Knowledge-based Indoor Positioning Based on LiDAR Aided Multiple Sensors System for UGVs

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***Abstract*—in this paper, an environment knowledge-based multiple sensors indoor positioning system is designed and tested. The system integrates a LiDAR sensor, an odometer and a light sensor onto a low-cost robot platform. While, a LiDAR point-cloud-based pattern match algorithm – Iterative Closed Point (ICP) is used to estimate the relative change in heading and displacement of the platform. Based on the knowledge of the construction's structure, outdoor weather, and lighting situation, the light sensor offers an efficient parameter to improve indoor position accuracy with a light intensity fingerprint matching algorithm on low computational cost. The estimated heading and position change from LiDAR are eventually fused by Extended Kalman Filter (EKF) with those calculated from the light sensor measurement. The results prove that the spatial structure and the ambient light information in indoor environment as knowledge base can be utilized to estimate and mitigate the accumulated errors and inherent drifts of ICP algorithm. These improvements lead to longer sustainable sub meter-level indoor positioning for UGVs.**

Keywords—liDAR; indoor position; light sensor; ICP; EKF

I. Introduction

The navigation and positioning systems have become increasingly significant with their development in accuracy, reliability, availability and affordability for automated Unmanned Ground Vehicles (UGVs) in last few decades. Global Navigation Satellite Systems (GNSS) provide such service in outdoor environment, including open sky areas, degraded city canyon, etc. However, indoor navigation remains a challenge for such platform because of the physical nature of the GNSS Radio Frequency (RF) signal which is greatly attenuated when it penetrates construction and the penetrated signal is below the sensitivity threshold of GNSS receivers.

A variety of navigation and positioning sensor have been adopted to improve navigation performance indoors [1]. Combining Wi-Fi[2], high-sensitivity GNSS [3], Bluetooth [4-10], spectrum of ambient light source[11] and/or dead reckoning using a selection of inertial sensors[1,5-6,8,12-14], magnetic compass[1,5,13,15], and barometric altimeter[1, 5-6] becomes more and more popular to enhance indoor position accuracy not only for pedestrian but also for UGV[16]. Other emerging sensors such as Electromyography (EMG) sensors have also been adopted for indoor positioning as well [17-18]. In this paper, a loosely-coupled integrated navigation system which integrates a LiDAR, an odometer and a light sensor on a low-cost robot platform is introduced and tested. A LiDAR point-cloud-based pattern match algorithm – Iterative Closed Point (ICP) is utilized to estimate the relative change in heading and displacement of its robot-borne platform [19-23]. A light sensor is also applied on the mobile platform to collect the ambient environment's light strength along the trajectory, which is used to calculate the absolute position with a light intensity fingerprint matching algorithm. The estimated changes and the absolute position calculated from LiDAR are fused by Extended Kalman Filter (EKF) with those computed from the data that light sensor collects to compensate its accumulated measurement error[24]. The proposed system was setup with iRobot® platform and tested in a typical official indoor environment. According to the test results, the proposed method can accurately estimate the accumulated errors and inherent drifts in ICP. As a result, these improvements lead to longer sustainable submeter-level accuracy for indoor UGV usages, which is a solid technical basis for various applications, such as indoor mapping.

This paper first describes the positioning methodology and algorithm for UGV with environment light and laser scans in section II, Then we introduce the robot based hardware

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platform and experiments in section III. Finally, discussion on the experiment results and conclusion are addressed in section IV and V respectively.

II. METHODOLOGY AND ALGORITHM

An overview of the system architecture is shown in Fig. 1. The environment knowledge discussed in this paper includes the spatial structure of the building and the ambient light. First, the spatial structure feature of the building is utilized by laser scanning (LS) point cloud to calculate the translation(Δx, Δy, $\Delta\emptyset$) of UGV, then the information of light intensity's change, which is a combination of light sources and spatial structure feature of indoor environment, is taken into account to estimate the absolute position and heading (x, y, $\emptyset$) with fingerprint matching method. As we known, LS based methods have a critical problem of the drift, caused by the accumulated errors, while fingerprint matching needs to narrow the matching boundary to avoid falling to local optimum, so we propose a fusion algorithm to combine the LS's ICP and light fingerprint matching method with EKF to reduce the estimate error of the two different datasets. When the result of ICP is inaccurate, the absolute position calculated from light intensity fingerprint matching will compensate it.

