SLAM ESTIMATION IN DYNAMIC OUTDOOR ENVIRONMENTS

Zheyuan Lu
Graduate School of Science and Technology,
Kumamoto University, Kumamoto, 860-8555, Japan
lu@navi.cs.kumamoto-u.ac.jp

Zhencheng Hu
Graduate School of Science and Technology,
Kumamoto University, Kumamoto, 860-8555, Japan
hu@cs.kumamoto-u.ac.jp

Keiichi Uchimura
Graduate School of Science and Technology,
Kumamoto University, Kumamoto, 860-8555, Japan
uchimura@cs.kumamoto-u.ac.jp

Received 8 12 2009
Revised 8 12 2009
Accepted 8 12 2009

This paper describes and compares three different approaches to estimate simultaneous localization and mapping (SLAM) in dynamic outdoor environments. SLAM has been intensively researched in recent years in the field of robotics and intelligent vehicles, many approaches have been proposed including occupancy grid mapping method (Bayesian, Dempster-Shafer and Fuzzy Logic), Localization estimation method (edge or point features based direct scan matching techniques, probabilistic likelihood, EKF, particle filter). In this paper, a number of promising approaches and recent developments in this literature have been reviewed firstly in this paper. However, SLAM estimation in dynamic outdoor environments has been a difficult task since numerous moving objects exist which may cause bias in feature selection problem. In this paper, we proposed a possibilistic SLAM with RANSAC approach and implemented with three different matching algorithms. Real outdoor experimental result shows the effectiveness and efficiency of our approach.

Keywords: SLAM; occupancy grid; localization; monocular; stereovision; lidar.

1. Introduction

The SLAM problem for a mobile robot is to build a consistent map of the environment and at the same time determine its location within this map [1]. The solution to the SLAM problem has been seen as the fundamental in making a robot truly autonomous [2]. One of the common assumptions used in SLAM is that the unknown environment is assumed to be static containing only rigid, stationary objects. Nonrigid or moving objects are processed as outliers and filtered out.

In the robotics literature, SLAM has been seen as the prime tool to solve the so-called DAMTO (detection and tracking of moving objects) problem. While SLAM provides the vehicle with a map of static parts of the environment as well as its location in the map, DATMO allows the vehicle being aware of dynamic entities around, tracking them and predicting their future behaviors. It is believed that if we are able to accomplish SLAM reliably in real time, we can detect every critical situation to warn the driver in advance and this will certainly improve driving safety and can prevent traffic accidents.

Basically, SLAM approaches have been proposed including the process of occupancy grid mapping, and the process of localization estimation. Occupancy grid mapping (OGM), which is also called Map-learning, is the process of memorizing the data acquired by the robot during exploration in a suitable representation. Bayesian, Dempster-Shafer and Fuzzy Logic are the typical methods for occupancy grid mapping. Localization is the process of deriving the current position of the robot within the map. Typical methods are features based direct scan matching (matching techniques such as ICP, RANSAC), probabilistic likelihood, particle filter and Extended Kalman Filter (EKF).

Sensor selection also takes a critical role in SLAM process. In this paper SLAM approaches are classified into three main categories: visual SLAM and Lidar SLAM. While visual and Lidar can also contain many types and levels, such as monocular camera, stereovision, laser scanner, sonar and fusion of these sensors. However, SLAM estimation in dynamic outdoor environments has been a difficult task since numerous moving objects exist which may cause bias in feature selection problem. In this paper, we proposed a possibilistic SLAM with RANSAC and implemented with three different matching algorithms. Real outdoor experimental result shows the effectiveness and efficiency of our approach.

This paper reviews a number of promising approaches and provides an overview of recent developments in this domain. The emphasis of this paper is to discuss the various methods with different sensor(s) data to estimate SLAM and global localization, and provide a comprehensive performance analysis among the common SLAM approaches, like computation speed, accuracy and cost.

The reminder of this paper is organized as follows. Section 2 presents a general review on occupancy grid mapping approaches and Section 3 describes the method of localization estimation. Practical analysis of different SLAMs is shown in Section 4. Section 5 concludes the paper.

2. Preprocess of SLAM

In the past two decades, occupancy grid maps have become a dominant paradigm for environment modeling in mobile robotics. It is based on the use of a two-dimensional representation called occupancy grid (OG), once acquired, they enable various key functions necessary for mobile robot navigation, such as localization, path planning and collision avoidance.

2.1. *The Mapping Problem*

To build a map, is to take a number of sensor readings, a sensor reading being a discrete-time sample, and integrate them into a map. This is not as straight forward as it might sound as there are many reasons why robotic mapping is a hard problem.

- **Sensor Noise.** Laser and stereovision are sensitive to differences in lighting, some surfaces does not reflect sound well enough to be sensed by sonar.
- **Sensor integration.** To integrate sensor information into a maps representation many objects has to be considered.
- **Localization errors.** To build maps the robots pose, that is the robots position and direction, has to be know.
- **Dynamic environments.** In reality environment are dynamic not static, and the mapping leads to many difficulties.
- **High computational complexity.** Time complexity is also a concern as robotic mapping algorithms are supposed to work in real time.

