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Driving Safety and Traffic Data Collection - A Laser Scanner Based Approach

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Abstract— **This research is motivated by two potential applications - enhancing driving safety and collecting traffic data in a large dynamic urban environment. A laser scanner based approach is proposed, in which SLAM (simultaneous localization and mapping) is developed with moving object detection and tracking using a laser scanner for perception, using GPS to achieve global accuracy, and using yaw rate and wheel speed to diagnose pose errors. Experiments are conducted to collect data along a course (4.5 km) with a test-bed vehicle run in a highly dynamic environment. The algorithms are examined, possibilities with respect to the two potential applications are demonstrated, and future works are discussed.**

I. INTRODUCTION

Our goal is to use a vehicle-borne sensor to perceive a large dynamic urban environment, such as an intersection or a crowded road in a downtown area. We are motivated by two potential applications. One is enhancing driving safety, where it is important to understand the state of both the host vehicle itself and the objects in its local surroundings. The other application involves collecting detailed traffic data, such as the motion trajectories of cars, bicycles and pedestrians, for control and traffic analysis, where it is important to associate the perceptions of local surroundings to a global coordinate system, and the traffic data are required to achieve a certain level of global accuracy. In other words, if perception of local surroundings could be registered to a global coordinate system, other data sources, such as a CAD map, could be used to assign higher level attributes to the perceived data. Both tasks could be assembled together as perception in a large dynamic environment with both local and global accuracy. Here, managing the data of a large, dynamic environment and achieving both local and global accuracy are major concerns.

In order to assist cars for driving safety, research efforts have shown the possibility of detecting and tracking objects in front of the car using a stereo [17,18] or monocular video camera [21], a laser scanner [15,16,24], or through sensor fusion [12,22]. This is reasonable and efficient when a car drives on a straight path. However when facing a complicated environment, such as an intersection in a downtown area, a wide-view and high-accurate perception are required. Vu[23] and Weiss[25] did on-line calculation of an occupancy map, and detected the objects that entered an object-free zone. This idea can be traced to a pioneering work of Wang[8].

Furthermore, there have been research efforts to collect traffic data using probe vehicles. Most of them use GPS (Global Positioning System) to find the speed and trajectory of the probe vehicle, and assume these parameters could somehow reflect the current traffic situation of the road. Some probe vehicles have environmental sensors to monitor the surroundings, such as video camera, laser scanner, radar and so on, while the subsequent data processing is still a great difficulty. Gandhi [26] developed a system platform to detect, classify and log the surrounding vehicles using a video camera. Gao [27] proposed a method using a laser scanner to identify surrounding vehicles and correct GPS error.

Perceiving a large dynamic environment, while achieving both local and global accuracy is a particularly challenging problem. Three approaches suggest themselves: 1) If we suppose position and orientation of the host vehicle could be perfectly known using positioning sensors like GPS, INS (Inertial Navigation System), or odometer, then the problem could be simplified to detection and tracking of moving objects from video [26] or laser scans [25,27]. Such an approach requires an accurate (always expensive) positioning system, while the slow motion objects (e.g., pedestrians) might not be detected reliably due to positioning error. 2) If we suppose a map of the environment is known, for example through previous exploration, then the map could be used to improve the accuracy and efficiency for localization by map matching, and subsequently the data on moving objects could be detected by subtraction from the map [10,11] or by region masking [13]. However this relies on the fact that a map of the dynamic environment with high enough accuracy has already been generated. 3) We can conduct on-line localization, mapping, moving object detection and tracking simultaneously [7,8,23]. This is the most difficult, but necessary, approach when exploring an unknown environment without an expensive positioning system.

