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A REVIEW OF SENSOR TECHNOLOGY AND SENSOR FUSION METHODS FOR MAP-BASED LOCALIZATION OF SERVICE ROBOT

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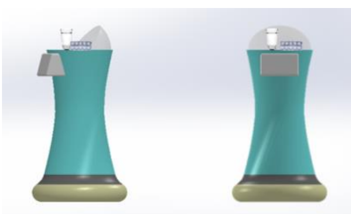
Graphical abstract



Abstract

Service robot is currently gaining traction, particularly in hospitality, geriatric care and healthcare industries. The navigation of service robots requires high adaptability, flexibility and reliability. Hence, map-based navigation is suitable for service robot because of the ease in updating changes in environment and the flexibility in determining a new optimal path. For map-based navigation to be robust, an accurate and precise localization method is necessary. Localization problem can be defined as recognizing the robot's own position in a given environment and is a crucial step in any navigational process. Major difficulties of localization include dynamic changes of the real world, uncertainties and limited sensor information. This paper presents a comparative review of sensor technology and sensor fusion methods suitable for map-based localization, focusing on service robot applications.

Keywords: Review, sensor technology, sensor fusion, service robot, map-based localization

Abstrak

Penggunaan robot perkhidmatan kini menjadi semakin ketara, terutamanya dalam industri berkaitan hospitaliti, penjagaan warga tua dan penjagaan kesihatan. Navigasi robot perkhidmatan memerlukan penyesuaian, fleksibiliti dan kebolehpercayaan yang tinggi. Oleh itu, navigasi berdasarkan peta adalah lebih sesuai untuk robot perkhidmatan kerana kemudahan dan fleksibilitinya dalam menentukan jalan optimum yang baru dengan perubahan persekitaran. Untuk menghasilkan navigasi berdasarkan peta yang teguh, kaedah penyetempatan yang tepat adalah perlu. Masalah penyetempatan ditakrifkan sebagai mengiktiraf kedudukan robot sendiri dalam persekitaran yang diberikan dan adalah satu langkah penting dalam proses navigasi. Kesukaran utama bagi penyetempatan termasuk perubahan dinamik dunia sebenar, maklumat sensor yang tidak tentu dan terhad. Kertas kerja ini membentangkan kajian dalam perbandingan teknologi sensor dan kaedah sensor fusion yang sesuai digunakan untuk penyetempatan berdasarkan peta yang memberi tumpuan kepada aplikasi robot perkhidmatan.

Kata kunci: kajian, teknologi sensor, sensor fusion, robot perkhidmatan, penyetempatan berdasarkan peta

1.0 INTRODUCTION

In recent years, there has been an explosive growth of interest in the development of service robot. One of the main reasons for this is that service robots are able to help individuals, including people with special needs, in a home or workplace. The robot will move in an environment, inhabited by a group of people, and perform physical tasks, such as to fetch and deliver objects [1]. The common applications of service robot include hospitality, geriatic care and healthcare. In order to navigate itself, a popular localization technique being researched and used is map-based localization. The map-based localization method matches a virtual or electronic map with location information from sensors to obtain the real position of the robot in a workspace.

Map-based localization highly relies on two distinct feedbacks. The first is the idiothetic feedback, which provides internal information about the robot's movements. The idiothetic feedback is usually obtained from proprioceptive sensor such as odometry sensors. The quality of idiothetic feedback can affect the performance of local localization or position tracking. Local localization provides new position estimate given a previous position estimate and new idiothetic feedback [2]. The second is allothetic feedback, which provides external information about the environment. This allothetic feedback can be obtained from exteroceptive sensor such as kinect and laser scanner sensors. A good quality of allothetic feedback can improve the performance of global localization. Global localization is a method to estimate the position of a robot without knowledge of its initial location and the ability to self-localize if its position is lost [3]. Hence, the robustness and accuracy of the map-learning and localization processes are highly related to the sensor technologies used.