2.2. *Techniques for Building OGMs*

The first OGM grid map algorithm was introduced by [14], its basic idea is represents the environment you want to map with a grid, each cell of the grid is assigned a probability of being occupied by an obstacle. This algorithm was implemented and a number of experiments were conducted to investigate how it would perform given different types of sensor noise [4][5][6][15]. In these cases, the environment is discretized into a regular OGM. Some irregular OGM may be used in [7][53]. In [7], the resulting model incorporates both a compact geometrical representation of the environment and a topological map of the spatial relationships between its obstacle free areas. The great advantage of these methods is that they can directly use sensor data without the need for feature extraction, often either computationally expensive or brittle. In [53], an method of building X-disparity gird map with stereovision to solve the problem that the independent object cannot be detected because of discontinuous occupied data in traditional X-Z gird map.

Nowadays many efforts in mobile robotics are directed to develop some kind of "uncertainty calculi" techniques for recovering spatial information from obtained sensor data. In the literature, three different uncertainty calculi techniques for building OGMs of an unknown environment based on sensor information are discussed. These techniques are based on Bayesian theory (probabilistic approach), Dempster Shafer theory of evidence (evidence theoretic approach), and fuzzy set theory (possibility approach). The probabilistic approach is the most widely found in mobile robotic literature [8][14][15][16][24]. The Bayesian method rules the greatest part of the work related to the probabilistic sensor fusion in building OGMs. This attraction stems from the property of the Bayes' updating rule which facilitates recursive and incremental schemes [10]. However, in order to avoid huge calculation processes, one must assume that the cell states are independent. It has been observed that this assumption may induce large errors in the presence of even a slight degree of dependence between the random variables, this is exactly the case for map building, since the occupied cells are not evenly distributed, but concentrated in clusters (obstacles). As a consequence, the convergence of the Bayesian updating procedure towards and acceptable characterization of the occupancy grid requires a large number of measures.

The articles [15][16]describe algorithms for acquiring OGMs with mobile robots, which rely on the probabilistic approach. These algorithms employ the expectation maximization (EM) algorithm for searching maps that maximize the likelihood of the sensor measurements. The approach presented in [15]relies on a statistical formulation of the mapping problem using forward models. Experimental results are presented, which are obtained using a RWI B21 robot equipped with 24 sonar sensors. The disadvantages of this approach are an apparent increased sensitivity to changes in the environment, and a need to go through the data multiple times, which prohibits its real-time application. Moreover, in [17], it is pointed out that the Embased techniques suffer from a high computational complexity. Besides, EM is not guaranteed to converge to a global optimum.

The articles [9]presents a novel application of the theory of evidence for map building. Compared with probabilistic methods, this method is different with the Bayes approach by allowing support for more than one proposition at a time, rather than a single hypothesis. It is interval based, as defined by the upper and lower probability bounds, allowing lack of data (ignorance) to be modelled adequately. This model no longer requires full description of conditional (or prior) probabilities and small incremental evidence can be adequately incorporated. Also, it allows to quantify the undistributed probability masses, thus making assessment about the quality of the posterior probabilities. The structure of 2D map is independent of the method and can be implemented by other representaions (grid, quadtrees).

In the articles [12], fuzzy logic concepts are used to introduce a tool useful for robot perception as well as for planning. A map of the environment is defined as the fuzzy set of unsafe points, whose membership function quantifies the possibility for each point to belong to an obstacle. The computation of this set is based on a sensor model and makes use of intermediate sets generated from range measures and aggregated by means of fuzzy set operators.

2.3. *Comparative Analysis of Building OGMs*

The well known techniques of OGMs building were experimented and comparisons were performed in [10][11]. It was shown that the possibilistic approach may produce the most suitable OGMs thanks to its robustness with respect to outliers. The probabilistic and the evidence theoretic approaches produce good results in certain cases, but their performances with respect to outliers are very poor. Moreover, The building algorithm of the probabilistic approach is the fastest and has minimum memory consumption. The processing time for the evidence theoretic and possibilistic approaches are approximately 1.5 times higher than the probabilistic approach. The experimental results indicated that the method based on fuzzy logic is more robust with respect to the occurrence of false reflections in the measuring process [13].

3. Estimation Approaches of SLAM

In this section we discuss the localization estimation of SLAM with different sensors. Camera is one of the most common sensor used in formations, due to its advantages of large FOV and lower cost, and stereovision also can further provide depth information. recently, active sensors such as sonar and laser have been widely used. For the main reasons of rich information and higher accuracy. We will be presenting different SLAM estimation approaches, can be divided into Feature-to-Feature, Point-to-Feature, Point-to-Point and other approaches.

3.1. *Feature-to-Feature approaches*

Feature-to-Feature matching approaches should have the shortest run-time, since by these approaches hundreds of range points are reduced to dozens of features. For most indoor applications, line segments [46], corners [34]and other simple geometrical features are rich and easy to detect. [35]picked a site that is similar to indoor environments and employed feature-to-feature approaches to construct an urban map successfully. [36]used intensity (reflectance) of laser signal and geometrical primitives to define and detect features. Their approaches are still limited to some specific environments or conditions.