In this research, we study the third approach using a horizontally profiling laser scanner as the major sensor for both perception and localization, using GPS, a yaw rate sensor and a speed encoder to assist in achieving global accuracy and robustness. Laser-based SLAM (Simultaneous Localization And Mapping) with moving object detection and tracking in a dynamic environment is developed, where our focuses are on managing a mixture of data from dynamic and static objects and achieving global accuracy in a large, non-cyclic environment. In order to achieve knowledge of

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global accuracy, especially when the vehicle makes 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 then adjusted to close the gap between the estimated vehicle pose and GPS measurement. Furthermore, in order to manage the mixture of data from both dynamic and static objects, a systematic framework is designed, and examined through real experiments. As has been addressed above, it is not reasonable to suppose a dynamic object moves all the time, in a normal populated environment. 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 a previous survey. The general idea behind our system is that for all clusters of a laser scan, we initially consider the objects to be in an unknown class (called "seed"). Classification of the clusters is not an independent module, but it occurs across 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 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 include a discussion in section 4, followed by conclusions and directions for future work.

II. SLAM WITH MOVING OBJECT DETECTION AND TRACKING

A. Problem Statement

The simultaneous localization and mapping (SLAM) problem has been widely studied for decades. In addition to the SLAM problem been theoretically 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 provides a foundation for learning the history, achievements, key problems and the future of SLAM. A broad survey can also be found in Thrun [3]. Here, we discuss two major problems - loop closure and dynamic environment - of current SLAM techniques.

1) Loop Closure: When a vehicle returns to a previously mapped region, a problem occurs in which the newly estimated location of landmarks does not match with previous ones. Loop closure is used to associate the landmarks in a current measurement with those in a map database to correct the vehicle pose, and subsequently, the map. When facing a large pose error (after a large loop or in a cluttered unknown environment), data association becomes much more difficult. An incorrect data association could cause a catastrophic failure of SLAM. Loop closure is also a data association problem. Many research efforts have focused on improving the accuracy of data association, including batch gating[4] and visual appearance [5,6], or reducing the risk in erroneous associations, such as multiple hypothesis [7].

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

2) Dynamic Environment: Most of the existing SLAM methods assume that the environment is static. If there is a moving object, and the data are erroneously associated with a landmark in the map database, many localization algorithms will fail, and the map will be deteriorated by the data of 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.

Without assuming any prior knowledge of the environment, and that the environment is not able to be intentionally controlled(a downtown area where people and cars always exist), a routine is required to discriminate the data from moving and static objects, before sending them to SLAM or moving an object's tracking modules. Hahnel [7] filtered out moving people by using the local minimal caused by legs, and subsequently created a difference map between consecutive scans to remove those static but people-like objects. An implicit assumption here is that dynamic objects move all the time during their measurement. However this is not reasonable in normal situations, because people and cars may stop for a while. Also, a classification based only on data appearance is risk, as a standing-still people looks similar with a pole in a horizontal laser scan. Wang [8], Vu [23] and Weiss [25] did on-line calculation of an occupancy map, and detected the objects that entered an object-free space. However the method is not able to detect the moving object if it does not enter the defined object-free space (moving in the space that flagged as "occupied" or "unknown"). In particular, when an object appears in an undeveloped area, it is difficult to say whether it is a static or moving object at the moment; a classification routine is required based on the history of the record.

B. Proposed Approach

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

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

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.

$$p(s_k|x_k, m, z_{0:k}) \cdot p(y_k|x_k, z_{0:k}) \cdot p(x_k, m|z_{0:k}, u_{0:k}) \quad (2)$$

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,

$$z_k = \{z_k^{(m)}, z_k^{(y)}, z_k^{(s)}, z_k^{(n)}\} \quad (3)$$

an estimate to Equ.1 can be achieved sequentially as follows.

