2008 IEEE International Conference on
Robotics and Automation
Pasadena, CA, USA, May 19-23, 2008

SLAM in a Dynamic Large Outdoor Environment using a Laser Scanner

Huijing Zhao, Masaki Chiba, Ryosuke Shibasaki, Xiaowei Shao, Jinshi Cui, Hongbin Zha

Abstract— **In this research, we propose a method of SLAM in a dynamic large outdoor environment using a laser scanner. Focus are cast on solving two major problems: 1) achieving global accuracy especially in non-cyclical environment, 2) tackling a mixture of data from both dynamic and static objects. Algorithms are developed, where GPS data and control inputs are used to diagnose pose error and guide to achieve a global accuracy; Classification of laser points and objects are conducted not in an independent module but across the processing in a framework of SLAM with moving object detection and tracking. Experiments are conducted using the data from two test-bed vehicles, and performance of the algorithms are demonstrated.**

I. INTRODUCTION

Advanced driver assistance system (ADAS) technologies have been studied extensively to assist cars or drivers intelligently. One of the most important tasks of ADAS is for cars to understand the state of both itself and its environment. Many research efforts have shown the possibility of detecting and tracking objects at the front of the car, using a video camera [17,18], a laser scanner [15,16], or a sensor fusion [12]. This is reasonable and efficient when a car drives on a straight path. In a complicated environment, such as an intersection in a downtown area, Wender [13] masked a ROI (region of interest) using a CAD map and, detected and tracked objects insides specified regions.

Our final goal is to enhance driver safety in a dynamic and unstructured large environment, where the intelligent vehicle might be close to other moving objects, so that high accuracy is required for understanding the situation of each object. We want to detect the moving objects in the surroundings, and track their states, such as speed, direction, and size, so that dangerous situations can be predicted. We also want to generate a map of global accuracy, and locate our vehicle on it. This is a particularly challenging problem. There could be two situations. For an unexplored environment, we might have to do all the things simultaneously, i.e. detect and track moving objects with simultaneous localization and mapping (SLAM). For a previously explored environment, a map could be used to improve the accuracy and efficiency for localization and moving objects' detection/tracking. However this relies on that a clear and accurate map of the dynamic environment has already been generated.

This work is partially supported by JSPS Grants-in-Aid for Scientific Research [19300067], 863 Grant [2007AA11Z225], and PKU 985-II Project.

H.Zhao, J.Cui and H.Zha are with the State Key Lab of Machine Perception, Peking University; M.Chiba is with the Technical Research Center, Mazda Motor Corporation; R.Shibasaki and X.Shao, are with the Center for Spatial Information Science, University of Tokyo. {zhaohj}@cis.pku.edu.cn

In this research, we propose a method of SLAM with simultaneous detection and tracking of moving objects using a laser scanner in a dynamic environment. The greatest difficulty here is the achievement of global accuracy in SLAM and to tackle a mixture of data from dynamic and static objects. We will first discuss the major problems below, then outline the approach of our research.

A. Problem Statement

1) SLAM in general: The simultaneous localization and mapping (SLAM) problem has been widely studied for decades. In addition to the problem of SLAM been theoretical formulated, many research efforts have demonstrated its implementation in a number of different domains, such as indoor, outdoor, underwater and airborne systems. A good tutorial to SLAM was given by Durrant-Whyte and Bailey [1,2], which could be a good start to learn SLAM from its history, achievement, key problems and its future. A broad survey can also be found in Thrun [3].

The problem of simultaneous localization and mapping can be formulated as the following probabilistic form, (refer [1] for details)

$$p(x_k, m | z_{0:k}, u_{0:k}) \tag{1}$$

where, given a sequence of observation $z_{0:k}$, a sequence of control inputs $u_{0:k}$, the objective is to generate a map (m) of the surrounding environment, and simultaneously locate vehicle's pose x_k at m.

The SLAM problem could be parsed on Baye's rule as follows.

$$\begin{aligned} \propto \quad & p(z_k|x_k, m) \times \\ & \int p(x_k|x_{k-1}, u_k) \cdot p(x_{k-1}, m|z_{0:k-1}, u_{0:k-1}) dx_{k-1} \end{aligned} \tag{2}$$

Here, $p(x_k|x_{k-1}, u_k)$ is the vehicle's motion model, and describes the probability for a state transition. $p(z_k|x_k, m)$ is the observation model (also called likelihood function), and describes the probability of making an observation z_k when a vehicle's pose x_k and a map m of the environment is known.

The SLAM problem could be solved practically as incrementally looking for a vehicle pose of the maximal probability [7],

$$\begin{aligned} x_k = \arg\max_{x_k^-} \{ & p(z_k|x_k^-, \hat{m}(x_{1:k-1}, z_{1:k-1})) \times \\ & p(x_k^-|x_{k-1}, u_k) \} \end{aligned} \tag{3}$$

while map $\hat{m}(x_{1:k}, z_{1:k})$ is considered as an integration of observations $z_{1:k}$ along vehicle poses $x_{1:k}$. In order for the discrimination, x_k^- denotes a pose prediction based on the vehicle's motion model, and x_k denotes the posterior of pose at time k.

Map consistency could be achieved through the above formulation, as an observation model confines a match between the observation and a map. A limitation exists in that there is no guarantee for the global (or absolute) accuracy in recovered vehicle pose and the map. Distortion could occur due to the featureless environment, error accumulation, and so on. This is crucial when fusing the result with a CAD map or other data resources.

