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 inside 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.

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)

\[ p(x_k, m|z_{0:k}, u_{0:k}) \]  \hspace{1cm} (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.

\[ \propto p(z_k|x_k, m) \times \]  \hspace{1cm} (2)

\[ \int p(x_k|x_{k-1}, u_k) \cdot p(x_{k-1}, m|z_{0:k-1}, u_{0:k-1})dx_{k-1} \]

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].

\[ x_k = \arg \max_{x_k} \{ p(z_k|x_k, m(x_{1:k-1}, z_{1:k-1})) \times \]  \hspace{1cm} (3)

\[ p(x_k|x_{k-1}, u_k) \} \]

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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 and visual appearance, or reduce the risk in erroneous ones, e.g. multiple hypothesis.

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.

\[ p(x_k, y_k, s_k, m|z_{0:k}, u_{0:k}) \]  

(4)

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

\[ p(s_k|x_k, m, z_{0:k}) \cdot p(y_k|x_k, z_{0:k}) \cdot p(x_k, m|z_{0:k}, u_{0:k}) \]  

(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,

\[ z_k = \{z_k^{(m)}, z_k^{(y)}, z_k^{(s)}, z_k^{(n)}\} \]  

(6)

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

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

(7)

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

(8)

\[ s_k = \arg \max_{s_k} \{p(z_k^{(s)}|x_k, s_{k-1}) \cdot p(s_{k-1}|s_{k-1})\} \]  

(9)

\[ m_k = \hat{m}(x_{1:k}, z_{1:k}^{(m)}) \]  

(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

\[ s_k^+ = \text{newseed}(z_k - z_k^{(m)} - z_k^{(y)} - z_k^{(s)}) \]  

(11)

\[ s_k = s_k^+ + s_k^- \]  

(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 \( \{z_k - z_k^{(m)}\} \) with a local map covering the region near \( x_{k-1}^- \), which is a cut out from \( \hat{m}(x_{1:k-1}, z_{1:k-1}^{(m)}(+)\) ), 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^- \cdot \hat{m}(x_{1:k-1}, z_{1:k-1}^{(m)}(+)\) ) \cdot p(x_k|z_k, u_k)\} \]  

(13)

With vehicle pose \( x_k \), through subtraction with map \( m_{k-1} \), \( z_k^{(n)} \) 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.
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 yaw rate sensor. Normally, control inputs are used to predict a vehicle pose $x_{k-1}$, 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 $\alpha$, which represents the error bound of control inputs. We convert $\Delta x_k = x_k - x_{k-1}$ to speed and yaw rate ($u_{k}^{(m)}$), and take the difference with $u_k$. If the difference is beyond $\alpha$, then $x_k$ is replace using the predicted state $x_{k-1}$. An example of training $\alpha$ 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 $\beta$, which represents...
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 $T_{s,...,k}$, 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 $t_{i,i+1}, s < i < k$, and $t_{i,i+1}$ is updated as follows.

$$\Delta t_{i,i+1}^j = \frac{1}{k-s} \cdot (t_{i,i+1,i+2}^j - \cdots - t_{k-1,k}^j - 1) \cdot T_k' \cdot T_s^{-1} \cdot (t_{s+1}s_{s+1}^j - \cdots - t_{i-1,i}^j - 1) \cdot t_{i,i+1}^j + 1$$

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

$$T_m = T_{m-1} \cdot t_{m-1,m}$$
$$= T_s \cdot t_{s,s+1} \cdots t_{i,i+1} \cdots t_{m-1,m}$$

**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
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 detected as a new object and assigned a different ID.

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

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

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, $\alpha$ and $\beta$, need to be defined previously.

Here we present how we define the threshold vectors $\alpha$. 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 $\beta$ 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
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