Therefore, our environment knowledge-based position system consists of the following three main components:

1. 2D LS's ICP calculating the translation of the position and heading angle;
2. Light intensity fingerprint matching estimating the position;
3. The EKF updating for compensation the weakness of ICP and light intensity fingerprint matching.

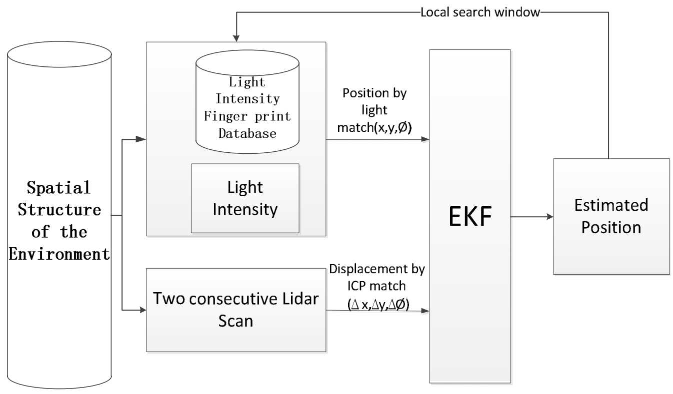

Fig. 1. The system architecture diagram of environment knowledge-based positioning.

A. Estimation of the translation and the heading angle from ICP algorithm

In well-matching condition, 2D LS ICP is a fast and accurate point-point matching method, which utilizes least square method to search the correspondences for all points in two scans [23]. However, it is very sensitive to the environment features. The whole processing chain of ICP can be expressed by following equations mathematically:

$$E = \sum_{i=1}^{N_1}(Rp_i + t - q_i)^2 = Min \quad (1)$$

$$\mathrm{Er} = RMS = \sqrt{\frac{E}{N_1}} \quad (2)$$

where N_1 is the number of points of each scan; *Rot* is the rotation matrix; m is the motion vector, transforming from scan p to its consecutive scan q in the scan q's local coordinate reference, where :

$$\mathrm{Rot} = \begin{bmatrix} \cos(d\theta) & -\sin(d\theta) \\ \sin(d\theta) & \cos(d\theta) \end{bmatrix} \quad (3)$$

$$\mathrm{m} = [\mathrm{dx} \quad \mathrm{dy}]^T \quad (4)$$

The final transformation matrix $T_{(icp)}$ in global map coordinate reference is:

$$T_{(icp)} = [\Delta x,\ \Delta y, \Delta\theta]^T = [\mathrm{Rot}_g m, d\theta]^T \quad (5)$$

where Rot_g is the UGV's rotation matrix in global map coordinate reference. Fig.2 shows the relationship between local and global map coordinate reference discussed in this research.

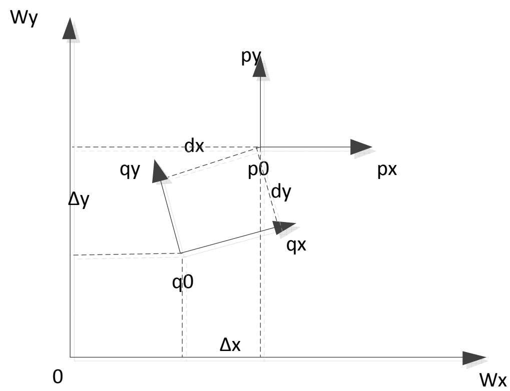

Fig. 2. Coordinate reference relationship

In the following EKF process, ICP provides the observing variable (Δx, Δy, Δ∅) of the displacement and heading change.