2) Loop Closure: When the vehicle returns to a previously mapped region, a problem occurs in which a newly estimated location of landmarks do not match with previous ones. Loop closure is used to associate the landmarks in a current measurement with those in a map database, so that to correct vehicle pose and subsequently the map. When facing a large pose error, e.g. after a large loop, or in a cluttered unknown environment, data association become much harder. An incorrect data association could cause a catastrophic failure of the SLAM. Loop closure is finally data association problem. Many research efforts have focused on improving the accuracy of data association, e.g. batch gating[4] and visual appearance[5,6,9], or reduce the risk in erroneous ones, e.g. multiple hypothesis[7].

However, when applying SLAM in a large outdoor environment, the vehicle may traverse through complicated road situations. Requirements of cyclic measurement, and of limited loop size are strong restrictions to real applications. Besides data association based solutions, the vehicle needs a different mean, to diagnose its pose error, and to guarantee an error bound, even though its trajectory does not cross after a long trip.

3) Dynamic Environment: Most of the existing SLAM methods assume that the environment is static. If there is a moving object, and the data is erroneously associated with a landmark in the map database, many localization algorithms will fail, and the map will deteriorate by the data of the moving object. If we can discriminate the data of a moving object from those of static ones, the problem could be solved, as we can send only the data of static objects to SLAM. However, data discrimination is the key, and in fact is the greatest obstacle for applying SLAM to a dynamic environment.

Assuming a previously generated map, Montemerlo [10] and Schulz [11] localized a robot's pose on map, and tracked dynamic objects in the environment. This is efficient when the robot traverses in a controllable environment. The problem could be solved in two subsequent steps. First, generate a clear and complete a map when the environment is free of dynamic objects. Secondly, localize the robot on a given map and simultaneously track the moving objects in the surroundings. Moving object detection here could be reliably achieved by taking the differential of each scan with the map. However in an environment that can not be intentionally controlled, e.g. in a downtown area where people and cars always exist, a SLAM here must manage moving objects: the data of moving objects can be detected and tracked, or discarded, but they can not be added to the map. Hahnel [7] aimed to generate an accurate map, while the data from dynamic objects are detected and discarded. In their approach, a routine is conducted to detect and remove the data from dynamic objects before sending each scan to the SLAM module. Moving people are filtered out by using the local minimal caused by legs, and subsequently creates a difference map between consecutive scans to remove those static but people-like objects. Vu [21] and Weiss [22] did on-line calculation of an occupancy map, and detected the objects that entered an object-free zone. This idea can be traced to the pioneering work of Wang [8]. Here the basic idea is, if an object is observed at the space that defined as "object-free" by previous scans, it must be a moving one. However, if an object appear, or even move, at a previously undeveloped zone, it is difficult to say whether it is static or moving according to the rule. In addition, laser hits are affected by the reflections from target objects. It has many uncertainties. For example, a black object or an object giving diffused reflection might difficult to be observed from laser hits; if the incidence angle of laser beam is shallow, the object might be invisible in laser hits even it is near to the sensor; etc. It is hard to reliably define an occupancy map only according to laser hits. In order to discriminate a moving or static object, a classification routine is required based on the object's history record.

B. Outline of the Method

In this research, we propose a method of SLAM with simultaneous detection and tracking of moving objects in a dynamic large outdoor environment using a laser scanner for perception. In order to achieve a map of global accuracy, especially when the vehicle does a non-cyclical measurement in a large outdoor environment, we propose a trajectory-oriented closure algorithm using occasionally available GPS signals, where GPS measurements are used to diagnose the error in vehicle pose estimation, vehicle trajectory is adjusted to close the gap between the estimated vehicle pose and GPS measurement. On the other hand, in order to manage the mixture of data from both dynamic and static objects, a systematic framework is designed, and examined through real experiments. In a normal populated environment, it is not reasonable to suppose a dynamic object moves all the time. For example, people or cars may remain static for seconds when they wait for traffic signals. In addition, people and cars at intersections or parking lots might get very close to each other, and thus it is risky to define moving or static objects by buffering an area using a data from other survey technologies at a previous time point. The general idea of our system is that for all clusters of a laser scan, we consider them at the beginning as the measurement to the objects of unknown class (called "seed"). Classification of the clusters is not an independent module, but across the procedures in each iteration. Moving or static objects are detected by examining

the seeds on their history of states, e.g. motion vector and shape, so that our method can also be referred to as a delayed mapping and tracking. In order to give a thorough explanation to our system, section 2 describes the framework of SLAM with simultaneous detection and tracking of moving objects using a laser scanner. The localization and trajectory-oriented closure algorithm using GPS measurements will be addressed in section 3. We show experimental results and includes a discussion in section 4, followed by conclusion and future works.

II. SLAM WITH MOVING OBJECT DETECTION AND TRACKING

The problem of SLAM with moving object detection and tracking is formulated as follows.

$$p(x_k, y_k, s_k, m | z_{0:k}, u_{0:k}) \tag{4}$$

where, y denotes the moving object, s are those of unknown class (seed). It can be further parsed based on the Baysian rule, if each of the posterior could be analytically solved.

$$p(s_k|x_k, m, z_{0:k}) \cdot p(y_k|x_k, z_{0:k}) \cdot p(x_k, m|z_{0:k}, u_{0:k}) \tag{5}$$

A measurement z_k is a mixture of the data from static, moving, seed, and newly detected objects. If the mixture can be classified as follows,

$$z_k = \{z_k^{(m)}, z_k^{(y)}, z_k^{(s)}, z_k^{(n)}\} \tag{6}$$

an estimate to Equ.5 can be achieved sequentially as follows.

$$x_k = \arg\max_{x_k^-} \{p(z_k^{(m)}|x_k^-, m_{k-1}) \cdot p(x_k^-|x_{k-1}, u_k)\} \tag{7}$$

$$y_k = \arg\max_{y_k^-} \{p(z_k^{(y)}|x_k, y_k^-) \cdot p(y_k^-|y_{k-1})\} \tag{8}$$

$$s_k^- = \arg\max_{s_k^-} \{p(z_k^{(s)}|x_k, s_k^-) \cdot p(s_k^-|s_{s-1})\} \tag{9}$$

$$m_k = \hat{m}(x_{1:k}, z_{1:k}^{(m)}) \tag{10}$$

For the measurements that could not be associated with an existing map, any of the moving objects or seeds, new seeds are generated for each as the newly detected objects, so that

$$s_k^+ = newseed(z_k - z_k^{(m)} - z_k^{(y)} - z_k^{(s)}) \tag{11}$$

$$s_k = s_k^+ + s_k^- \tag{12}$$

However things are not so easy, as dividing z_k into $z_k^{(m)}$, $z_k^{(y)}$, $z_k^{(s)}$, $z_k^{(n)}$ is much difficult. Erroneously classifying a measurement will cause incorrect data association, so that it leads to a failure in the system.