$$x_k = \arg\max_{x_k^-}\{p(z_k^{(m)}|x_k^-, m_{k-1}) \cdot p(x_k^-|x_{k-1}, u_k)\} \quad (4)$$

$$y_k = \arg\max_{y_k^-}\{p(z_k^{(y)}|x_k, y_k^-) \cdot p(y_k^-|y_{k-1})\} \quad (5)$$

$$s_k^- = \arg\max_{s_k^-}\{p(z_k^{(s)}|x_k, s_k^-) \cdot p(s_k^-|s_{s-1})\} \quad (6)$$

$$m_k = \hat{m}(x_{1:k}, z_{1:k}^{(m)}) \quad (7)$$

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

$$s_k^+ = newseed(z_k - z_k^{(m)} - z_k^{(y)} - z_k^{(s)}) \quad (8)$$

$$s_k = s_k^+ + s_k^- \quad (9)$$

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: discribes 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.

$$x_k = \arg\max_{x_k^-}\{p(z_k - z_k^{(y)}|x_k^-, \hat{m}(x_{1:k-1}, z_{1:k-1}^{(m)+(s)})) \cdot p(x_k^-|x_{k-1}, u_k)\} \quad (10)$$

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 mis-recognized 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 detected 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}. 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 yawrate sensor and speed encoder. We