Monocular cameras are in widespread use for SLAM, as they are simple and low power sensors that allows to estimate the bearing of interest points and, by means of camera motion and triangulation, the whole 3D structure of the environment [54]. Much work in monocular visual SLAM focuses on using point feature:

In their work, practical real-time monocular SLAM was first demonstrated by Davison [18], who uses the EKF, a mainstay of SLAM literature. He resolved the problem of real-time operation by careful maintenance of the map to ensure that it is sparse but sufficient, and by using the map uncertainty to guide feature matching. More recently, Pupilli et al. [19]have demonstrated real-time camera tracking using a particle filter, which provides a good robustness, but theirs is predominantly a tracking system; its mapping ability is currently rudimentary, which restricts its range of applications. Davison et al. [54], using an EKF to perform a real-time 6 DoF SLAM, used a non-parametric approach to initialize the feature depth and bounded the maximum feature depth to about 5m. Unfortunately, this delayed use can cause a loss of information. To avoid this delay and to exploit low-parallax features, Sol'a et al. [55]proposed to maintain several depth hypotheses combined in a Gaussian

Sum Filter, to cover the distribution along the whole ray to the feature. An alternative solution for both undelayed initialization and depth uncertainty modeling was introduced in [56]and [20]. They showed that the use of inverse depth parameterizations make the observation model nearly linear (at least for small camera displacements), while reducing both non-Gaussian-ness of depth measurement and EKF linearization. In this way, it is possible to model the uncertainty as Gaussian and use EKF filtering, without delay. In [57]Clemente et al. demonstrated that a different solution to filter inconsistencies is to use a Hierarchical map approach that, combined with the Joint Compatibility test, allows to perform a mapping of a large loop.

Line feature (or edge feature) are common in many environments and are arguably better features to track than points. Described just by a step change in intensity (which does mean that they lack discrimination), they are trivially stable under a wide range of viewing angles, and a number of measurements can be made along their length to localize them accurately. As a result, many camera-tracking systems have used line features [2][58]. Bosse et al. [48]use a single omnidirectional camera to detect and track parallel lines, both with reasonable results. Eade et al. [58]use a single camera to detect and track edges, and SLAM estimated with particle filter approach.

Point and line features are complementary in a camera localisation system: point features provide good discrimination, but are view-dependent, while line features are robust to viewing changes, but are more fragile. This idea has been studied recently by [22], who bootstrap line-tracking (using a prior accurately-known three dimensional model) with detected point features. They shows that monocular tracking with the fusion of point features and line features, and model-building with both types of feature, can be performed within a standard SLAM framework.

Stereovision has been employed for map building in decades, e.g., active stereo approach with spot lighting [23], 3D mapping from stereo range data with planar modeling assumption [24], and 3D SLAM based on feature point matching [25][26][27]. The most popular approach in recent years is the feature-point based one, in which the camera motion is estimated with feature-point matching between consecutive frames, and 3D point clouds are generated based on the estimated camera motion. As mentioned, however, the SLAM process is unstable in non-textured environments, where sufficient corner-like features cannot be extracted. Since many man-made environments are nontextured, the importance of alternative feature forms such as lines is indicated in [28][51]. In [49], Nister et al. dealed with the case of a stereovision but they also provided a monocular solution implementing a SLAM algorithm that takes advantage of the 5-point algorithm and RANSAC robust estimation.

Lines have also been used for some time in SLAM systems. In perhaps the earliest work in visual SLAM using lines, Ayache et al. [31]used a stereo pair of calibrated cameras to directly extract the three-dimensional location of line segments and filtered these within an EKF SLAM framework. More recently, Dailey et al.

[32]described the application of "FastSLAM" to the problem of estimating a map from observations of 3D line segments using a trinocular stereo camera rig. In [30], Tomono computes 3D points from the edge points detected in a stereo image pair, and then estimates the camera motion by matching the next stereo image with the 3D points. The proposed method estimates camera poses and builds detailed 3D maps robustly by aligning edge points between frames using the (Iterative Closest Points) ICP algorithm.

3.2. *Point-to-Feature approaches*

Point-to-Feature approaches, such as one of the earliest by [37], the points of a scan are matched to features such as lines. The line features can be part of a predefined map. Features can be more abstract as in [38], where features are Gaussian distributions with their mean and variance calculated from scan points falling into cells of a grid. Basically, Feature-to-Feature approaches try to use less information to represent the raw data in order to speed up algorithms. If features cannot be detected robustly and contain some uncertainties, the whole performance of the approaches will decrease. On the contrary, Point-to-Point based approaches do not have these disadvantages; instead, they use all the raw data.