Figure 1 shows the framework implemented in our system. The figure looks trivial. However we consider that technical details are always very important to ensure that a new technique can be applied to real situations. Three modules are highlighted in the figure.

1) Module A: is the estimation of vehicle pose x_k, which will be discussed in detail in the next section.

2) Module B: describes the sequential procedure of dividing z_k into $z_k^{(m)}$, $z_k^{(y)}$, $z_k^{(s)}$ and $z_k^{(n)}$. In order to prevent interference from the data of moving objects in SLAM, $z_k^{(y)}$ are first extracted through data association based on the prediction of existing moving objects y_{k-1}^- and vehicle pose x_{k-1}^-. SLAM is conducted by matching the measurement to motionless objects $\{z_k - z_k^{(y)}\}$ with a local map covering the region near x_{k-1}^-, which is a cut out from $\hat{m}(x_{1:k-1}, z_{1:k-1}^{(m)+(s)})$, containing the data of both static and unknown objects (seed). So that estimation of vehicle pose x_k is implemented as follows.

$$x_k = \arg\max_{x_k^-} \{p(z_k - z_k^{(y)}|x_k^-, \hat{m}(x_{1:k-1}, z_{1:k-1}^{(m)+(s)})) \cdot p(x_k^-|x_{k-1}, u_k)\} \tag{13}$$

With vehicle pose x_k, through subtraction with map m_{k-1}, $z_k^{(m)}$ are extracted, leaving seeds $z_k^{(s)}$ and newly measured objects $z_k^{(n)}$ at rest.

3) Module C: classifies seeds at the end of each iteration. Classification is conducted for each seed by examining its history of motion and shape. Our implementation is shown in figure 2. It is an extension to our previous work that uses a stationary laser scanner to monitor moving objects at an intersection [19], where moving objects are defined into three classes, i.e. 0-axis (e.g. people), 1-axis (e.g. bicycle), 2-axis (e.g. car), according to the maximal axes number that could be detected from an instant measurement of the object. In order to prevent that a temporarily motionless object be misrecognized as a static one, we did very carefully when the seed is still alive, i.e. be measured by the laser scanner.

For a still alive seed, if an obvious and continuous motion is detected, it is upgraded to the data base of moving objects; if its shape is obviously different with predefined models, e.g. much larger than any possible moving objects, it is added to map if no motion is detected in its history, or it is discarded as irregular data, e.g. reflections from the ground which always happen when the vehicle makes a turn and its platform slants toward the ground surface.

For an expired seed, we need to explain some trade offs. Many seeds might get lost before being recognized as moving or static objects, e.g. exit the measurement range of the moving laser scanner. Some of them are static objects that should be integrated into map. Some of them are dynamic but without enough evidence to distinguish them. These data could not be added to the map. Some are wrongly extracted seeds, which should be discarded. However, if a car or a people remain static during the measurements, it is difficult to discriminate them with other similar static objects, e.g.

