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Visible Light Communication-based Indoor Localization using Gaussian Process

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***Abstract*—For mobile robots and position-based services, such as healthcare service, precise localization is the most fundamental capability while low-cost localization solutions are with increasing need and potentially have a wide market. A low-cost localization solution based on a novel Visible Light Communication (VLC) system for indoor environments is proposed in this paper. A number of modulated LED lights are used as beacons to aid indoor localization additional to illumination. A Gaussian Process(GP) is used to model the intensity distributions of the light sources. A Bayesian localization framework is constructed using the results of the GP, leading to precise localization. Path-planning is hereby feasible by only using the GP variance field, rather than using a metric map. Dijkstra's algorithm-based path-planner is adopted to cope with the practical situations. We demonstrate our localization system by real-time experiments performed on a tablet PC in an indoor environment.**

I. Introduction

A. Motivation

Precise localization is the fundamental capacity of many robotic applications and healthcare services, because it is not only the basis for navigation, also it can be an important information source for further big data applications. It is also one of the most essential data shared in a cloud robotic system [1]. The indoor localization problem is especially challenging, where localization cannot be achieved by GPS due to the satellite signal being greatly attenuated. Although many methods are available such as WiFi-based [2] and visual indoor topological localization [3], they require dense coverage of WiFi access points or expensive sensors like high-performance cameras to guarantee the localization accuracy.

We propose to achieve robust and precise localization by using modulated visible light as stable global references. The possibility of achieving accurate localization using a single photonic sensor has been discussed in our previous work earlier last year [4]. We introduced a Gaussian Process-based sensor modeling technique and supplied a low-cost solution for personal localization services, considering a photonic sensor is common on most consumer electronic devices. As a key to realize global localization, the details of asynchronous decomposition of the light signal has been discussed in another previous work late last year [5]. Given the sensor modeling framework and light signal decomposition results, the intensity distributions of the signal components could be modeled for further probabilistic localization. Thus, by fusing these two existing work, the complete implementation of the localization system using VLC will be discussed in this paper.

The overall structure of the proposed approach is shown in Fig. 1. The mixed modulated light signal is captured by a photonic sensor, which is decomposed using an ad-hoc blind signal decomposition algorithm. The signal intensity of each light source is further used for both environment modeling process and Bayesian filter-based localization. The environment model is represented by the mean fields and variance fields of the observed components. Note that path-planning could be thus realized based on the variance fields.

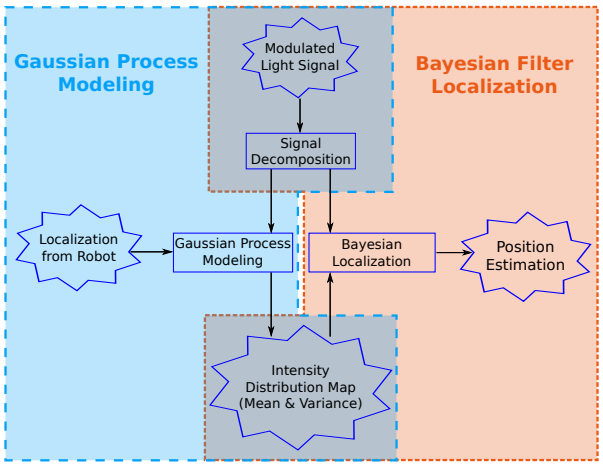

Fig. 1. The overall structure of the proposed solution for indoor localization

B. Contribution

- We realize a data-driven environment modeling scheme based on Gaussian Process Regression using the scalar

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output from a photonic sensor, such that no prior knowledge is required on the light distribution and indoor circumstance arrangement.

- We design a low-cost and precise indoor localization system with the support of a Bayesian framework by only using the modulated LEDs based on the GP results. We do realize the actual implementation and show the demo in a laboratory while many state-of-the-art VLC-based solutions only consider the simulation.

C. Organization

Section II of this paper introduces different localization solutions in the robotic areas. In section III, we briefly introduce the key LED tubes we use for localization reference and a typical working environment for the localization system. Section IV shows the scheme and implementation of the VLC-based indoor localization algorithm. Section V gives out the validation and experiment results, the implementation of path-planning is also introduced. Finally, we make a conclusion of our work and envision future work.