B. Position calculated by light intensity fingerprint matching with least MSD algorithm

Because of the inner drawbacks of the LS matching algorithm, in the environment with less features, ICP will calculate the poor results with immense error. Such results will be accumulated to the next positioning. Thus, the accumulated error might ruin the position accuracy very quickly. In this paper, the fingerprint matching to calculate absolute position method based on the light intensity of the environment is proposed to compensate the positioning results from ICP.

As we known, the most important part of fingerprint matching method is building a precise fingerprint database. In this paper, the database is collected semi-automatically with UGV platform running along a corridor for several times. The light sensor installed on robot platform collect light intensity information and onboard clock offers timestamp for synchronization with LiDAR sensor. The odometer measures the travel distance on a pre-setting direction between two consecutive sampling points. The value of light intensity of each cell of the database is a mean of several tests for mitigating the noise of measurement. And the size of cell is approximate 30 centimeters. We apply a ruler along the route that UGV traveles to verify the measurement of onboard odometer.

When the light intensity fingerprint database is ready, we utilize the least mean-squared-deviation algorithm (least MSD) for fingerprint matching to find the optimum position and the main function is as below:

$$E = \sum_{i=1}^{N_2}(FR_i - LR_i)^2 = Min \tag{6}$$

where FR_i is the light intensity value in database at certain position and LR_i is the sampling light intensity value. k is the number of match points, in this research, we select k to be 5, according to total experiment distance.

In EKF process, light intensity fingerprint matching provides the measurements for the 2D coordinate of the position, i.e. $[x, y]^T$.

C. EKF fusion algorithm

The EKF process includes two steps: prediction and update[25]. The additive disturbances of the motion model and the observation model are both assumed to be Gaussian.

In this work, the motion model and the measurement equation are expressed as:

$$\begin{bmatrix} x_k \\ y_k \\ \emptyset_k \end{bmatrix} = \begin{bmatrix} x_{k-1} + \Delta t s_k \cos(\emptyset_{k-1} + \alpha_k) \\ y_{k-1} + \Delta t s_k \sin(\emptyset_{k-1} + \alpha_k) \\ \emptyset_{k-1} + \alpha_k \end{bmatrix} + W_k \tag{7}$$

$$\begin{bmatrix} x_k \\ y_k \\ \Delta x_k \\ \Delta y_k \end{bmatrix} = \begin{bmatrix} x_k \\ y_k \\ \Delta t s_k \cos(\emptyset_{k-1} + \alpha_k) \\ \Delta t s_k \sin(\emptyset_{k-1} + \alpha_k) \end{bmatrix} + V_k \tag{8}$$

where x_k, y_k denotes the 2D position and $\emptyset_k$ is the heading angle. The moving speed s_k and the steering α_k are the control input of the motion model. Δt is the time difference between two consecutive time epoch, i.e. $\Delta t = t_k - t_{k-1}$. W_k is assumed as the additive Gaussian motion disturbances with the zero mean and covariance Q_k and V_k is the additive Gaussian motion disturbances with the zero mean and covariance R_k, i.e. $W_k \sim N(0, Q_k), V_k \sim N(0, R_k)$.

Define the state vector $X_k = [x, y, \emptyset]_k^T$, the control input vector $U_k = [s, \alpha]_k^T$ and measurement vector $Z_k = [x, y, \Delta x, \Delta y]_k^T$. Therefore, the vector form of (7) and (8) are

$$X_k = f(X_{k-1}, U_k) + W_k \tag{9}$$

$$Z = h(X_k) + V_k \tag{10}$$

where $f(\cdot)$ models the UGV's kinematics and $h(\cdot)$ describes the relation between state vector and measurements.

According to (9) and (10), the mean and covariance of the predicted state vector are

$$X_{k|k-1} = f_k\, X_{k-1/k-1} \tag{11}$$

$$P_{k|k-1} = \nabla f\, P_{k-1|k-1}\, \nabla f^T + Q_k \tag{12}$$

and the Kalman gain is

$$G_k = P_{k|k-1} \nabla {h_k}^T S_k^{-1}$$

$$= P_{k|k-1} \nabla {h_k}^T (\nabla h\, P_{k|k-1}\, \nabla {h_k}^T + R_k)^{-1} \tag{13}$$

where $\nabla f_k = \frac{\partial f}{\partial X}|_{X=X_{k|k-1}}$ and $\nabla h_k = \frac{\partial h}{\partial X}|_{X=X_{k|k-1}}$ are the Jacobian matrix derived from $f(\cdot)$ and $h(\cdot)$.