3.3. *Point-to-Point approaches*

Examples of Point-to-Point matching approaches are the following: iterative closest point (ICP), iterative matching range point (IMRP) and the popular iterative dual correspondence (IDC). ICP algorithm is one of the most successful and popular algorithms. The basic idea of ICP is that using a closest-point rule to initial guess of their relative pose, and then solving the Point-to-Point least-squares problem to compute their relative pose. Finally the relative pose is updated and the whole process iterates until the result is satisfying. Since ICP introduced by [39], many variants have been proposed on the basic ICP concept. In the [40]proposed ICP, where for each point of the current scan, the point with the smallest Euclidean distance in the reference scan been selected. IMPR was proposed by [41], where corresponding points are selected by choosing a point which has the matching range from the center of the reference scan's coordinate system. IDC also proposed by [41], combines ICP and IMRP by using the ICP to calculate translation and IMPR to calculate rotation. The mentioned point to point methods can find the correct pose of the current scan in one step provided the correct associations are chosen. Since the correct associations are unknown, several iterations are performed. Matching may not always converge to the correct pose, since they can get stuck in a local minima. In [42], Diosi presented a novel method for 2D laser scan matching called Polar Scan Matching (PSM). This method avoids searching for point associations by simply matching points with the same bearing. This association rule enables the construction of an algorithm faster than the iterative closest point (ICP).

3.4. *Other approaches*

probabilistic approach of Lider SLAM estimation is treated as a maximum likelihood estimation problem. Thrun et al. [44][45]have demonstrated their probabilistic approach in museum environment. Another Lidar SLAM estimation method has been done for example by minimizing an energy function [43], using local registration and global correlation [46]and using FastSLAM [47]. A Kalman filter implementation can be found in [48]. Based on correspondence establishment, categorized various SLAM estimation methods showed in Table 1.

4. Implementation of Lidar SLAMs

In this section, three kinds of approaches were implemented in C under Windows (Celeron(R) CPU 3.0GHz), to estimate SLAM in dynamic outdoor environments. The experimental real range data were gathered by a RIEGL laser scanner, running at 15Hz, with an angle resolution of 0.1 degree.

Generally, in order to perform SLAM in dynamic outdoor environments, a precise vehicle motion is essential. When good vehicle locations are estimated, by integrating laser measurements we are able to build a consistent global OGM of the vehicle, and achieve SLAM estimation. For the two-dimensional OGM, robot motion from pose $(X, Z, 0)$ to pose (X', Z', α) consists of translation T_x,T_z along X-, Z-axes and rotation α about Y-axe. The kinematics equations can be described by

$$\begin{bmatrix} X' \\ Z' \end{bmatrix} = \begin{bmatrix} \cos\alpha & \sin\alpha \\ -\sin\alpha & \cos\alpha \end{bmatrix} \begin{bmatrix} X \\ Z \end{bmatrix} + \begin{bmatrix} T_x \\ T_z \end{bmatrix} \tag{1}$$

where (a,b,c,d) are motion parameters by $a = \cos\alpha$, $b = \sin\alpha$, $c = T_x$, $d = T_z$. In our works, We implemented three kind of experiment approaches to estimated motion parameters and SLAM. These approaches are Probability edge matching approach, Maximum measurement probability approach and RANSAC approach.

In our OGM representation, the vehicle environment is divided into a two-dimensional cell with a real value in [0,1] indicating the probability that the cell is occupied by an obstacle or not. Here we apply Bayesian Update scheme (refer for detail section 2) that is the widely used in mobile robotic literature, to provides an recursive formula to update the grid map. The resolution of OGM (25m×40m)is 8 cm each cell.

4.1. *Probability edge matching approach*

In our test, after building the OGM with Bayesian theory method, the process is started by grouping all the measures of a scan, into several clusters: the readings are subdivided into sets of neighbor points, taking the proximity between each two consecutive points of the scan into account. A cluster is hence, a set of measures close enough to each other, which probably belong to the same object.

A simply clustering filter is adopted to remove outliers (small objects which maybe are moving objects) and find meaningful edge features in local OGM. When

Approach	System	Sensor	Comments
F-T-F	[2]	Monocular	vanishing points and 3D lines to recover mapping on a 946 meter path
	[32]	Monocular	resolved the problem of real-time operation
	[22]	Monocular	bootstrap line-tracking with detected point features
	[19]	Monocular	EKF based, first practical real-time monocular SLAM
	[20]	Monocular	combined particle filtering for localisation with Kalman filtering for mapping
	[14]	Stereovision	3D mapping from stereo range data with planar modeling assumption
	[31]	Stereovision	used stereovision to directly extract the 3D location of line segments and filtered these within an EKF SLAM
	[27]	Stereovision	3D SLAM based on feature point matching
	[32]	Stereovision	estimating a map from observation of 3D line segments using a trinocular stereovision
	[50]	Stereovision	build 3D maps robustly by aligning edge points between frames using the ICP algorithm
	[51]	Stereovision	build 3D maps by line features
	[46]	Lidar	using local registration and global correlation used line segments for feature matching
	[36]	Lidar	used intensity of laser signal and geometrical primitives to define and detect features
	[35]	Lidar	employed feature-to-feature approaches to construct an urban map successfully
	[34]	Lidar	used corners for feature
P-T-F	[52]	Lidar	utilizes Euclidean invariant features to match an input scan with reference scans without an initial alignment
	[37]	Lidar	scan points matched to features like lines
	[38]	Lidar	features are Gaussian distributions with their mean and variance calculated
P-T-P	[49]	Stereovision	used 5-point RANSAC and bundle adjustment to recover 3D map
	[41]	Lidar	based on matching points with tangent directions in two scans to compute the relative pose of two scans
	[40]	Lidar	used ICP for each point of the current scan, with the smallest euclidean distance in the reference scan been selected
Others	[44]	Lidar	used combination of maximum likelihood with posterior estimation
	[45]	Lidar	estimate of the vehicle pose with the measurement likelihood that is nearly unimproved

