}}$. Next, by similar triangle rule, we introduce a parameter $k_k$ from the elevation relationship between LED and Cam2 in Fig. 2b)

$$k_k \triangleq \frac{d_{k}^{obs}}{D_{k}^{\text{pos}}} \medspace = \frac{\sqrt{(u_{k}^{obs} - c_x)^2 + (v_{k}^{obs} - c_y)^2}}{\sqrt{(x_{k}^{\text{cam}} - x_k)^2 + (y_{k}^{\text{cam}} - y_k)^2}}.$$ \hspace{1cm} (4)

Similarly, by applying the Pauta criterion to all the previously observed $k_k$’s, we can acquire a refined parameter $\hat{k}_k$. Notice that $f$, the focal length of Cam2, is an intrinsic parameter and $H^1$, the height of Cam2, can be measured in advance, we can calculate the height of LED $H_k$ in $k_{th}$ observation with the following equation

$$H_k = H^1 + H^2_k = H^1 + \frac{f}{k_k}.$$ \hspace{1cm} (5)

\(^1\)A well-known data processing principle, also referred to as 3σ principle.

Then, a posterior function $\text{Pos}_{k}(X_k, P_k)$ is designed to rectify the $k_{th}$ observation $\text{Obs}_k$

$$\text{Pos}_{k}(X_k, P_k) = \left(\hat{k}_k * \sqrt{(x_{k}^{\text{cam}} - x_k)^2 + (y_{k}^{\text{cam}} - y_k)^2} \arctan(x_{k}^{\text{cam}} - x_k, y_{k}^{\text{cam}} - y_k)\right)$$
$$= \left(\hat{k}_k * D_{k}^{\text{pos}} \varphi_{k}^{\text{pos}} \right)$$ \hspace{1cm} (6)

where $X_k = (x_{k}^{\text{cam}}, y_{k}^{\text{cam}})$, $P_k = (x_k, y_k)$ are unknown variables.

Then, an enhanced cost function consisting of $\text{Obs}_k$ and $\text{Pos}_{k}(X_k, P_k)$, which will contribute to the optimization of LED position, is proposed. An error function is defined as follows

$$\text{error}(X_k, P_k) \triangleq ||\text{Obs}_k - \text{Pos}_{k}(X_k, P_k)||_2^2$$
$$= 2 \text{errdist}(X_k, P_k)^2 + errang(X_k, P_k)^2$$ \hspace{1cm} (7)

where

$$\text{errdist}(X_k, P_k) \triangleq d_{k}^{obs} - \hat{k}_k * D_{k}^{\text{pos}}$$
$$= 2\sqrt{(u_{k}^{obs} - c_x)^2 + (v_{k}^{obs} - c_y)^2} - \hat{k}_k * 2\sqrt{(x_{k}^{\text{cam}} - x_k)^2 + (y_{k}^{\text{cam}} - y_k)^2}$$ \hspace{1cm} (8)

and

$$\text{errang}(X_k, P_k) \triangleq \varphi_{k}^{obs} - \varphi_{k}^{\text{pos}}$$
$$= (\arctan(u_{k}^{obs} - c_x, v_{k}^{obs} - c_y) - \theta_{k}^{obs})$$
$$- \arctan(x_{k}^{\text{cam}} - x_k, y_{k}^{\text{cam}} - y_k).$$ \hspace{1cm} (9)

We substitute $\hat{X}_k$ for $X_k$ in (7) and propose an enhanced cost function

$$J_1(P_k) = \sum_{l=1}^{k} \frac{1}{2} ||\text{error}(\hat{X}_l, P_k)||_2^2.$$ \hspace{1cm} (10)

By solving the following least squares problem

$$\hat{P}_k \in \arg \min J_1(P_k)$$ \hspace{1cm} (11)

we can acquire the optimized position of LED $\hat{P}_k = (\hat{x}_k, \hat{y}_k)$. Together with $H_k$ in (5), we acquire the 3-D position of LED in $k_{th}$ observation $(\hat{x}_k, \hat{y}_k, H_k)$, which can be used in VLP systems for robot localization.

---

\(1\)A well-known data processing principle, also referred to as 3σ principle.
III. EXPERIMENT AND DISCUSSION

In this module, an indoor experiment is carried out in order to verify the mapping accuracy of our proposed method together with the LED map construction performance.