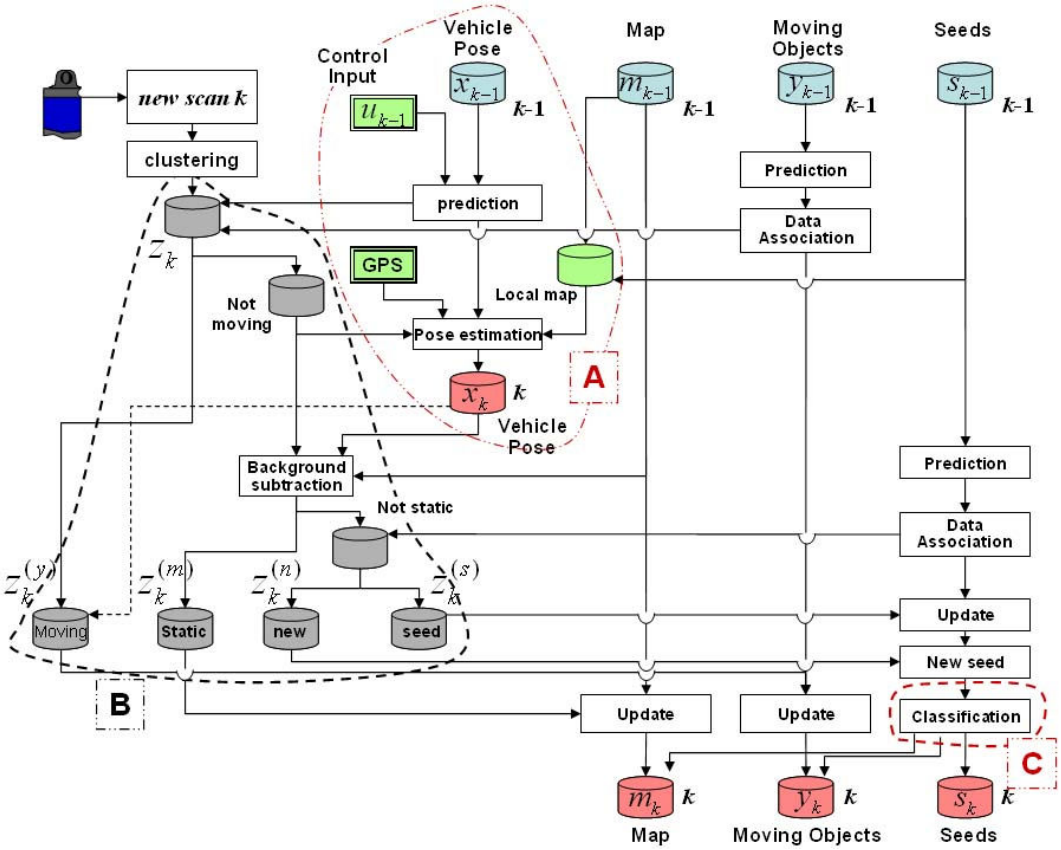

Fig. 1. Implementation of SLAM with moving objects' detection and tracking

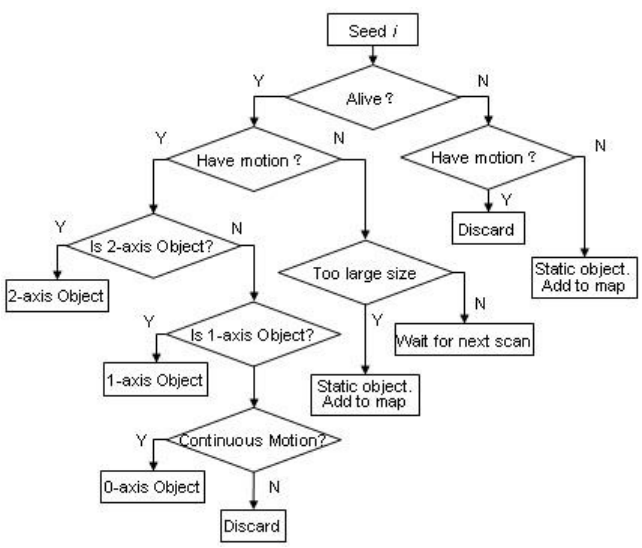

Fig. 2. Implementation of the classification module

tree, pole, small square objects, etc. In this research, we add the seeds to map if they remain static during their life. We are going to integrate visual-based methods to solve the above problem in a future study.

III. LOCALIZATION GUIDED BY GPS DATA AND CONTROL INPUTS

A. Outline of the Localization Algorithm

The processing in Figure 3 corresponds to module A of Figure 1. It describes the flow of estimating vehicle pose x_k, where a scan matching is to achieve local consistency of the map, control inputs u_k and GPS data are used to detect pose error and to achieve global accuracy. In this research, control inputs are vehicle speed and yawrate sensor. Normally, control inputs are used to predict a vehicle pose x_k^-, which is then updated by maximizing a matching between observation z_k and map m_{k-1}, as defined in Equ.3. This is a biased definition. Its efficiency relies heavily on whether the geometric relationship between z_k and m_{k-1} could be uniquely defined. So that an independent diagnosis method is required to detect erroneous scan matching. In this research, we previously train a threshold vector α, which represents the error bound of control inputs. We convert $\Delta x_k = x_k - x_{k-1}$ to speed and yawrate ($u_k^{(m)}$), and take the difference with u_k. If the difference is beyond α, than x_k is replace using the predicted state x_k^-. An example of training α can be seen in the next section. On the other hand, whenever a pair of continuous GPS coordinates with good signal conditions are measured, a vehicle pose $x_k^{(gps)}$ could be calculated based on the GPS coordinates. If the difference with x_k is larger than a previously defined threshold β, which represents

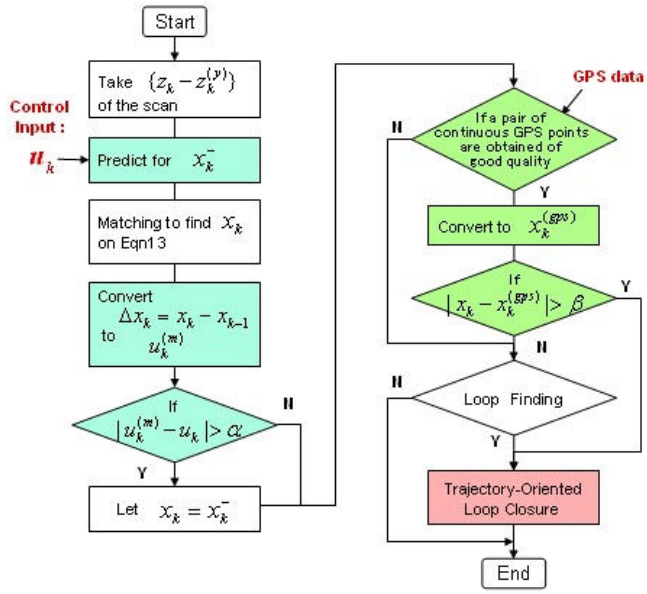

Fig. 3. Flow of localization algorithm, corresponding to the Module A of figure 2

the error bound of GPS measurement, a trajectory-oriented closure is conducted to meet the trajectory's end point x_k to the GPS measurement $x_k^{(gps)}$, while maintaining the local consistencies of the trajectory. The same algorithm is used when a trajectory crosses at a certain point. A $x_k^{'}$ is estimated by matching the current scan with a previously generated map, and the trajectory-oriented closure is conducted to meet x_k to $x_k^{'}$, while maintaining the local consistencies of the trajectory.