II. Related Work

Robotic localization is a well-discussed problem. Localization using 3G networks [6] is a practical solution based on existing infrastructures, but it requires large-scale coverage of the expensive base stations. Localization via ultra-wideband(UWB) radios is another practical localization solution based on sensor network [7], the bandwidth used in this kind of system is more than 500 MHz. The dedicated hardware has to be well designed and distributed even though it allows centimeter accuracy in ranging. Efficient visual localization methods using omnidirectional cameras were introduced in our previous works [8], [9], [10], [11].

VLC is a type of wireless communication technique, which makes use of visible light as the transmission medium of information. A key advantage of VLC is that it can be simultaneously used for illumination and communication. XW Ng et al. proposed a medical healthcare information system based on VLC, mainly considering the disturbance of electromagnetic waves to medical instruments [12]. Also, VLC could be used as a communication channel for autonomous control and remote manipulation [13], [14].

VLC-based positioning systems have also been discussed in literature [15]. However, most of these systems require several types of sensors to work together, such as the high-accuracy positioning system based on VLC proposed by M. Yoshino *et al.* [16], [17]. Kim *et al.* tried to overcome this disadvantage by using an intensity modulation/direct detection and radio frequency carrier allocation method [18], but the transmission channel consumption is relatively high in this case. Zhou Zhou *et al.* achieved $0.5mm$ simulation localization accuracy [19] by studying the ideal Lambertian transmission models of the LED sources. The mentioned accuracy is also calculated inside an ideal simulation situation without considering the complex light reflection in the real world. All of these methods require geometrical computation, rather than sensor data-driven modeling which has been proved to be sufficient for precise localization in our previous work [4]. We further realize a practical localization implementation in the real world based on the previous work in this paper, filling the gap between the ideal model and reality.

III. Hardware and System Setup

A typical setup is described as follows: in an indoor environment, several modulated LED tubes are distributed arbitrarily. Each LED has a unique modulation waveform, which is carefully selected to ensure high auto-correlation and low cross-correlation responses between every two tubes. Our demo VLC system is based on the previously proposed LED tube as shown in Fig. 2 [4]. According to the latest standard, the LED driver is already contained in the LED tube, so the micro-controller is the only additional cost to a common tube. Since the base working frequency used in our system is as low as 1 kHz, the most basic micro-controller could meet the need, which ensures the low modification cost to the regular illumination LED tubes.

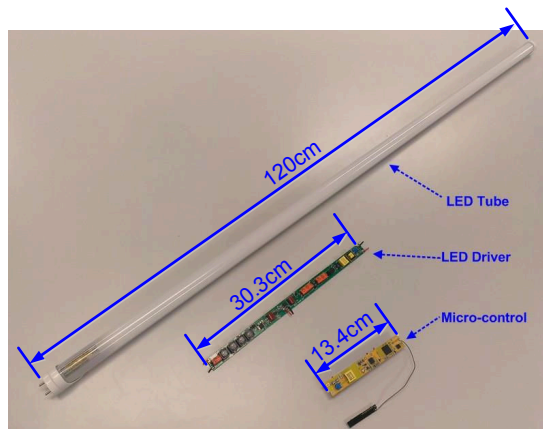


Fig. 2. VLC light sources used in this paper

It emits white visible light using LEDs at a high frequency. A typical test environment using 12 modulated LEDs is shown in Fig. 3, which replaces the original illumination condition.

In real situations, a device connected with a photonic sensor will be used inside this environment, which receives all the lights from different LED beacons at the same time. A large amount of noise will be introduced due to asynchronism and the existence of environment light. These noises will affect the accuracy of decomposition results or even make the decomposition results totally wrong. Thus in order to get relatively precise intensity of each beacon code, the extracted intensity will be corrected by minimizing the error between decomposed signals and original signals [5].

IV. Localization

A. Model Construction

Firstly we need to model the luminous distribution of a certain room so that the specific location of each LED

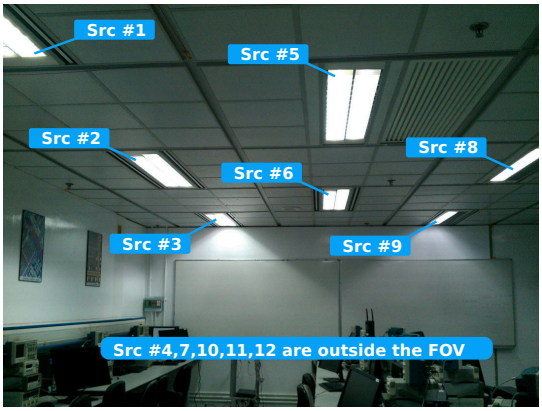


Fig. 3. A typical setup for the light sources of the VLC system

beacon is no longer needed once the indoor environment is determined, in other words, the localization works in a data-driven mode. Therefore, a data collection process is a prerequisite, which should be carefully arranged and cover all the possible operating area since the accurate localization and path-planning are only possible where the sensor has been in the data collection phase.