The quality and reliability of local localization decrease over time because it involves an integral process which is subject to cumulative error [4]. On the contrary, global localization suffers from perceptual aliasing problem in which two distinct places in the environment may appear the same [5]. Hence, in order for robot to accurately navigate over a long time, both of the feedbacks must be combined. Allothetic feedback must compensate for the idiothetic feedback drift while idiothetic feedback must allow allothetic feedback to be disambiguated [6]. There are several sensor fusion methods being researched to fuse both feedbacks in order to obtain a robot position in a map, for example, using Extended Kalman Filter (EKF), Unscented Kalman Filter (UKF) and Particle Filter (PF).

Generally, the two major factors which can affect the performance of map-based localization are the sensor technologies and the sensor fusion method. Section 2.0 reviews several sensor technologies whereas in section 3.0, different sensor fusion methods are presented. A discussion and evaluation of both factors are presented in section 4.0.

2.0 SENSOR TECHNOLOGIES

2.1 Odometry Sensor

Optical encoder is the most commonly used odometry sensor, also known as proprioceptive sensor, typically mounted on driver motor to count the wheel revolutions [7]. Figure 1 shows a typical type of optical encoder which provides idiothetic feedback (motion) to update the mobile robot position through local localization. Figure 2 shows the representation of the robot in the global frame.

Figure 1 Optical encoder

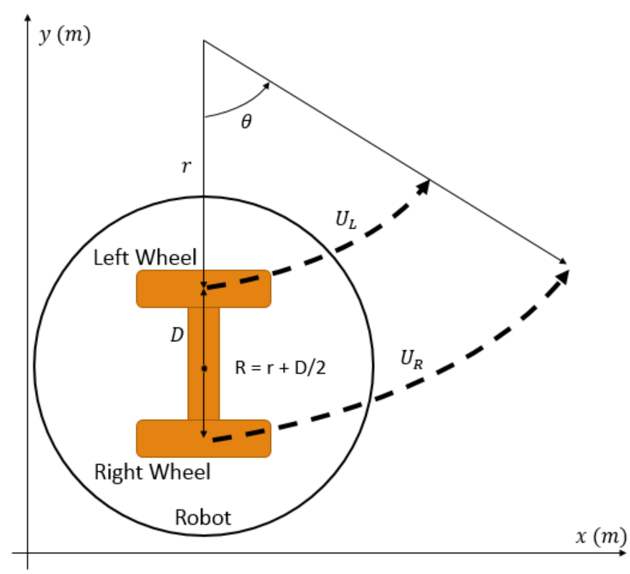


Figure 2 Representation of the robot in global frame

A state of the robot can be modelled as $S_k = [x_k \;\; y_k \;\; \theta_k]^T$ where $[x_k \;\; y_k]$ are the Cartesian coordinates, and θ_k is the orientation respective to global environment. From the output of encoders, the robot position is calculated by the odometry equation (1) - (2),

$$S_{k+1} = S_k + \begin{bmatrix} \sin(\delta + \theta_k) & -\sin(\theta_k) & 0 \\ \cos(\theta_k) & -\cos(\delta + \theta_k) & 0 \\ 0 & 0 & \delta \end{bmatrix} \begin{bmatrix} R \\ R \\ 1 \end{bmatrix} \qquad (1)$$

$$S_k = \begin{bmatrix} x_k \\ y_k \\ \theta_k \end{bmatrix}; \; R = \frac{D\,(U_R + U_L)}{2\,(U_R - U_L)}; \; \delta = \frac{(U_R - U_L)}{D} \qquad (2)$$

where U_R, U_L are the incremental displacement from the right and left wheels respectively. δ is the change of robot rotation angle from its previous state. D is the tread distance between the two wheels. R is the radius of the arc to the centre of the robot's axle.

However, it is well known that using solely the data from odometry is not sufficient because odometry accumulates unbounded position error [8]. The position estimation accumulates errors over time due to different wheel diameters, wheel-slippage, wheel misalignment, and finite encoder resolution [9].