B. Trajectory-Oriented Closure Algorithm

In this section, we discuss vehicle pose x_k using the form of a transformation matrix T_k from the vehicle (or laser scanner)'s coordinate system to a global one, while relative vehicle motion is represented as the relative transformation of a vehicle's coordinate system, $t_{ij} = T_i^{-1} \cdot T_j$. Normally, t_{ij} has better local consistencies, and could reflect the local features of sensor' motion in detail. However T_k has an absolute drift due to the error accumulation of t_{ij}s. Let T_k' represents the transformation matrix of $x_k^{(gps)}$ or $x_k^{'}$. Given a history of trajectory nodes $T_{s,\ldots,k}$, if $|T_k - T_k'| > E_T$, a loop closure is conducted by adjusting each $t_{i,i+1}, s < i < k$ iteratively until $|T_k - T_k'|$ is smaller than a given threshold or can no longer be minimized,

In each iteration j, a $\Delta t_{i,i+1}^j$ is calculated for each $t_{i,i+1}^j, s < i < k$, and $t_{i,i+1}^j$ is updated as follows.

$$\begin{aligned} \Delta t_{i,i+1}^j &= \frac{1}{k-s} \cdot {t_{i+1,i+2}^j}^{-1} \ldots {t_{k-1,k}^j}^{-1} \cdot \\ & \quad T_k' \cdot T_s^{-1} \cdot {t_{s,s+1}^j}^{-1} \ldots {t_{i-1,i}^j}^{-1} \\ t_{i,i+1}^{j+1} &= \Delta t_{i,i+1}^j \cdot t_{i,i+1}^j \end{aligned} \tag{14}$$

Denote $\bar{t}_{i,i+1}$ and $\bar{T}_m$ as the rectified $t_{i,i+1}$ and T_m respectively. $\bar{T}_m, s < m \leq k$ are obtained by sequentially aligning $\bar{t}_{i,i+1}s, s < i < m$ as follows.

$$\begin{aligned} \bar{T}_m &= \bar{T}_{m-1} \cdot \bar{t}_{m-1,m} \\ &= \bar{T}_s \cdot \bar{t}_{s,s+1} \cdot \ldots \bar{t}_{i,i+1} \ldots \cdot \bar{t}_{m-1,m} \end{aligned} \tag{15}$$

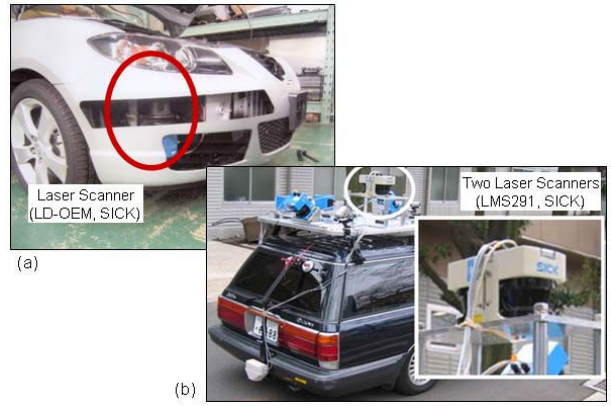

Fig. 4. Pictures of two test-bed vehicles

IV. EXPERIMENTAL RESULTS

We have developed two test-bed vehicles. Test-bed #1 (Figure 4(a)) is for the purpose of developing the technical components and algorithms for safe driving, where two laser scanners, LD-OEM by SICK, are mounted on both left and right front of the car, monitoring an omni-area of the vicinity. A video camera is mounted in between the laser scanners. In this research, we use the video camera to examine and visualize the results of laser-based processing, while in future, we are going to fuse both sensors to achieve higher intelligence and accuracy. Test-bed #2 (Figure 4(b)) is a mobile mapping system, for the purpose of generating a three-dimensional representation of large outdoor environment from the viewpoints on the street. Two horizontally scanning laser scanners, LMS291 by SICK, on the top layer of the sensor system, are used to achieve high accurate localization. Both systems have a GPS, a vehicle motion sensor (or wheel encoder) and a FOG-IMU. Although the final purpose of the systems are different, both require a SLAM that tackling moving objects, and both require a SLAM that has global accuracy in an extensive outdoor environment. In the followings, we discuss some of the experimental results focusing on these two aspects.

A. SLAM with Moving Object Detection and Tracking

Figure 5 shows a result sequence of SLAM with moving object detection and tracking using the data from test-bed #1. Each result is composed of two screen captures. The right one shows the processing of laser data, the left one is the overlapping of the laser-based result onto a video image for better understanding and visualization. Laser scans are processed at a rate of 10Hz. The number shown at the right bottom corner denotes for frame (scan) number. At the start of measurement (see Frm#090), a car in front of the