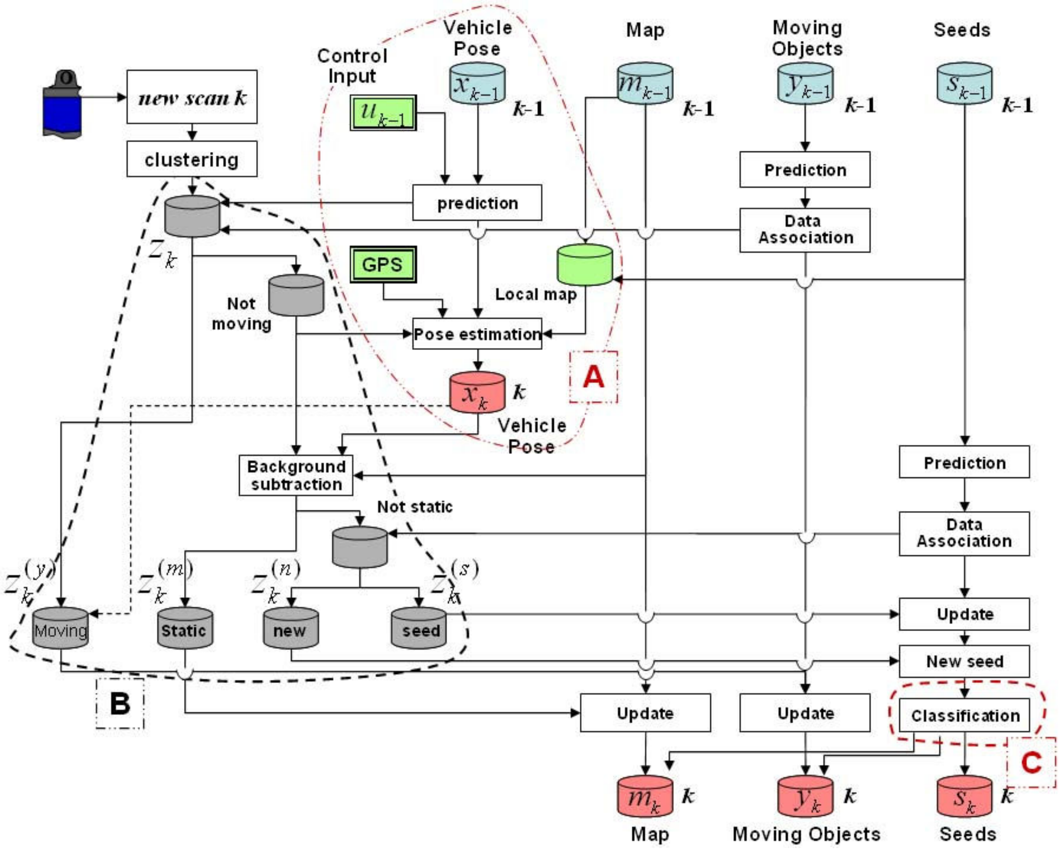

Fig. 1. Implementation of SLAM with moving objects' detection and tracking

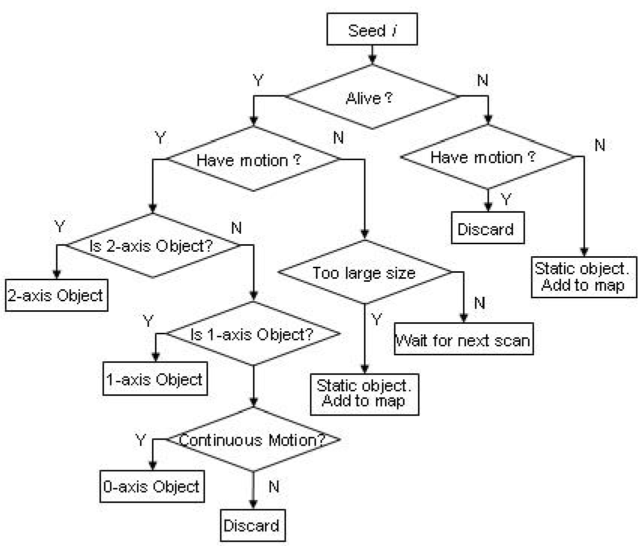

Fig. 2. Implementation of the classification module

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^-. 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 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 $t_i j$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,

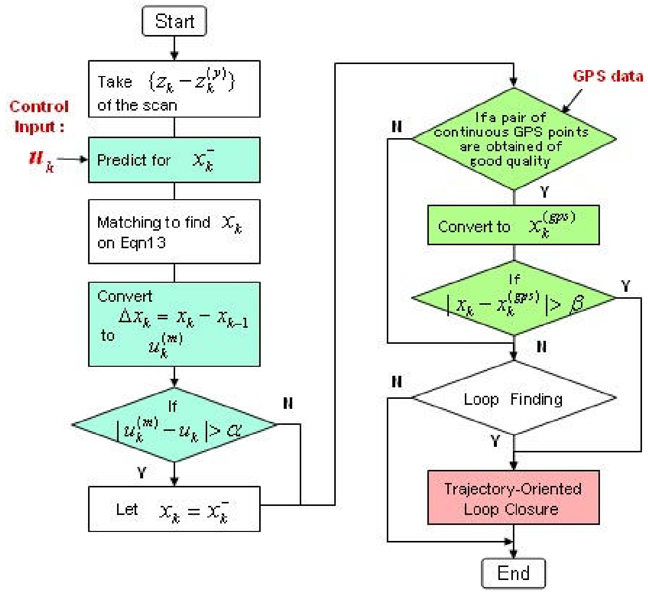

Fig. 3. Flow of localization algorithm, corresponding to the Module A of figure 2

Fig. 4. Pictures of two test-bed vehicles

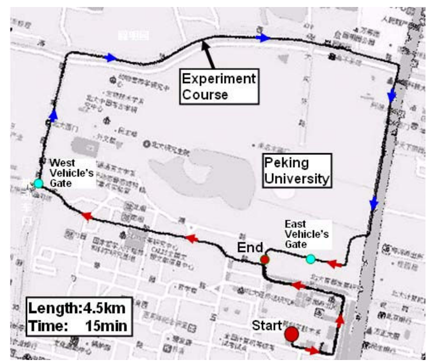

Fig. 5. Experimental Course

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

$$\begin{aligned}
\Delta t^j_{i,i+1} &= \frac{1}{k-s} \cdot {t^j_{i+1,i+2}}^{-1} \ldots {t^j_{k-1,k}}^{-1} \cdot \\
&\quad T'_k \cdot T_s^{-1} \cdot {t^j_{s,s+1}}^{-1} \ldots {t^j_{i-1,i}}^{-1} \\
t^{j+1}_{i,i+1} &= \Delta t^j_{i,i+1} \cdot t^j_{i,i+1}
\end{aligned} \tag{11}$$