There are two ways to model the mapping from decomposed light intensity vector to location using Gaussian Process Regression:

- The first one is similar to the existing WifiSLAM [20], where a direct mapping from signal to location is modeled. For example, if twelve light sources are presented, a mapping function from light component intensity $\boldsymbol{s} = \{s_1 \dots s_{12}\}$ to 2-D location $\boldsymbol{x}(x, y)$

$$\hat{\boldsymbol{x}} = g(\boldsymbol{s}) : \mathbb{R}^{12} \rightarrow \mathbb{R}^2 \tag{1}$$

  needs to be estimated.
- The second way is to solve the dual problem, where the inverse mapping

$$\hat{\boldsymbol{s}} = g(\boldsymbol{x}) : \mathbb{R}^2 \rightarrow \mathbb{R}^{12} \tag{2}$$

  is estimated. After that the Bayesian rule is adopted to calculate a posterior for localization.

In both cases, the independent variables of the GP are, however, unknown. A mobile robot with SLAM capability is adopted to provide this latent information with Gaussian noise. We can see that despite that the second way has higher computational complexity, it has higher robustness because the training of the model is much more lightweight and easier to converge, considering the low dimensionality. Besides this, the likelihood $P(g(\boldsymbol{x}) \mid \boldsymbol{x})$ is usually a product of independent observations as discussed later in the next subsection. Therefore, even with partially sheltered light signal, it will not greatly affect the location of the likelihood maximal.

As for the Gaussian Process model, we follow the function-space definition described by Rasmussen [21]. Let $D = (\mathrm{x}_1, y_1), (\mathrm{x}_2, y_2), ..., (\mathrm{x}_n, y_n)$ be a set of training samples drawn from a noisy process

$$y_i = f(\mathrm{x}_i) + \varepsilon \tag{3}$$

where each x_i is an input sample in $\mathbb{R}^d$ and each y_i is an observation result in $\mathbb{R}$. ε is zero mean, additive Gaussian noise with known variance σ_n^2. In practice, x_i denotes the 2D position and y_i denotes a component of the received signal. For notational convenience, we aggregate the n input vectors x_i into a $d \times n$ matrix X, and the target values y_i into the vector denoted y. A Gaussian Process estimates posterior distributions over functions f from training data D. These distributions are represented non-parametrically by using training samples. The key idea underlying GPs is the requirement that the function values at different positions are correlated, where the covariance between two function values, $f(\mathrm{x}_p)$ and $f(\mathrm{x}_q)$ are dependent on the input values x_p,x_q. This dependency can be specified via an arbitrary covariance function, or so-called kernel $k(\mathrm{x}_p, \mathrm{x}_q)$. The choice of the kernel function is typically left to the user, the most widely used being the squared exponential, or Gaussian kernel:

$$k(\mathrm{x}_p, \mathrm{x}_q) = \sigma_f^2 \exp(-\frac{1}{2l^2})|\mathrm{x}_p - \mathrm{x}_q|^2 \tag{4}$$

where σ_f^2 is the signal variance and l is the length scale that determines how strongly the correlation between points maintains. Both parameters control the smoothness of the functions estimated by a GP. The variance between function values decreases with the distance between their corresponding input vales.

Since we do not have direct access to the function values but only noisy observations, it is necessary to represent the corresponding covariance function for noisy observations:

$$\mathrm{cov}(y_p, y_q) = k(\mathrm{x}_p, \mathrm{x}_q) + \sigma_n^2 \delta_{pq} \tag{5}$$

where σ_n^2 is the Gaussian observation noise and δ_{pq} is one if $p = q$ and zero otherwise. For an entire set for input values X, the covariance over the corresponding observation y becomes

$$\mathrm{cov}(\mathrm{y}) = K + \sigma_n^2 I \tag{6}$$

where K is the $n * n$ covariance matrix of the input values, that is, $K[p, q] = k(x_p, x_q)$.