2.2 Laser Scanner Sensor

Laser scanner sensor is an exteroceptive sensor for navigation and map building tasks in the robotics community. Figure 3 shows an example of laser scanner sensor which is mounted on a mobile robot. It obtains the data of surrounding environment through its laser scan and hence providing allothetic feedback. With the capability, it has been widely used in localization [10, 11], dynamic map building [12, 13] and collision avoidance [14]. Figure 4 shows the overview of the laser scanner which has a bearing resolution of $\theta°$ between each adjacent scan. The output from the laser scanner also provides the ranges data from right to left in term of meters i.e. from q_1, q_2, …, q_n.

Figure 3 Laser scanner sensor

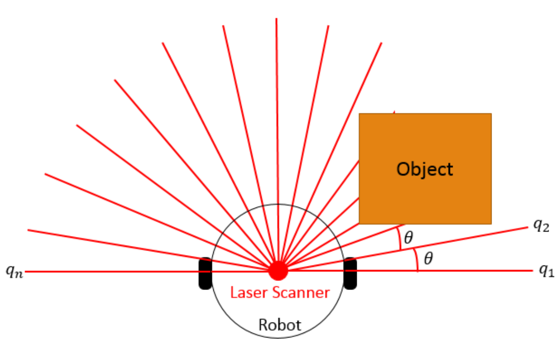


Figure 4 Overview of laser scanner

The raw feedback data will go through extraction technique such as point-based or feature-based extraction [15]. Point based extraction such as spike extraction uses extrema to determine spikes [16]. Feature-based extraction are done with line extraction technique using Split and Merge [17, 18], Random Sampling Consensus RANSAC [19] or Expectation- Maximization (EM) [20] algorithm. Next is data association process which matches a map feature from one observation to another same feature found in another observation [21]. The techniques for data association can be Joint Compatibility [22], Sequential Compatibility Nearest Neighbour [22], or Joint Maximum Likelihood [23].

Compared to other sensor technologies, the laser scanner provides more accurate range and bearing measurements. It has high sampling rate, high angular resolution, good range distance and resolution with the big field of view (FOV) [15]. However, since the laser scanner sensor works with light, the main problems are reflective surface. Mobile robots equipped with laser scanners may face problems in environments having window panes [24]. The laser sensor produces unexpected and suspicious measurements as it encounters glass panes in office environments [25]. Additionally, the sensing frequency affects performance since it has to rotate the mirror which reflects the emitting laser beam. Besides, mobile robot using fixed laser scanner sensor can only detect obstacle on a particular plane level [26]. This may lead to collision during navigation when the obstacles appear on different plane level other than laser plane level.

2.3 Vision Sensor: Kinect

Low-cost range or vision sensor is an alternative to the expensive laser scanner sensor for indoor mapping and robotics. Currently, the Kinect sensor has become a popular choice in mobile robot navigation due to its low cost. Figure 5 shows the Kinect sensor mounted on a mobile robot. It is also RGB-D camera providing RGB and Depth images [26]. It is another exteroceptive sensor which can be used to extract data in indoor environments to provide allothetic feedback.

It provides a 640x480 pixel colour image from an RGB camera and a depth image provided by an infrared (IR) camera supported by an IR emitter and an IR depth sensor, capturing at 30 frames per second (fps) [27]. The RGB image first undergoes feature extraction and matching algorithm. Features are extracted from the RGB image of the current frame and then, are matched back to those features in the previous frame [27]. The feature matching algorithm can be Oriented FAST and Rotated BRIEF (ORB) [28] and Speeded-Up Robust Features (SURF) [29]. After the detection of the features, feature locations from the images are projected to 3D space using the depth measurement through the Random Sample and Consensus (RANSAC) algorithm [19]. The 3D coloured point cloud produced contains about 300,000 points in every frame [30]. 3D point cloud can be processed to get useful information such as object detection, and laser scan data [26].

Kinect offers significant advantages over conventional laser scanners, such as 3D model building at considerably lower price, and the inclusion of colour into the maps [31]. A demonstration of the potential of Kinect for 3D modelling of indoor environments can be seen in the work of Henry *et al*. [32]. It is able to detect obstacles that went undetected by a normal laser scan system [26]. It can provide fast real time scanning frequency, at about 30 frame per second. The implementation of Kinect camera lowers the computing power compared with using other depth sensors. More expensive sensors typically need more computing power due to the use of high end equipment that generated much details and large amount of data [33]. However, the kinect sensor has lower precision and accuracy in terms of 2D mapping [30]. It has small field of view (FOV) and detects object only at close range [29]. Similar to laser range scanner, glare and light reflection may cause wrong measurements [33]. From a research work, Kinect cannot replace laser scanner for robotic applications due to small monitoring angle [34].