As shown in Fig. 3, a two-wheeled differential driving mobile robot, Turtlebot2, equipped with a Kinect V1 for Xbox360 RGB-D camera, a MindVision UB-300 industrial camera with prior extrinsic calibration and a laptop Module HASSE CW85S07 with Intel(R) Core(TM) i5-9400 and 8.00 GB RAM is the main instrument to execute LED mapping task. A remote control workstation Module DELL Precision 3561 with 11th Gen Intel(R) Core(TM) i7-11850H and 32 GB RAM sends the operational command to robot with the aid of Secure SHell connection on Ubuntu 16.04 LTS.

Four LEDs of the same specification are used in experiment (Fig. 3(a)). In order to acquire the exact positions of the four LEDs, we measure and mark four static points on the world coordinate system (Fig. 4(a)). We then mark the LED center and install it on anchor (Fig. 4(e)). Next, an infrared emitter is placed on the static point and we let the infrared ray shines on the mark point of LED, which means that the projection point of LED center on the horizontal plane and the static point coincide (Fig. 4(b)). We hang a plumb from the LED so that the end of plumb just touches the ground (Fig. 4(c)). Then we remove the plumb, measure the diameter of the plumb (Fig. 4(d)) and the length of the string, and add the two numbers together to get the height of LED. The above measurements are made with tapeline and vernier caliper. We treat the manual survey result as ground truth. Subsequently, we combine infrared transmitter with industrial camera and shoot it vertically on the ground to form a red dot. There is a fixed coordinate transformation between the infrared emitter and the lens center of the industrial camera (red fixed transformation in Fig. 4(f)). Through this fixed coordinate transformation, the coordinate of the red point can be converted to the coordinate of the lens center of the industrial camera. Therefore, in order to achieve the positioning of LED, we only need to control the robot to move the red point to the static point (Fig. 4(g)). We get the measurement error by subtracting the ground-truth value from the measured value and the error accuracy is 0.1cm because the minimum scale of tapeline is 0.1cm.

In the experiment, we artificially set the departure position of robot to be the origin of world coordinate system so that RGB-D camera position can be acquired by VO algorithm from ORB-SLAM2. Each LED’s position is measured 50 times. As shown in Fig. 5, more than 90% 3-D mapping errors are less than 13.8cm. The confidence interval (90% confidence level) of the 3-D mapping error is [8.1, 8.9]cm, and the average error is 8.5cm. Moreover, the LED map is built and visualized with the aid of Pangolin library. Fig 6 illustrates a snapshot of map construction result.

We compare the performance of the proposed geometry method with the state-of-the-art (SOTA) works in LED mapping field. The average mapping error, correctly decoded LED-ID and receiver type are displayed objectively in Table I. Compared with works in [12], [13], our method can achieve 3-D LED mapping accuracy with 8.5cm average error. It is obvious that there is no need for our method to force a correctly decoded LED-ID, which means that our method is more stable and robust when faces some unpredictable fragile transmission environments. Besides, the odometer price is much lower than that of LiDAR and IMU, which indicates a low-cost deployment in wide adoption.

IV. CONCLUSION

In this letter, we propose a LED map construction method for VLP systems based on geometrical relationship between LED and industrial camera. By utilizing inputs from RGB-D camera, industrial camera and wheel odometer, the location of LED can be detected without a guarantee of precisely decoded LED-ID. In order to optimize the acquired LED position, an enhanced cost function consisting of observation and a posterior function is proposed, turning optimization step into solving a least square problem. Moreover, an indoor experiment is conducted so as to verify the mapping accuracy (8.5cm error) together with LED map construction performance of our method, and the comparison with SOTA works demonstrates its advantages.

REFERENCES

[1] Y. Cai, W. Guan, Y. Wu, C. Xie, Y. Chen and L. Fang, “Indoor High Precision Three-Dimensional Positioning System Based on Visible Light

2A lightweight library belonging to OpenGL for graphics drawing.
Fig. 5. Cumulative distribution function (CDF) curves of 3-D LED mapping error.

TABLE I
PERFORMANCE OF PROPOSED LED MAPPING METHOD

| Method       | Average Mapping Error | Correctly Decoded LED-ID | Receiver Type |
|--------------|-----------------------|--------------------------|---------------|
| Ref. [12], [13] | 6cm (2D) required     | Camera+LiDAR              |               |
| Ref. [14]     | 2.2cm (3D) required   | Camera+IMU                |               |
| Ref. [18]     | ≥ 10cm (3D) required  | PD receiver               |               |
| Our Method    | 8.5cm (3D) not required | Camera+odometer          |               |

* IMU: Inertial Measurement Unit.
* PD: Photodiode.