Note that for any set of values X, one can generate the matrix K and then sample a set of corresponding targets y that have the desired covariance. The sampled values are jointly Gaussian with $\mathrm{y} \sim N(0, K + \sigma_n^2 I)$. Additionally, it is the posterior distribution over functions given training data X, y. From Eq. 4 it follows that the posterior over function values is Gaussianly distributed:

$$p(f(\mathrm{x}_*)|\mathrm{x}_*, X, y) = N(f(\mathrm{x}_*); \mu_{\mathrm{x}_*}, \sigma_{\mathrm{x}_*}^2) \tag{7}$$

where

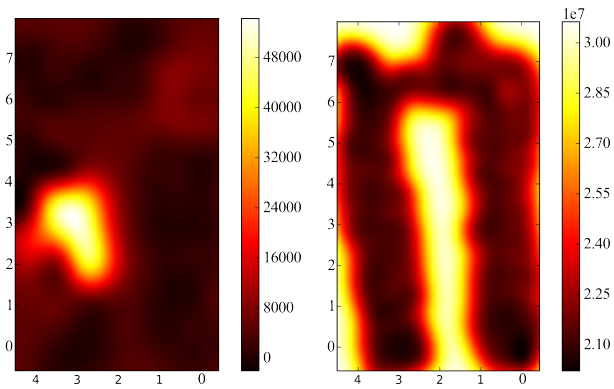
$$\begin{aligned} \mu_{\mathrm{x}_*} &= k_*^T (K + \sigma_n^2 I)^{-1} y \\ \sigma_{\mathrm{x}_*}^2 &= k(\mathrm{x}_*, \mathrm{x}_*) - k_*^T (K + \sigma_n^2 I)^{-1} k_* \end{aligned} \tag{8}$$

Here k_* is an n-dimensional column vector, describing the covariances between x_* and the n training inputs X, and K is

the covariance matrix of the inputs X. After that the Bayesian rule is adopted the optimal localization can be represented as that:

$$\hat{\mathrm{x}} = \arg\max_{\mathrm{x}_*} p(f(\mathrm{x}_*) \mid \mathrm{x}_*) \tag{9}$$

At the end of the modeling step, we get several intensity distribution maps including the mean maps and the corresponding variance maps, regarding each LED light source. A pair of example results is shown in Fig. 4. The regression mean represents the expected light signal observation; the variance field represents the observation likelihood. The "shape" of the variance field roughly represents the traversable areas, since the observations over these areas are with higher confidence and thus low variance values.



(a) The mean field of light 6 (b) The variance field of light 6

Fig. 4. A typical example of the Gaussian Process results

B. Bayesian Localization

An intuitive graph model of Bayesian dynamic filtering is shown in figure 5, where the standard plate representation is adopted to show the relation among random variables in time series. The goal of localization is to estimate the

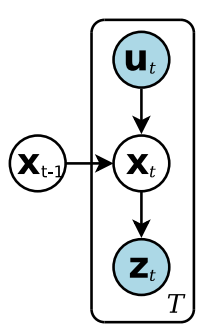


Fig. 5. Bayesian filtering graph model

current position $\boldsymbol{x_t}$ by knowing history estimations $\boldsymbol{x}_{0:t-1}$ and observations $\boldsymbol{y}_{0:t-1}$ [22], namely:

$$\begin{aligned} &P(\boldsymbol{x}_t|\boldsymbol{y}_{0:t}, \boldsymbol{u}_{0:t}) \\ \propto &P(\boldsymbol{y}_t|\boldsymbol{x}_t) \times \sum_{\boldsymbol{x}_{t-1}} P(\boldsymbol{x}_t|\boldsymbol{x}_{t-1}, \boldsymbol{u}_{t-1}) P(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{0:t-1}, \boldsymbol{u}_{0:t-1}) \end{aligned} \tag{10}$$

where

- $P(\boldsymbol{y}_t|\boldsymbol{x}_t)$: the observation model learnt by GP;
- $P(\boldsymbol{x}_t|\boldsymbol{x}_{t-1}, \boldsymbol{u}_{t-1})$: motion model. In this case, a zero-mean Gaussian is used, since no motion estimation is introduced, i.e. $\mathcal{N}(0, \sigma^2)$, where σ is a tunable parameter. Here we empirically choose $\sigma = 0.033m$, considering the average maximal walking speed of a human is $1.0m/s$ and the algorithm refreshing rate is $30Hz$. We can actually adjust this parameter according to the real working speed.
- $P(\boldsymbol{x}_{t-1}|\boldsymbol{y}_{0:t-1}, \boldsymbol{u}_{0:t-1})$: previous position estimate.