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.

$$\begin{aligned}
\bar{T}_m &= \bar{T}_{m-1} \cdot \bar{t}_{m-1,m} \\
&= \bar{T}_s \cdot \bar{t}_{s,s+1} \cdot \ldots \bar{t}_{i,i+1} \ldots \cdot \bar{t}_{m-1,m}
\end{aligned} \tag{12}$$

IV. EXPERIMENTAL RESULTS

Figure 4 shows the test-bed vehicles developed in this research. Sensor configurations of the vehicles are slightly different, but their functions are similar and their data are processed using the same approaches. We present the latest experiment, in which the data are taken by using test-bed vehicle (b).

A. Sensor and Data Configuration

A laser scanner (LMS291 by SICK) is mounted at the front of the test-bed vehicle monitoring a wide angle (180 degree, and 0.5 degree/point) of the vicinity. In this experiment, we use a video camera on the roof of the vehicle to examine and visualize the results of laser-based processing, while in the future we are going to fuse both sensors to achieve higher intelligence and accuracy. A differential GPS (DGPS) is used to assist in achieving global accuracy. As the yaw rate sensor and wheel encoder were not ready in the experiment, we produced the values using the GPS data. In order to guarantee a certain reliability of the estimation, only the continuous GPS values when the vehicle ran on a straight path, and of good signal condition, are chosen (refer to $\{g_k\}$). The values of yaw angle $\{y_k\}$ and speed $\{s_k\}$ are calculated from $\{g_k\}$, so that the control inputs in this experiment are temporally broken segments. On the other hand, the coupled values $\{x_k^{gps}\} = \{g_k, y_k\}$ (see the red dots in Figure 8) are used to adjust the trajectory of test-bed vehicle to achieve global accuracy.

B. Experimental Course

The experimental course is shown in Figure 5, where the test-bed vehicle started from the campus of Peking University along the red arrows, left campus at the west vehicle's gate, ran on public roads along the blue arrows, and entered the campus at the east vehicle's gate. The course lasted for 4.5 km, and the run took 15 min following the normal traffic flow. The course inside of the campus is very crowded with pedestrians, bicycles and parked cars. The course outside of the campus is also very dynamic, composed of a number of intersections and crowded roads. Comparing with the other data sets that we have collected, this is the most challengeable one.

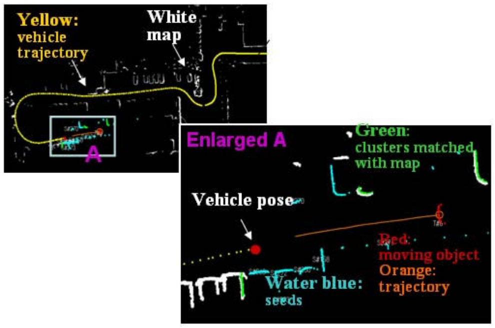

Fig. 6. Color definition of the on-line processing program on laser scans

C. SLAM with Moving Object Detection and Tracking

Figure 7 demonstrates some results of SLAM with moving object detection and tracking from the viewpoint of driving safety. Nine pairs of results are presented, each contains a screen capture of the on-line processing program on laser scans, and a back projection of the current laser scan onto the corresponding video image for visualization. Definitions for the different colors are summarized in Figure 6. The laser points of current scans are labeled as static, moving and seed objects, which are colored in green, red and blue respectively. They are consistent in both results. To gain better understanding, the green arrow lines in each pair of results are manual draws, denoting the correspondences between the laser points in different views. The results are indexed. Their locations are denoted in Figure 8. It can be found from the results that most moving objects are successfully detected and tracked (marked in red), especially those near the test-bed vehicle. The laser scanner is very efficient in monitoring a wide angular surrounding. This is demonstrated in result 3. Although we can only find one person in the video image, from laser data we captured three in vicinity. The motion trajectories of moving objects are also clearly grasped. For example in result 4, two people did not notice the existence of the test-bed vehicle initially, later they walked away. In the case of a group of persons, the program shows unstable results. For example in result 6, the groups were tracked successfully. However in later frames, a person in the right group walked slightly apart from the others, so that one more cluster was detected and many state parameters of the trajectory had discontinuous change. This iterated a couple of times. Finally in result 7, the trajectories were rejected as unreliable one, and a new seed object was created. Result 8 and 9 are the detections on public roads, which are crowded with cars and bicycles.