By applying the EKF, the state vector is updated as

$$X_k = X_{k|k-1} + G_k(Z_k - \nabla h_k X_{k|k-1}) \tag{14}$$

III. SYSTEM OVERVIEW AND EXPERIMENT

The system is based on a low-end home cleaning robot – iRobot® platform[26], an IBEO LUX laser scanner, which provides a 110° Field-of-View (FOV) with 0.25 degree angular resolution and 25 Hz scan frequency, up to 90 meters maximum range measurement indoors, and a light sensor based on light-dependent resistor (LDR). As is shown in Fig.3, this system is used to collect original data along a corridor in 2nd floor at the main building of Finnish Geodetic Institute (FGI) (see Fig.4). During the tests, the system was running at a speed of 25 centimeters per second along the corridor. The LiDAR, the light sensor, the data logging computer (Fit-PC-2) and the battery were rigidly installed on the robot platform. The light intensity information was collected at 1 sample per second. All the data were post processed in Matlab.

The light intensity is an output of onboard 10-bits Analogy to Digital Converter (ADC) of iRobot platform. We design a simple current to voltage circuit based on a LDR and a 10 Kohms resistor, which is plugged on iRobot' ADC via cargo bay connector which is a 25-pin of D-type socket[26]. From Fig.5, it is obvious that the light intensity measurements are not saturated whatever we turn on corridor light or not during the test. Since the output of light sensor is not calibrated with any standard light sources, the raw ADC output adopted in this research is for investigation purpose rather than measuring the absolute value of light intensity.

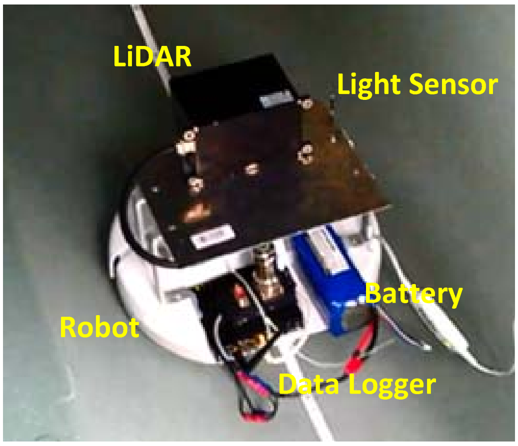

Fig. 3. Experiment Platform

To investigate the potential of the purposed method, in totally 15 tests, we turned off the corridor light in 7 of them to study whether different type of light source effect on position accuracy or not. The total length of corridor is about 40 meters, and the travel distance for each text is 38 meters.

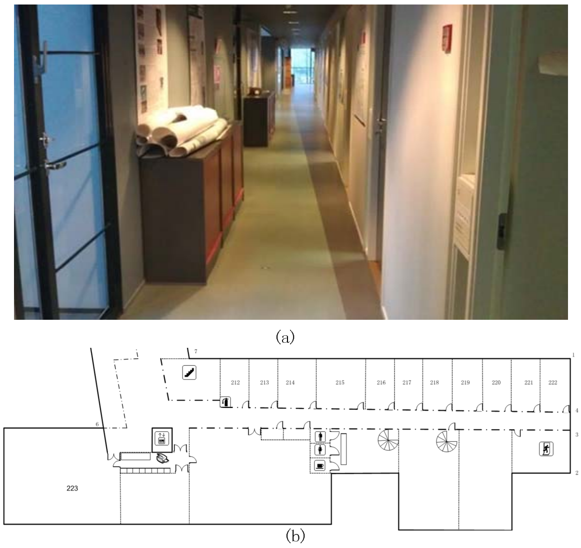

Fig. 4. (a) Photo image of the experiment corridor (b)Overview map of the experiment corridor

IV. EXPERIMENTAL RESULT

As is shown in Fig.1, before applying light intensity fingerprint matching, we have to create the fingerprint database. Fig.5 shows the result of the light intensity fingerprint feature with and without light along the corridor. In our experiment environment, the ambient light is composed of two parts: nature light and man-made light. The red line depicts the situation when we turned off the light and we can see the three peaks, representing the locations with windows that let the nature light in. The blue line illustrates the situation when we turned on the lights on the ceiling of the corridor. We could the see the little peaks equally distributed along the corridor, representing the light's position.