The localization prior is initialized by a uniform distribution. The product of the individually observed light components represents the observation model, because the observation of light sources is theoretically independent, namely:

$$p(\boldsymbol{y}_t|\boldsymbol{x}_t) = \prod_{s=1}^{S} p(\boldsymbol{y}_{s_t}|\boldsymbol{x}_t) \tag{11}$$

where s represents the index of the observed light sources.

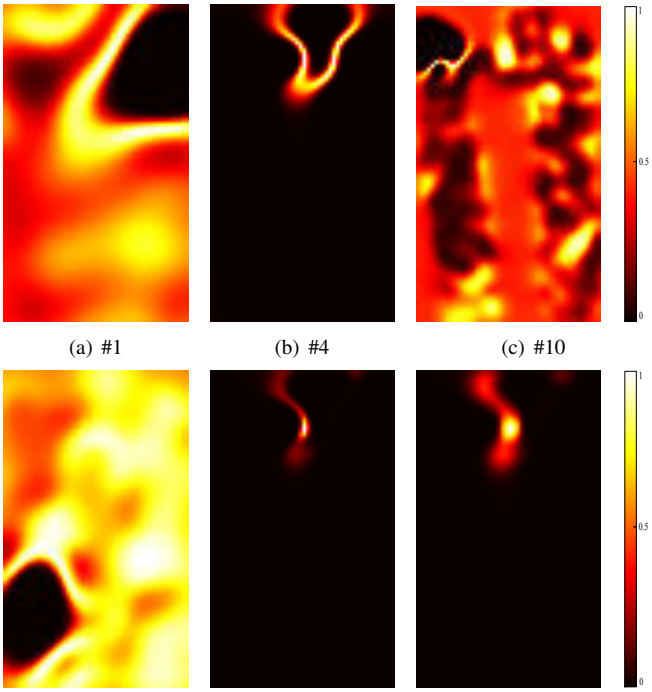
V. Experimental Results

We conducted experiments in a $4.7\ m \times 8.6\ m$ indoor environment with 12 modulated LED lights. Note that neither larger size of the environment nor larger number of the light sources will deteriorate the localization accuracy thanks to the global localization nature. All the functions are realized on a Tablet connected with a photonic sensor. The details of experimental data collection is introduced in another work [23].

Given an observed intensity vector in the real localization phase, the likelihood distribution with respect to each related beacon can be calculated based on the aforementioned mean fields and variance fields. The overall likelihood distribution is computed by Eq. 11. We can then localize the sensor by applying a Bayesian dynamic model, which includes a motion model as prior to the precise localization. For example, with an input intensity vector $(9183, 0, 0, 30298, 0, 0, 0, 0, 0, 7681, 0, 6966)$ where the #1, #4, #10, #12 lights are useful for the localization, the four likelihood distributions are shown in Fig. 6(a)(b)(c) and (d), respectively, while the overall likelihood distribution and the motion update result are shown in (e) and (f), respectively. The mentioned two kinds of localization results are calculated by maximizing the probability distributions of (e) and (f) respectively. The observation update and the motion update are iteratively computed once a new observation is received.

A. Localization precision

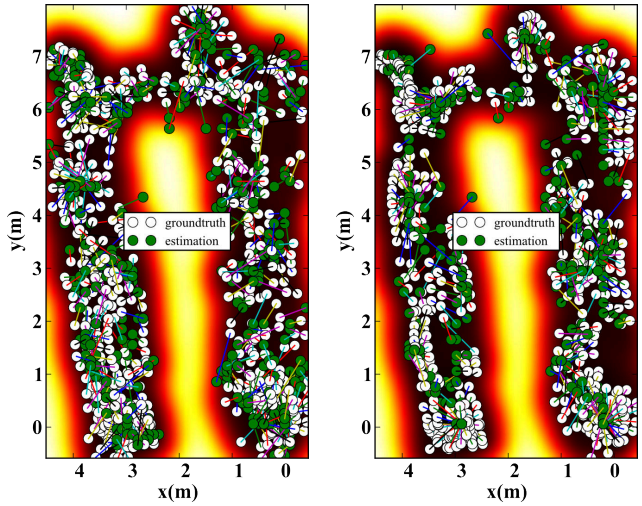
Fig. 7 shows the 2D localization results between the ground truth and the estimation results without and with a Bayesian model, each location with ground-truth is marked with white (empty) circles, while the estimated locations using the received light signal are marked with green (filled) circles. The correspondences are represented by line-segment linkages. It is clear that the posterior results are somehow better than