D. Localization Guided by GPS data and Control Inputs

Figure 8 shows some of the localization results. The red dots, denoted by "GPS", are the $\{x_k^{gps}\}$ that are picked up for adjustment. The black dots, denoted by "NN", are the localization results with neither the assistance of $\{y_k\}$, $\{s_k\}$, nor $\{x_k^{gps}\}$. It had a catastrophic failure in scan matching, and aborted halfway. The blue dots, denoted by "WN", are generated with the assistant of $\{y_k\}$ and $\{s_k\}$

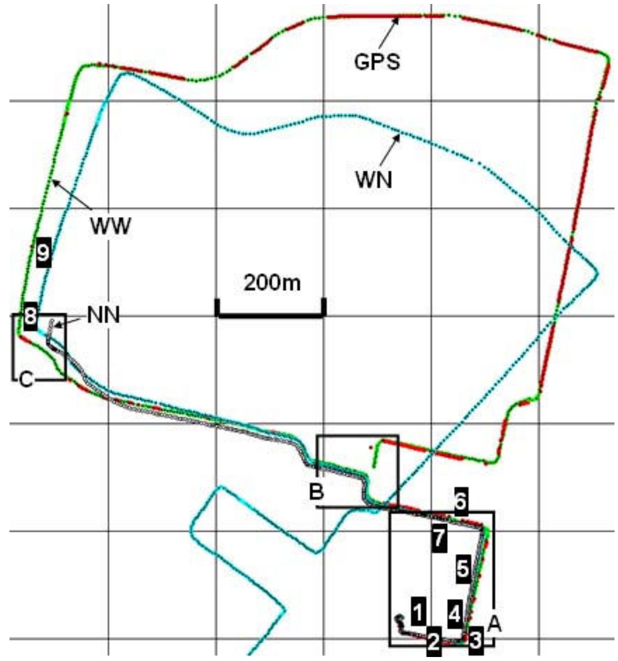

Fig. 8. Localization results

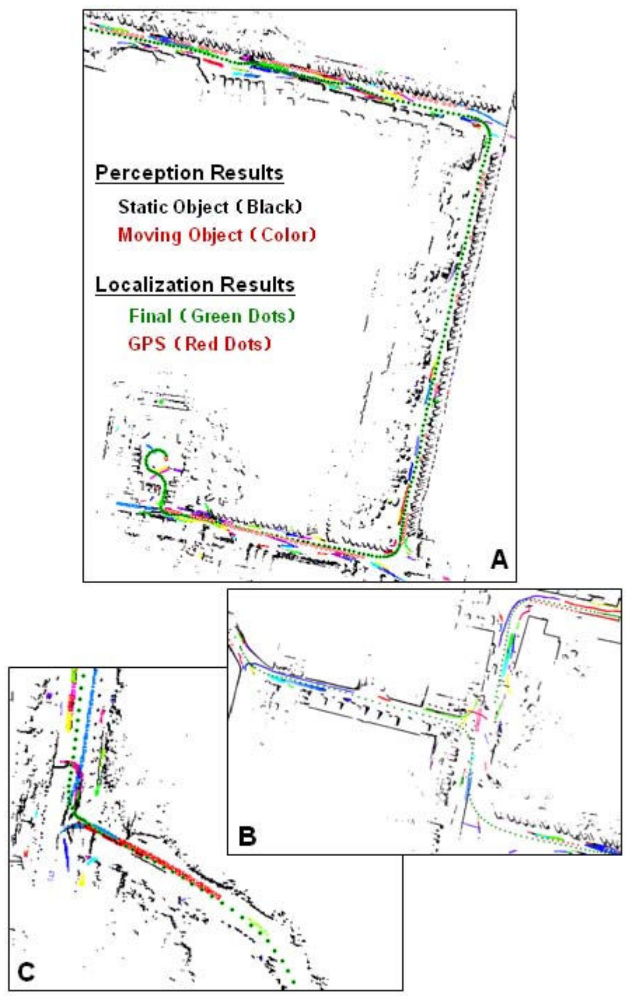

Fig. 9. Map of both static and dynamic objects

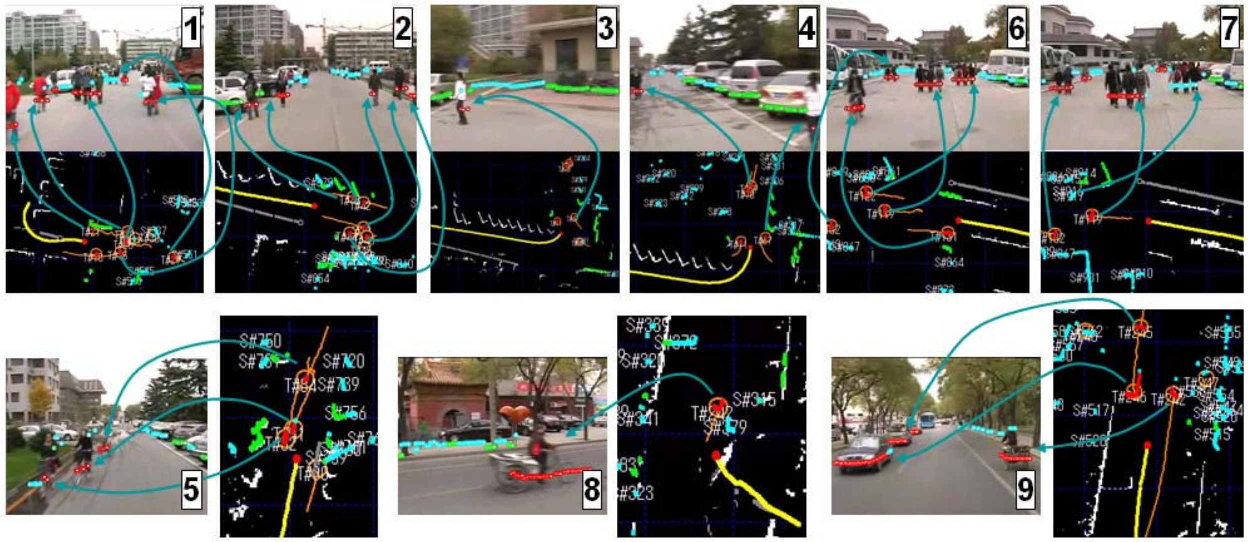

Fig. 7. Experimental results of SLAM with moving object detection and tracking

but without trajectory-oriented loop closure using $\{x_k^{gps}\}$. A large global error happened. One of the reasons could be found in the erroneous scan matching in highly dynamic environment, and error accumulation during a long and non-cyclic measurement. The green dots, covered by other dots in many places and denoted by "WW", are generated with the assistance of both $\{y_k\}$, $\{s_k\}$ and $\{x_k^{gps}\}$. The threshold β in Figure 3 is arbitrarily defined to 10m in this experiment, meaning that the trajectory-oriented loop closure will be conducted only when the distance from estimated trajectory point to $\{g_k\}$ is larger than 10m.