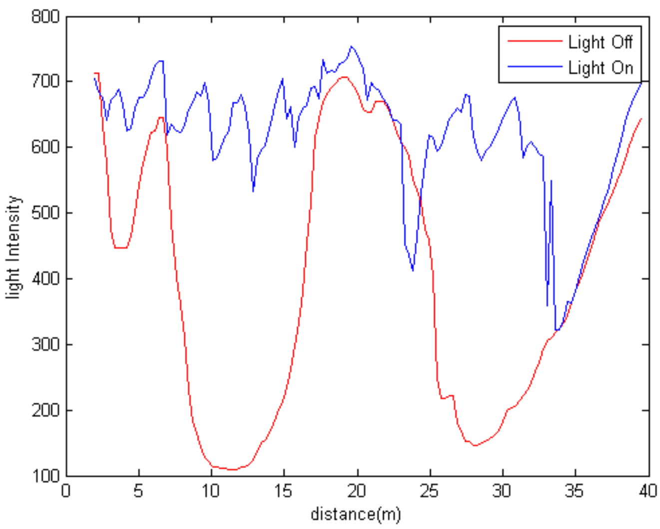

Fig. 5. Light Fingerprint Database

Fig.6 shows the spatial structure of environment acquired by lidar sensor. The light blue lines outlining the structure of the FGI building, which is extracted from the construction blueprint proportionally, coincides with the white dots which are processed point clouds collected by the IBEO LUX sensor. The experiment trajectory is presented in Fig.6 in green line from pose A to pose B, and the liDAR sensor only provides a 110^{o} field-of-view. Features can only be detected ahead of the platform. Furthermore, the robot platform is trembling in some rough ground, which makes a lot of noise points in the laser scans beyond about 20 meters. Thereby, the scan points that are utilized for the pattern matching are limited within 15 meters in the experiment. ICP algorithm is heavily dependent on features of environment, and it implies the position accuracy in the location which yellow rectangle marked in Fig.6 will be bad, where is lacking of features in each laser scan within 15 meters range in 110 degrees FOV ahead. As the trajectories are shown in Fig.7, The length of trajectory of ICP standalone solution is about 8 m shorter than the reference trajectory. And it is obviously that the RMS error deteriorated after 15 meters (marked as Point C in Fig.6) away from start point A, as is shown in Fig.8. It is just the place after UGV passed the area of yellow rectangle marked in Fig.6.

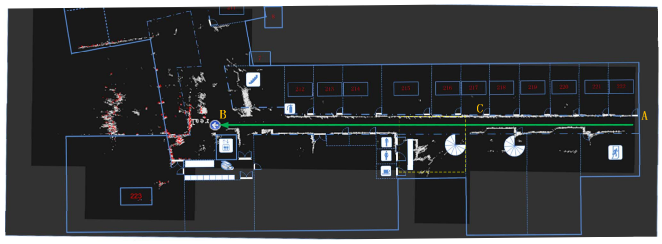

Fig. 6. Spatial knowlidge sensored by lidar

On the contrary, it is more accurate, when ambient light information is utilized (red and green line). Especially in the center open area with windows where yellow rectangle marked in Fig 6. , the light intensity fingerprint matching compensate error which introduced by ICP mis-matching in less features area. The statistical results is list in Tab.1, the RMS errors of ICP are 1.07 meters and 1.21 meters, with precision promotion by 75% and 72% respectively, on the condition turning off and turning on the lights.