Table 1. Comparison of SLAM Estimation Method. F-T-F=Feature to Feature, P-T-F=Point to Feature, P-T-P=Point to Point

edge features have been established in each local OGM, a image process technology of pattern matching is used for edge matching between two consecutive local OGM, and estimate motion parameters. The resulting pose is then used to generate a global OGM. This approach is similar to [33]. The total computational time is about 70-100 ms.

4.2. *Estimation maximum likelihood approach*

We used an approach of matching problem as a maximum likelihood problem to estimate SLAM (quite similar to [45]approach). Given an underlying vehicle dynamics constraint, the current scan's pose is corrected by comparing with the local OGM constructed from all observations in the past. By this way, we can reduce the ambiguity and weak constraint especially in outdoor environment and when the vehicle moves at high speeds.

To find the current scan's pose of maximum corrected, hill climbing strategy can be used but may suffer from a local maximum. The resulting pose will be the pose at which the measurement probability achieves a maximum value. The resulting pose is then used to generate a global OGM. Because of the inherent discretization of the grid, the approach turns out to work very well. In practice, with a grid map resolution of 8 cm, it is to generate enough pose samples to obtain a good estimate of the vehicle pose with the measurement likelihood that is nearly unimproved even with more samples. The total computational time is about 40-80 ms.

4.3. *RANSAC approach*

In this test, the process is also started by clustering that is described in the above. After the clustering process, line fitting is used to detect start points, end points and break points for each cluster. During the clustering and line fitting processes, no effort is made to adjust the lines to the most common objects that can be found. For that reason, the segmentation can be very faithful regarding to the measure points, however not corresponding to the related objects. This problem arises specially for targets like walls or big obstacles with smaller ones in between them and the laser scanner, resulting in the division of the big one in two or more object. In order to avoid those problems, the Broken lines algorithm is proposed, that is the detection of walls or other big obstacles partially occluded by smaller objects in front of them, can be partially hidden in one of the invisible areas. Afterwards, checking for end point and start point of behind objects in last cluster and next cluster. Joining them that not exceed a given threshold.

The correspondences between features identified in two successive frames are found by comparing the region (the angle is not exceed 5 degree and distance is not exceed 2 meters). For a feature in the landmark set of the first frame, we assume that the features in the region of the second frame are its corresponding point. The resulting set of point correspondences is used as input for the RANSAC algorithm. The total computational time is about 20-50 ms.

An overview of the algorithm is shown in follow: Repeat the following steps until stop condition satisfied:

- Choose a random subset of two set of corresponding points and calculate and by least-squares algorithm.
- Compute the consensus set by applying the calculated rotation and translation to all points of and then computing the distance to the corresponding points of set , add points whose distance is below a certain threshold.
- Save the consensus set if its size is bigger than a certain number.

Stop condition: iteration number is over N, or, the consensus set size is larger than a pre-defined threshold. If at least one consensus set is found, use the one with the most elements and calculate from these points the rotation and translation . If no consensus set is found, the algorithm outputs nothing.

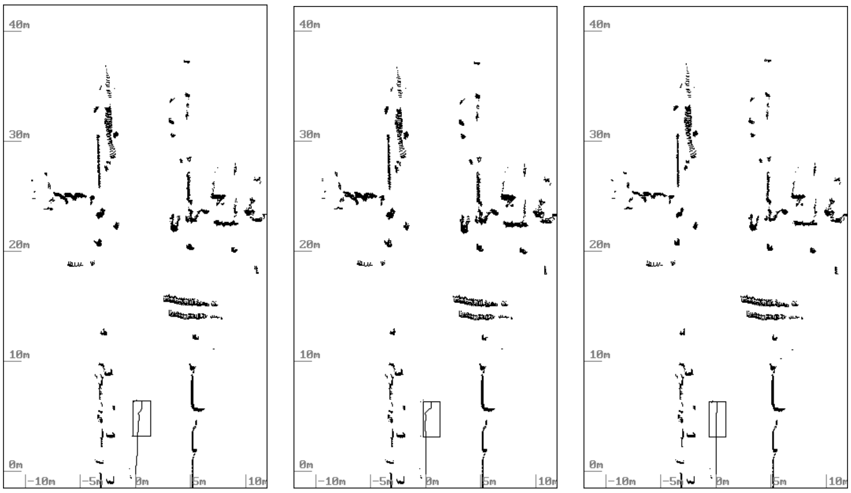
4.4. ***Comparative Analysis of SLAM results***