E. Final Results

A global map, containing the data of both static and dynamic objects, with pixel size of 5cm*5cm, is generated by summarizing the local perceptions to a global coordinate system. Three areas, A-C, in Figure 8 are enlarged in Figure 9. The black pixels on the map denote static objects. Colored pixels denote moving objects, and different colors represent different moving objects. This demonstrates that after a run of the test-bed vehicle, a global map of the environment, containing the information of both static and dynamic objects, can be generated. Also, the states of each moving objects, such as speed, direction, and size, have been tracked in the global coordinate system, which could be used for further traffic analysis.

F. Time Cost

The experiment is conducted by measuring data first, and processing the data later in an on-line procedure. After acquiring data from the test-bed vehicle, all processing is carried out on a ThinkPad X32, which has a 1.8GHz CPU and 1.5GB RAM. The laser scan covers a range of 180 deg with an angular resolution of 0.5 deg. The processing is conducted at a rate of 10Hz, which means that only one-third of the laser scans are used in processing, comparing to

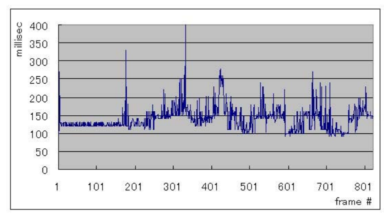

Fig. 10. Computation cost of each frame

the scanning rate (≈ 37.5Hz). The computation cost of each frame is demonstrated in Figure 10, which has an average of 140 millisec per frame. Compared to the laser scan rate (10Hz), the current computation cost is high, but not far from real-time level.

G. Discussions and Future Studies

Up to now, we have demonstrated the possibility of a laser scanner-based approach for the purpose of both enhancing driving safety and traffic data collection. Besides positive discussions, there are still many problems with respect to real applications. Some of them could be solved through improving system implementations, while some of them need further studies to find a solution. Here we discuss some of the later ones, which are going to be solved through future studies.

1) Duplicated Courses: In Figure 5, the start and end of the experiment course are at different locations, while in data acquisition, the test-bed vehicle returned back to its start place, and data were measured till then. The reason for us to cut the duplicated course is that we failed in generating a consistent map using the current system and algorithm. As we used only one laser scanner covering the front 180 degree, matching the back and forth laser scans are difficult, especially in such a dynamic environment. For the application of driving safety, a consistent map and global accuracy is not a must. However, an algorithm of updating a previously explored map in a highly dynamic environment is required for traffic data collection.

2) If a moving object remains static at the beginning: A parked car or a person standing still is a temporarily static object. Some of them might start to move suddenly, while some of them remain static during the period when they are measured. If we keep tracking all the moving-object-like ones, computation cost will be too high for an on-line system. A balance between accuracy and time cost should be taken. In this research, we made rules that, if is an object (or a pixel) is continuously tracked at the same location for more than 30 frames, it is considered as a static one; If a continuous motion could be reliably detected from an object at any time during the measurement, it is considered as a moving one; If a trajectory expired as a seed object, and no obvious motion is detected, it is treated as static object, etc.

3) Accuracy examination: Designing an accuracy examination rule is always a challenge. For the false alarms, such as misclassifying a static object as a moving one, things are clear. In fact, we had such false alarms during the experiments, but not many. For the false alarms such as misclassifying a moving object as static one, things are difficult. If a moving object remains static at the beginning for more than 30 continuous frames in this experiment, the moving object is most probably recognized as a static one. This happened for the cars waiting at traffic signals. The most complicated question is how to treat seed objects. Many moving and static objects expired as seed objects due to short measurement time. Further studies also require a solution to evaluate the over- or under- detection/tracking, especially for a crowd of people.

V. CONCLUSIONS

This research is motivated by two potential applications: enhancing driving safety and collecting traffic data. A laser scanner-based approach is proposed, which focuses on solving two major problems: 1) achieving global accuracy, especially in a non-cyclical large environment, and 2) tackling a mixture of data from both dynamic and static objects. Experiments are conducted using data collected in a highly dynamic environment. Possibilities of the approach with respect to the two potential applications are demonstrated, and future works are discussed.

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