(a) #1 (b) #4 (c) #10

(d) #12 (e) perception update (f) motion update

Fig. 6. Normalized probability distributions of the four independent likelihoods, the overall likelihood (perception update) and the posterior (motion update)

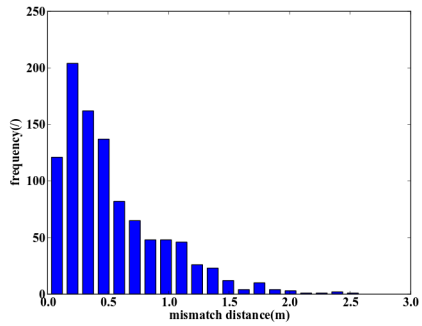


(a) Localization results using maximum likelihood (b) Localization results using maximum posterior

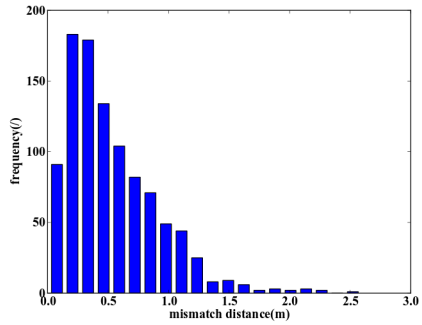
Fig. 7. Comparison of the localization results (green, filled circles) and ground-truths (white, empty circles)

the direct output using maximum likelihood. The "clustered" appearance of the posterior distribution is due to the static motion model.

Fig. 8 shows the corresponding mismatch distances. Obviously the Bayesian filter significantly decreases the large mismatch distances and leads to higher precision especially when sudden sensor orientation change happens, but the accuracy improvement is slight to the testing points with small



(a) Localization result using maximum likelihood



(b) Localization result using maximum a posterior

Fig. 8. Histogram of the mismatch distances

mismatch distances, which points out that much of the localization accuracy is due to the signal observation. And the large mismatch values, especially those bigger than $1\ m$, are most likely from the orientation change of the working photonic sensor. Finally our localization system can achieve localization accuracy at $0.56\ m$ on average with variance $0.23\ m^2$, which is good enough for common personal localization services and commercial applications such as healthcare service.

B. Discussion

We need to keep in mind that this localization precision is achieved from a photonic LED sensor with a cost less than 1 USD, with only scalar output. The modification cost to the light source is also minimal, since any MCU would be applicable for the operation rate in the test. Besides this, for typical indoor location-based services, the precision of the proposed system is sufficient, such as for delivery services or shop-customer localization. Furthermore, the hardware is already compatible for nowadays personal electronic devices; the software is fully supported at standard Android or iOS platforms. Therefore, we believe with further development of the localization algorithm, the proposed scheme can be potentially widely used in the future.

C. Path-planning

The famous A* algorithm is then applied besides the localization module to realize real-time path-planning and re-

planning. The specific path-planning algorithm could be replaced by other advanced searching algorithms such as A*[24], D*[25], etc. To construct the cost-map used in the graph-based searching algorithms, the map made by SLAM robot is naturally the first choice. It means we can use the metric map created during the data-gathering phase to guide the path-planning. However, in several situations, the map calculated by the laser scanner has a noisy boundary. More importantly it is coupled with dynamic objects in the mapping process. This means a pre-denoising step is needed. Comparatively, the variance field computed by the Gaussian Process is a better choice since it naturally provides references regarding the trust to the original data. The details of this part are introduced in our another work [26].

VI. Conclusion

In this paper, we proposed a low-cost solution for indoor localization using a VLC-based system. We integrated signal decomposition, Gaussian Process regression, Bayesian model to solve the localization problem. The results showed the accuracy and practicality of our system, which tends to be a better solution for indoor localization with minor cost, for both robotic applications and positioning of human users. In the future, we want to further improve the accuracy and robustness of the system in terms of the pattern selection method of the modulated LEDs, and the training method of the Gaussian Process. Also, we'd like to validate our localization system in a large-scale indoor environment and do more research on the situation with salient sensor orientation change.

Video Supplement

The attached video shows the dynamic localization and real-time path-planning results. Note that we mimic an environment of a big shopping mall and demonstrate our indoor localization and path-planning system. Different regions in the map are decorated with commercial brands to vividly demonstrate the idea for indoor positioning-based services. The user is moving in the test environment with a hand-held tablet. The screenshots for the localization and path-planning results and two real views are simultaneously presented. The real-time demo shows the localization accuracy is still acceptable even thought the operating height and orientation are not stable(hand-held case).

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