(a) Frame 139 (b) Frame 324

Fig. 1. Comparison SLAM results with three kind of method

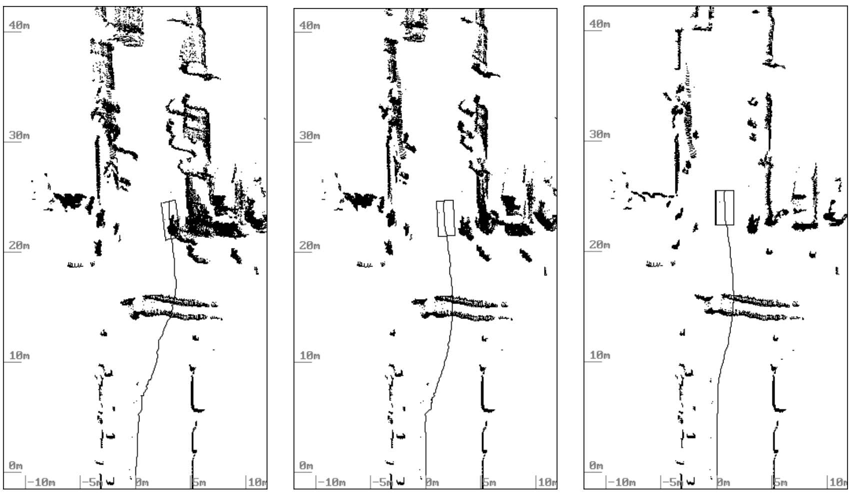
Figure 1 shows two camera images in frame 139 and 324. In frame 139, our vehicle was moving in a straightaway, and two pedestrians were ready for across the crossing from right to left. From frame 324, our vehicle was moving and turning right slightly to avoid two pedestrians. In this scene, there are also other walking pedestrians.

Figure 2 shows the estimated SLAM results by three test methods. Since most of objects were static, our SLAM results show not significant difference. However the vehicle path, we can see, RANSAC method shows the best performance, because another method were very sensitive to the dynamic objects. In figure 3, since many dynamic objects (walking pedestrians) exist, the RANSAC results were much better than another methods.



(a) edge matching (b) probability (c) RANSAC

Fig. 2. SLAM built from Frame 139



(a) edge matching (b) probability (c) RANSAC

Fig. 3. SLAM built from frame 324

5. Conclusions

This paper reviews a number of promising approaches and provides an overview of recent developments in the domain of SLAM, which aims at building a consistent map of the environment and at the same time determine the location of moving robot within this map. In this paper, we classify SLAM by the processes (occupancy grid mapping and localization estimation), sensors (visual SLAM, Lidar SLAM and SLAM by sensor fusion) and uncertainty calculation (probabilistic, evidence theoretic and possibilistic SLAMs). In this paper, we proposed a possibilistic SLAM with RANSAC estimation, which shows better performance in a noisy environment to build the occupancy grid maps in our experiment.

References

1. R. Hartley, A. Zisserman, Multiple View Geometry in Computer Vision, Second Edition. Cambridge University Press, (2004) ISBN: 0521540518.
2. M. Bosse, R. Rikoski, J. Leonard, S. Teller, Vanishing points and 3d lines from omnidirectional video, ICIP02, vol.3 (2002) 513-516.
3. H.P. Moravec, A. Elfes, High Resolution Maps from Wide Angle Sonar, Proceedings of the IEEE International Conference on Robotics and Automation, March, (1985) 116-121.
4. M. Deans, Bearing-Only Localization and Mapping, PhD thesis, tech. report CMU-RI-TR-05-41, Robotics Institute, Carnegie Mellon University (2005).
5. R. Groecke, A. Asthana, N. Pettersson, L. Petersson, Visual vehicle egomotion estimation using the fourier-mellin transform, IEEE Intelligent Vehicles Symposium, Istanbul (2007) 450-455.
6. J. Tardif, Y. Pavlidis, K. Daniilidis, Monocular visual odometry in urban environments using an omnidirectional camera, IEEE IROS, (2008) 2531-2538.
7. A. Arleo, J.R. del Millan, D. Floreano, Efficient learning of variable-resolution cognitive maps for autonomous indoor navigation, IEEE Transactions on Robotics and Automation 15 6, (1999) 990–1000.
8. A. Elfes, Multi-source spatial data fusion using Bayesian reasoning, in M.A. Abidi R.A. Gonzalez (Eds.), Data fusion in robotics and machine intelligence, NY: Academic Press, Chapter 3 (1992).
9. D. Pagac, E.M. Nebot, H. Durrant-Whyte, An evidential approach to map-building for autonomous vehicles, IEEE Transactions on Robotics and Automation, 14 (1998).
10. M. Ribo, A. Pinz, A comparison of three uncertainty calculi for building sonar-based occupancy grids, Inernational Journal of Robotics and Autonomous Systems 35 (2001) 201-209.
11. F. Gambino, G. Oriolo, G. Ulivi, Comparison of three uncertainty calculus techniques for ultrasonic map building, Proc. SPIE Int. Symp. On Aerospace/Defense Sensing and Control, Vol.2761 (1996) 249-260.
12. G. Oriolo, G. Ulivi, M. Vendittelli, Fuzzy maps: a new tool for mobile robot perception and planning, Journal of Robotic Systems, 14(3) (1997) 179-197.
13. G. Oriolo, G. Ulivi, M. Vendittelli, Real-time map buildiing and navigation for autonomous robots in unknown environments, IEEE Transactions on Systems, Man, and Cybernetics 5, (1999).
14. H.P. Moravec, A. Elfes, High Resolution Maps from Wide Angle Sonar, Proceedings of the IEEE International Conference on Robotics and Automation, March, (1985) 116-121.