Recovery in Visible Light Communication,” in IEEE Transactions on Control Systems Technology, vol. 25, no. 1, pp. 247-261, Jan. 2017, doi: 10.1109/TCST.2016.2554062.

[3] P. Lin et al., “Real-time visible light positioning supporting fast moving speed,” Opt. Exp., vol. 28, no. 10, pp. 14503–14510, 2020.

[4] W. Guan et al., “Robot Localization and Navigation Using Visible Light Positioning and SLAM Fusion,” in Journal of Lightwave Technology, vol. 39, no. 22, pp. 7040-7051, 15 Nov, 2021, doi: 10.1109/JLT.2021.3113358.

[5] H. Li et al., “A fast and high-accuracy real-time visible light positioning system based on single LED lamp with a beacon,” IEEE Photon. J., vol. 12, no. 6, pp. 1-12, Dec. 2020.

[6] T.-H. Do and M. Yoo, “An in-depth survey of visible light communication based positioning systems,” Sensors, vol. 16(5), pp. 678-, 12. May 2016.

[7] C. Chang et al., “A 100-Gb/s Multiple-Input Multiple-Output Visible Laser Light Communication System,” in Journal of Lightwave Technology, vol. 32, no. 24, pp. 4723-4729, 15 Dec, 2014, doi: 10.1109/JLT.2014.2365451.

[8] Z. Yan, W. Guan, S. Wen, L. Huang and H. Song, “Multirobot Cooperative Localization Based on Visible Light Positioning and Odometer,” in IEEE Transactions on Instrumentation and Measurement, vol. 70, pp. 1-8, 2021, Art no. 7004808, doi: 10.1109/TIM.2021.3086887.

[9] G. Simon, G. Zachar, and G. Vakulya, “Lookup: Robust and accurate indoor localization using visible light communication,” IEEE Trans. Instrum. Meas., vol. 66, no. 9, pp. 2337–2348, 2017.

[10] Q. Liang, J. Lin, and M. Liu, “Towards robust visible light positioning under LED shortage by visual-inertial fusion,” in Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN), IEEE, pp. 1–8.

[11] Q. Liang, Y. Sun, L. Wang, and M. Liu, “A novel inertial-aided visible light positioning system using modulated LEDs and unmodulated lights as landmarks,” IEEE Trans. Autom. Sci. Eng., pp. 1–19, 2021.

[12] R. Amsters, E. Demeneester, P. Slaets, D. Holm, J. Joly, and N. Stevens, “Towards automated calibration of visible light positioning systems,” in Proc. Int. Conf. Indoor Positioning Indoor Navigat. (IPIN), IEEE, 2019, pp. 1–8.

[13] R. Amsters, E. Demeneester, N. Stevens, and P. Slaets, “Calibration of visible light positioning systems with a mobile robot,” Sensors, vol. 21, no. 7, p. 2394, 2021.

[14] Q. Liang, Y. Sun, C. Liu, M. Liu and L. Wang, “LedMapper: Toward Efficient and Accurate LED Mapping for Visible Light Positioning at Scale,” in IEEE Transactions on Instrumentation and Measurement, vol. 71, pp. 1-12, 2022, Art no. 8500612, doi: 10.1109/TIM.2021.3123293.

[15] Song, H.; Wen, S.; Yang, C.; Yuan, D.; Guan, W. Universal and Effective Decoding Scheme for Visible Light Positioning Based on Optical Camera Communication. Electronics 2021, 10, 1925. https://doi.org/10.3390/electronics10161925

[16] Liu, Y.; Chow, C.-W.; Liang, K.; Chen, H.-Y.; Hsu, C.-W.; Chen, C.-Y.; Chen, S.-H. Comparison of thresholding schemes for visible light communication using mobile-phone image sensor. Opt. Express 2016, 24, 1973.

[17] R. Mur-Artal and J. D. Tardós, “ORB-SLAM2: An Open-Source SLAM System for Monocular, Stereo, and RGB-D Cameras,” in IEEE Transactions on Robotics, vol. 33, no. 5, pp. 1255-1262, Oct. 2017, doi: 10.1109/TRO.2017.2705103.

[18] C. Zhang and X. Zhang, “Pulsar: Towards ubiquitous visible light localization,” in Proc. 23rd Annu. Int. Conf. Mobile Comput. Netw. (MobiCom). ACM, 2017, pp. 208–221.