Figure 5 Kinect sensor

2.4 Laser Scanner with Stereo Camera

Another approach that provides allothetic feedback is to use laser scanner combined with stereo camera. Figure 6 shows a robot installed with stereo camera and laser scanner. In the work of Labayrade *et al.*, the laser scanner and stereo camera are fused together for on-board road obstacle detection [35]. The use of this method leads to a robust and accurate detection and improves the results provided by a single sensor [35]. Besides, this method is also used for building the 3D environment map in another research [36]. Besides, 2D laser scanner and a stereo camera are used for accomplishing simultaneous localization and mapping (SLAM) in 3D indoor environments, in which the 2D laser scanner is used for SLAM and the stereo camera is used for 3D mapping [37]. Their results show that fused sensors have higher obstacle detection rate than using only either one sensor.

For this technique, the inputs of laser scanner and stereo camera are first collected. Then laser scanner performs scan matching and stereo camera performs depth noise filtering to update both their occupancy maps. Both these occupancy maps are then fused to obtain one single map, which is more accurate, to be used for localization.

With this combination of sensor technologies, it solves the plane level problem by using only laser scanner and also improves the accuracy in building the map. However, the depth measurement from stereo camera is uncertain and inaccurate [37] which may lead to poor map building. It also will consume high computational power due to the use of both stereo camera and laser scanner sensors.

Figure 6 Stereo camera

3.0 SENSOR FUSION METHODS

3.1 Extended Kalman Filter (EKF)

EKF is a non-linear version of the Kalman filter which linearizes around the estimate of current mean and covariance. This filter has the common prediction - correction cycle of recursive state estimators to approximate the optimality of Bayes' rule through linearization [38]. The process algorithms for EKF are shown in Figure 7.

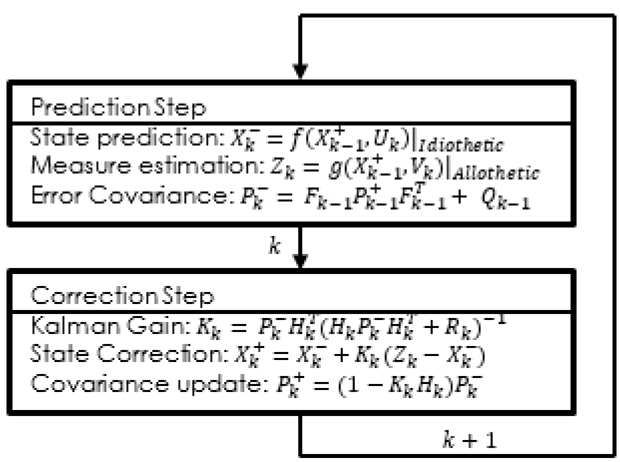


Figure 7 EKF algorithm

During the prediction step, X_k^- is computed which is the prediction of the state in term of robot position and orientation. The f function is related to the odometry model used to obtain the idiothetic feedback with the odometry system. X_{k-1}^+ is the correction of the pose state predicted value in the previous time step and U_k is the process noise. Z_k is the estimation of measure from g function taking X_{k-1}^{+} and the measurement model based on the allothetic sensor. P_k^{-} is the prediction of error covariance matrix, using the corrected value of error covariance matrix from the previous time step P_{k-1}^{+}, as well as the noise covariance matrix Q_{k-1} of the odometry measurements' model, and the Jacobian F. And in the correction step, K_k is the Kalman gain computed by using noise covariance matrix R_k of allothetic sensor model, Jacobian H_k and P_k^{-}. And also X_k^{+} and P_k^{+} are updated.