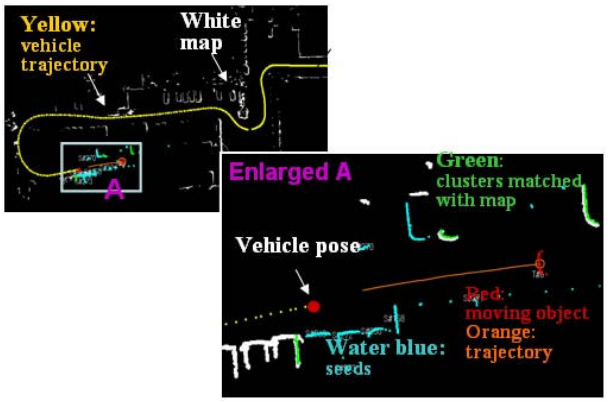

Fig. 6. Definition of the different colors of laser points

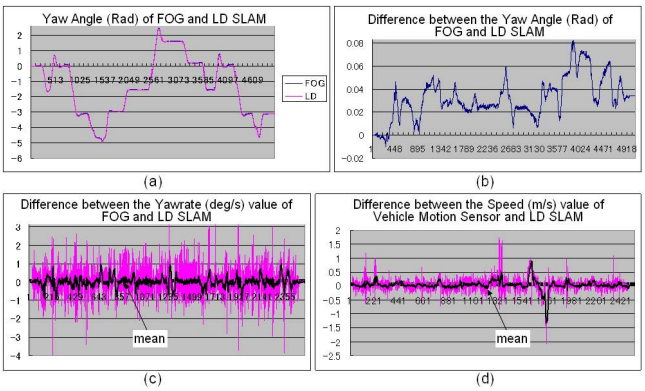

Fig. 8. Comparison of the values of control inputs with those from LD SLAM

test-bed vehicle, as well as other static object nearby, were measured. Two large piece of wall were recognized soon as static objects (green points are those in current scan and recognized as static data), because no motion was detected from them, and their size exceeded the model of normal moving object. While for other objects, although no motion was detected, they may be either static or moving objects, so that they were treated as seed (water blue). The definition of the different colors are explained in Figure 6. When the front car began to move, after a few frames (see Frm #98), it was proved to be a moving object (red with orange trajectory). At about Frm#262, the front car began to make a left turn, and it was soon got lost at Frm#289. When the front car appeared again at Frm#321, it was treated as a seed at the beginning, then after a few frames, it was recognized as a moving object again (see Frm#330). Later the front car made a turn again, and it was lost from the video image, while still measured and tracked by the laser scanner (see Frm#417). When the car entered the video image, it was directly located as a moving object using the laser-based result (see Frm#426).

Figure 7 gives some of the final results. Figure 7(a) shows the map and the trajectory of the test-bed vehicle that was recovered by the algorithm. The experiment was conducted where many cars were parked in the surrounding area (see Figure 7(c,d)). It is a difficult question, whether we should leave the data of parked cars in the map. A parked car is a temporarily static object. Some of them might start to move suddenly, while most of them remain static during the period when they are measured. In this research, we made a rule that if motion could be reliably detected from an object at any time during the measurement, it was considered as a moving one. Otherwise, we treated it as static and integrated its data into the map. Figure 7(b) shows a labeling result, where colored points are those labeled to as moving objects, and color denotes for different ID. As has been discussed in Figure 5, the front car was lost when it made turns. When it appeared again, it was detected as a new object and assigned a different ID.

B. Localization Guided by GPS data and Control Inputs

In the algorithm of Figure 3, control inputs are used to diagnose and correct pose error, while the GPS data with good signal conditions, are used to guide for global accuracy, especially when cyclic measurement is not available. Two threshold vectors in Figure 3, α and β, need to be defined previously.

Here we present how we define the threshold vectors α. In an environment of rich feature/landmarks, pose geometry could be uniquely decided with high accuracy. In this research, we did a traditional SLAM (e.g. [20]) at an environment of horizontal ground and rich geometrical features, obtained a time series of vehicle pose , and subsequently converted them into a time series for speed and yawrate (denote these data as LD SLAM). Figure 8 shows comparisons of the control inputs, yawrate and yaw angle from FOG-IMU, speed from vehicle motion sensor, with the values by LD SLAM. It can be found in Figure 8(a) that the yaw angles from FOG match the LD SLAM in general, while by taking a difference between them, a tendency of gradually enlarged residual is obvious (Figure 8(b)). This is an often seen phenomenon, called Gyro drift. On the other hand, the residuals between yawrate demonstrate a uniform distribution, within [-2,2](deg/s) (Figure 8(c)). Similarly, the residuals between speed are mostly bound within [-0.5,0.5](m/s) (Figure 8(d)). Thus, the pose updates with residuals beyond the above ranges are detected and disregarded.

In this research, the GPS data quality above 2m were used to diagnose pose error, so that β is assigned to 2m. Figure 9 demonstrates the performance of localization at an extensive outdoor environment, the global accuracy of which is guided by the occasional good GPS measurements. Red dots denote for the GPS data of good qualities. They are selected to perform a trajectory-oriented closure to meet the vehicle pose to GPS coordinates. Green dots are the time series of vehicle pose. For comparison, blue dots represent the results without GPS adjustment.

C. Time Cost

The experiment is conducted on an off-line mode. After acquiring data from the test-bed vehicles, the experiment in