15. S. Thrun, Learning occupancy grids with forward sensor models, Autonomous robots, Vol.15 (2003) 111-127.
16. D. Fox, W. Burgard, S. Thrun, Probabilistic methods for mobile robot mapping, in Proc. Of the IJCAI-99 Workshop on Adaptive Spatial Representations of Dynamic Environments (1999).
17. T. Duckett, A. Saffiotti, Building globally consistent gridmaps from topologiesC in Proc. of the 6th Int. IFAC Symp. on Robot Control, SyROCO, Austria (2000).
18. A.J. Davison, Real-time simultaneous localisation and mapping with a single camera, In Proc. IEEE International Conference on Computer Vision (2003) 1403-1410.
19. M. Pupilli, A. Calway, Real-time camera tracking using a particle filter, In Proc. British Machine Vision Conference, Oxford, UK (2005) 519-528.
20. E. Eade, T. Drummond, Scalable monocular SLAM. In Proc, Conference on Computer Vision and Pattern Recognition, USA (2006) 469-468.
21. M. Bosse, P. Newman, J. Leonard, S. Teller, Simultaneous localization and map building in large-scale cyclic environments using the Atlas framework, The International Journal of Robotics Research, 23(12) (2004) 1113-1139.
22. E. Rosten, T. Drummond, Fusing points and lines for high performance tracking, In Proc.IEEE International Conference on Computer Vision, Beijing (2005) 1508-1515.
23. D. Scaramuzza, F. Fraundorfer, R. Siegwart, Real-Time Monocular Visual Odometry for On-Road Vehicles with 1-Point RANSAC, Proceedings of the IEEE International Conference on Robotics and Automation, Japan (2009) 4293-4299.
24. H. Moravec, DARPA MARS program research progress, Carnegie Mellon University, http://www.frc.ri.cmu.edu/hpm/talks/Report.
0107.html, 2001.
25. L. Iocchi, K. Konolige, M. Bajracharya, Visually Realistic Mapping of a Planar Environment with Stereo, Proc. of ISER2000 (2000).
26. P. Elinas, R. Sim, J.J. Little, SLAM: Stereo Vision SLAM Using the Rao-Blackwellised Particle Filter and a Novel Mixture Proposal Distribution, Proc. of ICRA2006, (2006) 1564-1570.
27. M.A. Garcia, A. Solanas, 3D Simultaneous Localization and Modeling from Stereo Vision, Proc. of ICRA2004 (2004) 847-853.
28. S. Se, D. Lowe, J. Little, Local and Global Localization for Mobile Robots using Visual Landmarks, Proc. of IROS2001 (2001).
29. D.C. Herath, K.R.S. Kodagoda, G. Dissanayake, Stereo Vision Based SLAM: Issues and Solutions, Vision Systems, G. Obinata and A. Dutta (Eds), Advanced Robotic Systems (2007) 565-582.
30. M. Tomono, Robust 3D SLAM with a stereo Camera Based on an Edge-Point ICP Algorithm, IEEE International Conference on robotics and Automation, Japan, May, (2009) 4306-4311.
31. N. Ayache, O.D. Faugeras, Building, registrating, and fusing noisy visual maps. International Journal of Robotics Research, 7(6) (1988) 45-65.
32. M.N. Dailey, M. Parnichkun, Landmark-based simultaneous localization and mapping with stereo vision, In Proc. Asian Conference on Industrial Automation and Robotics, Bangkok, Thailand (2005).
33. J.S. Gutmann, Robuste Navigation autonomer mobiler Systeme, PhD thesis, Universityy of Freiburg (2000).
34. K. Lingemann, H. Surmann, A. Nuchter, J. Hertzberg, Indor and outdoor localization for fast mobile robots, In IROS'04, volume 3 (2004) 2185-2190.
35. H. Zhao, and R. Shibasaki, Reconstructing Urban 3D Model using Vehicle-borne Laser Range Scanners, Proc. Of the Third Int. Conf. on 3-D Digital Imaging and Modeling