The results in Fig. 8, Tab. I and Tab. II prove that light intensity information can be applied for positioning with fingerprint matching method to greatly improve the positioning accuracy for various indoor applications, Such information acts like the Wi-Fi or Bluetooth fingerprint as another kind of Signals of Opportunity (SOP), no matter whether it is natural light or manmade light. This preliminary feasibility research proves that the most critical premise for utilizing such SOP is to setup the precise light intensity fingerprint databases under different light condition.

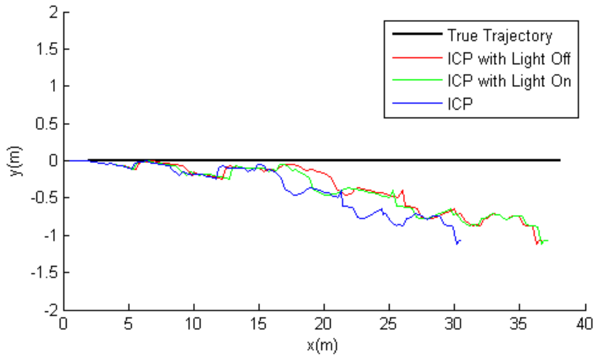

Fig. 7. Trajectory Result

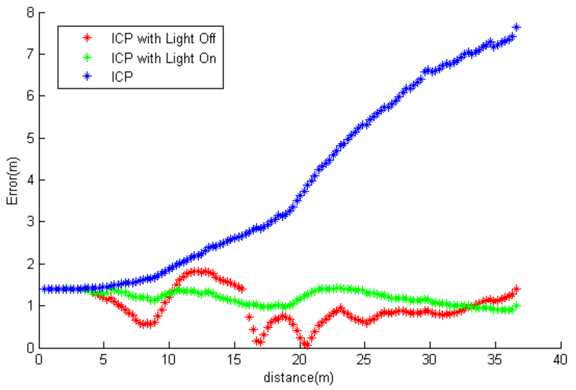

Fig. 8. The Position Error

TABLE I. THE POSITION ERROR STATISTICS

	RMS ERROR	*MEAN ERROR*	*MAXIMUM ERROR*
ICP with Light Off	1.07	0.89	1.82
ICP with Light On	1.21	1.19	1.43
ICP	4.41	3.86	7.63

(unit:m)

TABLE II. THE POSITION ACCURACY PROMOTION TO ICP

	RMS ERROR	*MEAN ERROR*	*MAXIMUM ERROR*
ICP with Light Off	75%	77%	76%
ICP with Light On	72%	69%	81%

V. DISCUSSION AND CONCLUSION

This paper described a knowledge-based indoor positioning based on LiDAR aided multiple sensors system. We utilize the spatial structure and the ambient light information in indoor environment as the knowledge base for positioning with LiDAR, Odometer and light sensor on the low-cost robot platform. The field test results prove that,

i) the proposed method is about 4 times more accurate than ICP standalone method in a feature rich environment, because the light intensity fingerprint matching can compensation the extra error introduced by ICP on less feature environment;

ii) combining the ambient light information with traditional ICP matching algorithm, the robot platform maintains longer sustainable submeter-level positioning accuracy in feature rich indoor environment.

Our result of experiments shows that the intensity of natural ambient light is significantly related to spatial structure of the building; the intensity of manmade light shows a distinct sine-like pattern with respect to its geographical locations, on the other word, if the corridor light positions are known, we can count the number of light intensity peak to calculate even more precise position. These lights, as one of important SOP, like Wi-Fi or Bluetooth, can be used to solve the absolute or relative positioning problem for ubiquitous navigation.

Ambient light intensity is the only parameter we consider as environment knowledge in this research. The idea we adopted in this paper can be easily extended to other physical characteristics of ambient light such as spectrum information [1], which needs minor modification on current setups. Other SOP like magnetic field [15] can also be integrated into this research to enhance positioning accuracy.

Last but not least, the sample rate of light intensity measurement is 1 Hz with cost less than one euro, comparing with 11000 Hz sample rate of laser scanner which cost several tens of thousands euros, which implies the former algorithm is more suitable for real-time applications in term of cost, availability, computational complexity.

ACKNOWLEDGMENT

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