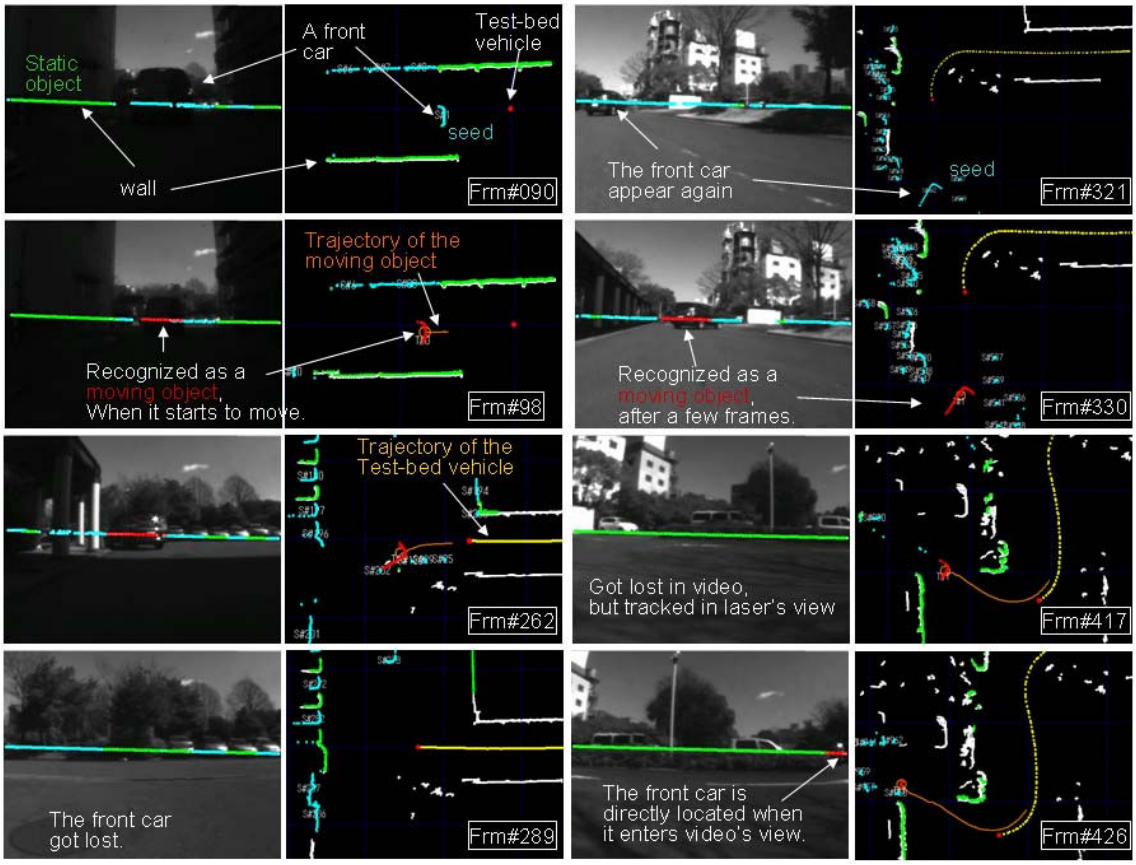

Fig. 5. Experimental results of SLAM with moving object detection and tracking

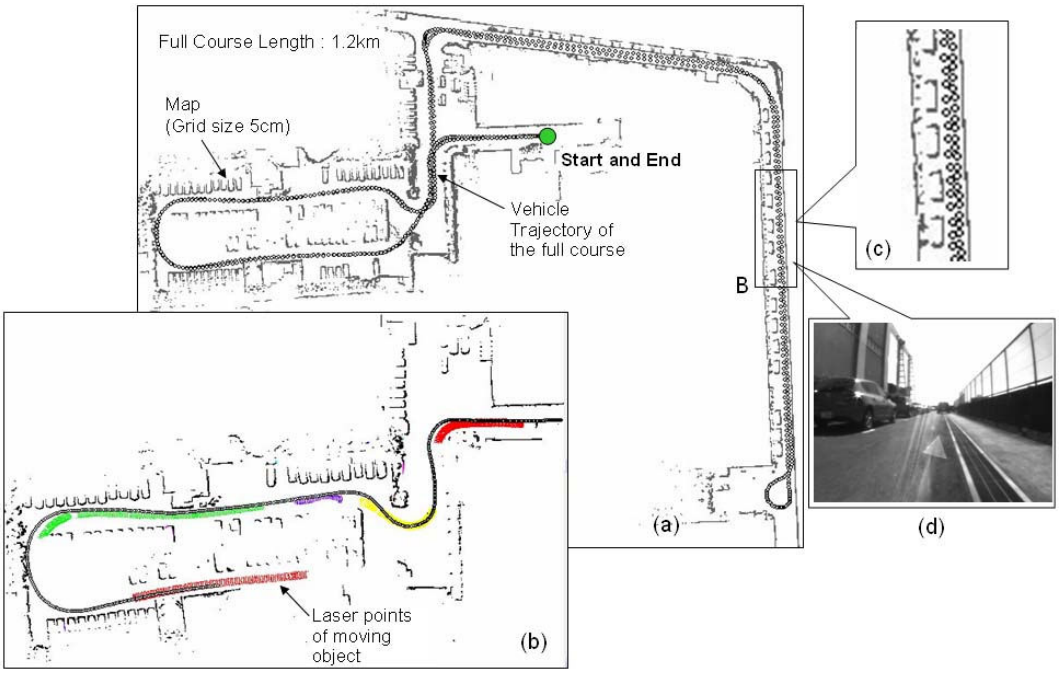

Fig. 7. Final results of map generation, localization and laser points labeling

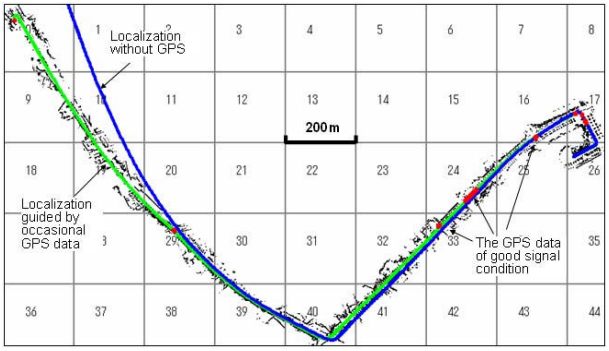

Fig. 9. Results of the localization guided by occasional GPS coordinates

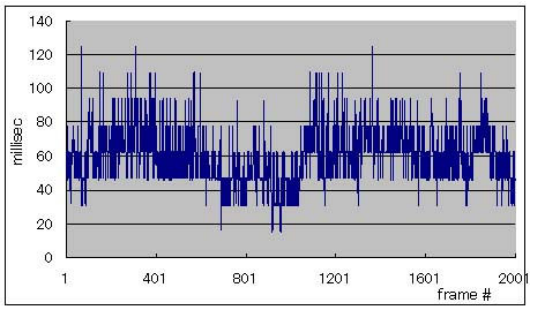

Fig. 10. Computation cost of each frame

Figure 5-7 is conducted using the data from one laser scanner that covering a range of 200 deg with an angular resolution of 0.25deg. When processing on a desktop PC that has a 1.8GHz CPU and 2.0GB RAM, the computation cost of each frame is demonstrated in Figure 10, with an average of 64 millisec per frame. Considering the laser scanning rate of 10Hz, a real-time processing would be available.