(2001) 349-56.
36. J. Guivant, E. Nebot, and S. Baiker, High accuracy navigation using laser range sensors in outdoor applications, IEEE Int. conf. on Robotics and automation, vol. 4 (2000) 3817-3822.
37. I.J. Cox, Blanche.an experiment in guidance and navigation of an autonomous robot vehicle. IEEE Transactions on Robotics and Automation, vol.7, issue.2 (1991) 193-203.
38. P. Biber, W. Straser, The normal distributions transform: A new approach to laser scan matching, In IROS'03, vol.3 (2003) 2743-2748.
39. Y. Chen, G. Medioni, Object Modeling by Registration of Multiple RangeImage, Proc. IEEE Int. Conf. On Robotics and Automation (1991).
40. P. Besl, N.D. Mckay, A method for registration of 3D shapes, IEEE Transactions on Pattern Analysis and Machine Intelligence, 14(2) (1992) 239-256.
41. F. Lu, E.E. Milios, Robot pose estimation in unknown environments by matching 2D range scans, Computer Vision and Pattern Recognition (1994) 935-938.
42. A. Diosi, L. Kleeman, Laser scan matching in polar coordinates with application to SLAM, Intelligent Robots and Systems (2005) 3317-3322.
43. F. Lu, Shape Registration Using Optimization for Mobile Robot Navigation, PhD thesis, University of Toronto (1995).
44. S. Thrun, W. Burgard, D. Fox, A real-time algorithm for mobile robot mapping with applications to multi-robot and 3D mapping, In ICRA'2000, vol.1 (2000) 321-328.
45. T.D. Vu, J. Burlet, O. Aycard, Mapping of environment, Detection and Tracking of Moving Objects using Occupancy Grids, Intelligent Vehicles Symposium, IEEE (2008) 684-689.
46. J.S. Gutmann, Robuste Navigation autonomer mobiler Systeme, PhD thesis, Universityy of Freiburg (2000).
47. D. Hahnel, W. Burgard, D. Fox, S. Thrun, An efficient fastSLAM algorithm for generating maps of large-scale cyclic environments from raw laser range measurements, In IROS'03, vol.1 (2003) 206-211.
48. M. Bosse, P. Newman, J. Leonard, S. Teller, Simultaneous localization and map building in large-scale cyclic environments using the Atlas framework, The International Journal of Robotics Research, 23(12) (2004) 1113-1139.
49. D. Nister, O. Naroditsky, J. Bergen, Visual odometry for ground vehicle applications, Journal of Field Robotics (2006).
50. W.Y. Jeong, K.M. Lee, Visual SLAM with Line and Corner Features, Proc. of Intelligent Robots and Systems (2006) 2570-2575.
51. D.C. Herath, K.R.S. Kodagoda, G. Dissanayake, Stereo Vision Based SLAM: Issues and Solutions, Vision Systems, G. Obinata and A. Dutta (Eds), Advanced Robotic Systems (2007) 565-582.
52. M. Tomono, A scan matching method using euclidean invariant signature for global localization and map building, In ICRA'04 (2004) 866-871.
53. Z. Lu, Z. Hu, K. Uchimura, Sensor Fusion with Occupancy Fusion Map for Pedestrian Detection in Outdoor Environment, IEEE International Conference on Vehicular Electronics and Safety, USA (2008) 199-204.
54. A.J. Davison, I.D. Reid, N. Molton, and O. Stasse, MonoSLAM: Real-time single camera SLAM, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol.29, no.6 (2007) 1052-1067.
55. J. Sol'a, A. Monin, M. Devy, and T. Lemaire, Undelayed initialization in bearing only slam, IEEE International Conference on Intelligent Robots and Systems (2005) 2499-2504.
56. J. Montiel, J. Civera, and A. Davison, Unified inverse depth parametrization for

monocular slam, Proceedings of Robotics: Science and Systems (2006).
57. L.A. Clemente, A.J. Davison, I.D. Reid, J. Neira, and J.D. Tardos, Mapping large loops with a single hand-held camera, In Proceedings of Robotics: Science and Systems (2007).
58. E. Eade, T. Drummond, Edge landmarks in monocular SLAM, Image and Vision Computing, 27, (2009) 588-596.

Zheyuan Lu is currently a doctoral candidate at Kumamoto University since October 2006. He received his B.Eng degree from Beijing Institute of Technology University, China in 2004, and his M.Eng. degree from Kumamoto University, Japan, in Aug 2006. His current research interests are sensor fusion based objects detection and tracking in dynamic outdoor environments.

Zhencheng Hu received his B.Eng degree from Shanghai Jiao Tong University, China in 1992, and his M.Eng. degree from Kumamoto University, Japan, in 1998. He received his Ph.D. degree in System Science from Kumamoto University, Japan, in 2001. Dr. Hu has held various positions in computer science and machine vision industry. He is currently an associate professor with the Department of Computer Science, Kumamoto University, Japan. His research interests include camera motion analysis, augmented reality, machine vision applications in industry and ITS. Dr. Hu is a member of IEEE, and the Institute of Electronics and Information Communication Engineers of Japan (IEICE).

Keiichi Uchimura received the B. Eng. and M. Eng. degrees from Kumamoto University, Kumamoto, Japan, in 1975 and 1977, respectively, and the Ph. D. degree from Tohoku University, Miyagi, Japan, in 1987. He is currently a Professor with the Department of Computer Science, Kumamoto University. He is engaged in research on intelligent transportation systems, and computer vision. From 1992 to 1993, he was a Visiting Researcher at McMaster University, Hamilton, ON, Canada. Dr. Uchimura is a Member of the Institute of Electronics and Information Communication Engineers of Japan (IEICE).