The EKF is fairly easy to implement, works very well in practical estimation problems and is computationally efficient [39]. However, there is tendency for EKF to diverge due to the fact that EKF is based on the linearization about the current estimate. If the preceding estimates are poor or if subsequent estimates should take the filter out of the linear region, the estimate often diverge [40]. Linearization can only be applied if the Jacobian matrix exists according to Julier *et al.* [41]. Calculating Jacobian matrices can be a very difficult and error-prone process [41]. In term of consistency, the true noise covariance matrices Q and R tend to be underestimated and result in inconsistencies [42]. The noise covariance matrices must be accurately obtained to produce optimal solution, but it is hard to obtain in non-linear system [43]. There are research works solved the divergence problem by integrating adaptive system [44, 45]. Besides, other research works also have integrated fuzzy logic to adjust the noise covariance of EKF in order to improve the performance [46 - 48].

3.2 Unscented Kalman Filter (UKF)

UKF is another version of Kalman Filter. It addresses the approximation issues of the EKF i.e. the poor approximating properties of the first order approximation, and the requirement for the noises to be Gaussian [41, 49]. It is more suitable for cases where prediction and correction functions are highly non-linear [50]. The concept of the UKF is that of finding a transformation that allows approximating the mean and covariance of a random vector of length when it is transformed by a nonlinear map [51]. Instead of using Taylor series expansion as linearization algorithm for non-linear function, Unscented Transform (UT) is used [41]. UT estimates the result of a probability distribution by computing a finite set of weighted sigma points and transforms each of those sigma points through a nonlinear function [52]. The comparison between linearization of EKF and UT of UKF can be seen in Figure 8.

UKF has better approximation than EKF to obtain the position of robot [51, 54]. However, UKF requires multiple integrations to propagate the sigma points through time, resulting in high computational cost, while the EKF perform integration only once. Besides, performance of UKF differs with different values of the UKF parameters. Thus, the UKF parameters need to be determined correctly [55] and the trade-off between computational cost and performance has to be carefully considered. Besides, UKF has advantage over EKF when using laser scanner as idiothetic sensor due to problem in getting the laser scanner Jacobian matrix [56]. There is also a research work, integrating adaptive capability on UKF on the basis of the innovation covariance matrix and the MIT adaptive law [57]. The result shows that adaptive UKF outperforms the conventional UKF in terms of fast convergence and estimation accuracy.

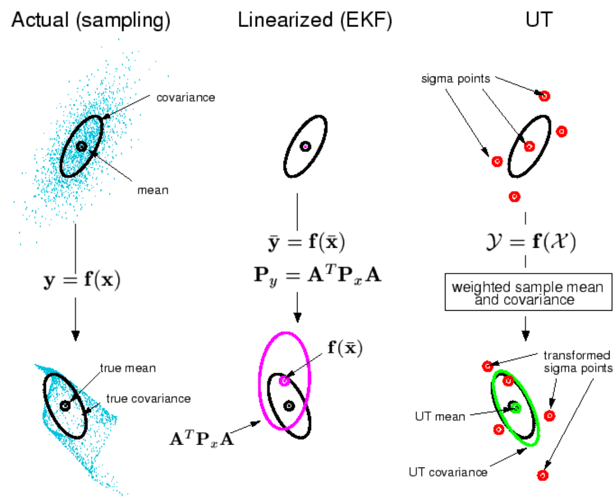


Figure 8 Comparison of EKF and UKF [53]

3.3 Particle Filter (PF)

Particle filter is used to track a variable of interest as it evolves over time, typically with non-Gaussian and potentially multi-modal probability density function [58]. It approximates the exact probability distribution through a set of state samples [59]. Figure 9 depicts the overview of particle filter processes.