V. CONCLUSIONS AND FUTURE WORKS

In this research, we propose a method of SLAM in a dynamic large outdoor environment using a laser scanner. Focus are cast on solving two major problems: 1) achieving global accuracy especially in non-cyclical environment, 2) tackling a mixture of data from both dynamic and static objects. Algorithms are developed, where GPS data and control inputs are used to diagnose pose error and guide to achieve a global accuracy; Classification of laser points and objects are conducted not in an independent module but across the processings in a framework of SLAM with moving object detection and tracking. Experiments are conducted using the data from two test-bed vehicles, and performance of the algorithms are demonstrated.

There are still many research tasks left. A major limitation of the proposed method is that if a moving object remain static during the measurement, it is almost impossible to discriminate it with the static one that has a similar shape at the scanning plane. In addition, many static objects are tracked as seed all through their measurement. This is not efficient, especially when simultaneously processing the data from a number of laser scanners, the time cost will be very high. Integrating visual-based methods will be a good solution for both of the problems. This will be addressed in our future study.

REFERENCES

[1] Durrant-Whyte, H., Bailey, T., "Simultaneous localization and mapping : Part I" *IEEE Robotics & Automation Magazine*, vol.13, issue 2, pp.99-108, 2006.

[2] Bailey, T., Durrant-Whyte, H., "Simultaneous localization and mapping : Part II" *IEEE Robotics & Automation Magazine*, vol.13, issue 3, pp.108-117, 2006.

[3] Thrun, S., et al., "FastSLAM: An efficient solution to the simultaneous localization and mapping problem with unknown data association" *Journal of Machine Learning Research (to appear)*, available at http://www.thrun.org/papers/Thrun03g.html.

[4] Bailey, T., "Mobile robot localisation and mapping in extensive outdoor environment," *Ph.D. dissertation*, Univ. Sydney, Australian Ctr. Field Robotics, 2002.

[5] Newman, P., Cole, D., Ho, K., "Outdoor SLAM using visual appearance and laser ranging," *Proc. IEEE Int. Conf. Robotics Automation*, 2006.

[6] Ramos, F. T., Nieto, J., Durrant-Whyte, H.F., "Recognising and modelling landmarks to close loops in outdoor SLAM" *Proc. IEEE Int. Conf. Robotics Automation*, pp.2036-2041, 2007.

[7] Hahnel, D., Burgard, W., Fox, D., Thrun, S., "An efficient FastSLAM algorithm for generating maps of large-scale cyclic environments from raw laser range measurements" *Proc. Conf. on Intelligent Robots and Systems*, 2003.

[8] Wang, C. C., C. Thorpe, "Simultaneous localization and mapping with detection and tracking of moving objects" *Proc. IEEE Int. Conf. on Robotics and Automation (ICRA), Washington, DC*, 2002.

[9] Burgard, W., et al. "Experiences with an interactive museum tour-guide robot" *Artificial Intelligence*, Vol. 114, Issues 1-2, pp.3-55, 1999.

[10] Montemerlo, M., Thrun, S., Whittaker, W., "Conditional particle filters for simultaneous mobile robot localization and people-tracking (slap)" *Proc. IEEE Int. Conf. Robotics Automation*, Vol. 1, pp.695-701, 2002.

[11] Schulz, D., et al., "People tracking with a mobile robot using sample-based joint probabilistic data assiciation filters" *Int. Journal of Robotics Research (IJRR), 22(2)*, 2003.

[12] Kaempchen, N., Dietmayer, K. C. J., "Fusion of laserscanner and video for advanced driver assistance systems" *IEEE Int. Conf. on Intelligent Transportation System*, 2004.

[13] Wender, S, Weiss, T., Fuerstenberg, K., Dietmayer K. C. J., "Object Classification exploiting High Level Maps of Intersections" *Proc. Advanced Microsystems for Automotive Applications*, 2006.

[14] Howard, A., Wolf, D.F., Sukhatme, G.S., "Towards 3D mapping in large urban environment" *Proc. Conf. on Intelligent Robots and Systems*, pp.419-424, 2004.

[15] Streller, D., Dietmayer, K., "Object tracking and classification using a multiple hypothesis approach" *IEEE Image Understanding Workshop*, 1998.

[16] Mendes, A., Nunes, U., "Situation-based multi-target detection and tracking with laserscanner in outdoor semi-structured environment" *Proc. Conf. on Intelligent Robots and Systems*, 2004.

[17] Yu, Q., Araujo, H., Wang, H., "A stereovision method for obstacle detection and tracking in non-flat urban environments" *Autonomous Robots*, vol.19, no.2, pp.141-157, 2005.

[18] Broggi, A., Caraffi, C., Porta, P., Zani, P., "The single frame stereo vision system for reliable obstacle detection used during the 2005 DARPA grand challenge on TerraMax" *IEEE Intelligent Transportation System Conference*, pp.745-752, 2006.

[19] Zhao, H., Shao, X., Katabira, K., Shibasaki, R., "Joint tracking and classification of moving objects at intersection using a single-row laser range scanner" *IEEE Intelligent Transportation System Conference*, pp.287-294, 2006.

[20] Zhao, H., Shibasaki, R., "A vehicle-borne urban 3D acquisition system using single-row laser range scanners" *IEEE Trans. SMC Part B: Cybernetics*, 33-4, 658-666, 2003.

[21] Weiss, T., Schiele, B., Dietmayer, K., "Robust Driving Path Detection in Urban and Highway Scenarios using a Laser Scanner and Online Occupancy Grids"

[22] Vu, T., Aycard, O., Appenrodt, N., "Online Localization and Mapping with Moving Object Tracking in Dynamic Outdoor Environment"