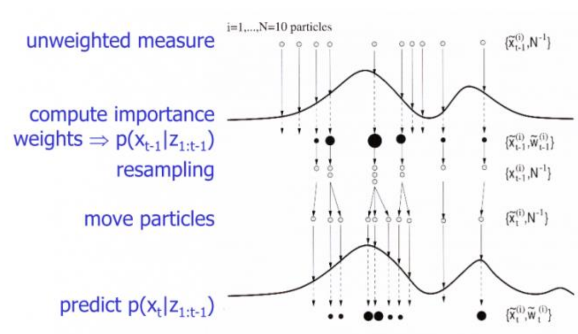


Figure 9 Visualization of particle filter [60]

The particle filter consists of several steps. The first step is initial distribution of unweighted particles with initial state value. And then the filter enters a recursive process where it starts from prediction step which involves acquiring idiothetic feedback from proprioceptive sensor and predicts the position of robot [61]. The next step is updating, which computes and updates the weights of the each particle accordingly based on the allothetic feedback from exteroceptive sensor. The following step is resampling and move particles in which it duplicates and rejects the particles according to their weights [61]. The filter then goes back to the prediction step again. Particles which are consistent with the allothetic feedback are more likely to be chosen and particles which are inconsistent are seldom selected. With that, particles tend to converge towards a better estimate of the robot's state. This is expected since a robot becomes increasingly sure of its position as it senses its environment.

PF is good in robot localization because robot localization is a state estimation problem for non-linear system with non-Gaussian noise [62]. Neither EKF nor UKF can handle the non-Gaussian noise, but particle filter can deal with the state estimation problem of nonlinear system with non-Gaussian noise [63]. From a research work, PF has better performance than EKF and UKF for nonlinear estimation [64]. Besides, a better localization performance can be obtained with high number of particles [65], but with high computational cost [66]. According to Fox, a method of KLD-sampling adaptive particle filter is proposed which adapts the number of samples over time because the complexity of the posterior distribution can vary drastically over time [67]. An unscented particle filter is also proposed by Van Der Merwe to solve the problem of particle degeneracy and improve the accuracy of PF [68].

4.0 DISCUSSION

The laser scan based localization has better accuracy and wide range of field of view (FOV) but slow response time. The Kinect based localization has better update frequency and object detection in 3D but poorer accuracy and FOV compared to laser sensor. Stereo camera combined into laser scanning has the best localization performance but high computational cost. However, the depth measurement from stereo camera is poor. Therefore, the proposed approach is to combine Kinect sensor in laser scanner localization instead of using stereo camera for depth perception. Kinect sensor has better depth measurement than stereo camera and this combination is worth investigating.

For sensor fusion method, EKF has issues with the divergence, inconsistency and complex Jacobian matrix problems. An adaptive system can be integrated to solve the divergence problem and also adjusting the noise covariance for better performance. UKF is superior to EKF but requires multiple integration processes that translate into higher computational costs. PF outperforms the Kalman filters (UKF and EKF) in terms of position estimate in robot localization, which is a non-linear system with non-Gaussian noise. However, only the model with high number of particles can produce good performance. The drawback of this method is the requirement for high computational resources, which reduces the efficiency of real time localization. An adaptive system can be integrated to adapt the number of particles over time to improve the efficiency. In short, the main considerations for selecting of sensor fusion method is the estimation accuracy, timing and computational costs. The enhancement of the methods can be investigated for better performance in robot localization.

Generally, for service robots in the medical care or elderly care sectors, robot navigational speed is typically slow due to safety reasons. Hence, computational speed is not a major problem. The main consideration for service robots in these sectors should be localization accuracy, obstacle detection and collision avoidance. The higher accuracy can be obtained with better sensor fusion methods (UKF or PF), at the expense of computational speed and hardware costs. In the hospitality sector, the variety of applications will need to consider variety of performance requirements. A food delivery robot in a restaurant may want to move at a higher speed to preserve freshness and reduce customer waiting time, thus, computational speed may become a major issue. Hardware costs to accommodate such performance could also play a role in determining the type of sensors and fusion methods to be used for this food delivery robot.

5.0 CONCLUSION

The selection of sensor technology and sensor fusion method should be carefully considered depending on specific applications and resources available. For a service robot with the focus of localization accuracy, obstacle detection and collision avoidance, the laser – Kinect based localization is proposed to be used because it can produce a higher accuracy and obstacle detection for map-based localization. Besides, the combined sensors will require an optimal sensor fusion method to fuse idiothetic and allothetic feedbacks for map-based localization. The adaptive PF is also proposed to be integrated into the system because it can produce better localization accuracy than Kalman filters.

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