LASER-BASED SENSING ON ROADS

K. R. S. Kodagoda[1], Chieh-Chih Wang[2], G. Dissanayake[1]
ARC Centre of Excellence for Autonomous Systems
University of Technology, Sydney[1], University of Sydney[2]
Email address: s.kodagoda, bob.wang, g.dissanayake@cas.edu.au

Abstract—**To improve safe driving and prevent traffic injuries caused by human factors such as speeding, fatigue and distraction, techniques to understand the surroundings of the vehicle are critical. We believe that being able to detect and track every stationary object and every moving object, to reason about the dynamic traffic scene, to detect and predict every critical situation, and to warn and assist drivers in advance, is essential to prevent these kinds of accidents. As an initial step towards understanding whole scenario around a vehicle, in this paper we have made an attempt to address the issues related to roadway environment monitoring by only utilizing laser measurement systems (LMS) as a perception sensor. Extensive experiments were carried out to analyze the robustness of the proposed methodologies in real campus and city environments. The results are appealing and robust to various traffic and road scenarios.**

***Keywords*—Localization, Mapping, Tracking, Safe Driving.**

I. INTRODUCTION

Road safety is a major concern for today's automotive industry. The endeavors in solving this problem include a complete understanding and monitoring of whole traffic scene around a vehicle, which is a safety cushion for safe driving. The interested traffic scenes include, but not limited to road boundary and other visual traffic sign detection, moving and stationary obstacle detection, pedestrians and other vehicle monitoring and vehicle localization.

The most extensively favored, researched, tested, and evaluated automotive perception sensor is the camera. Being a passive non-invasive sensor, camera has the advantages of high information content, lower costs, lower operating power and absence of a sweep time. However, ill-illumination due to night time, bad weather, over illumination due to sun's glare, head lights of other passing by vehicles, and poor depth estimations make the usage of camera based systems less effective. On the other hand, laser based measurements, do not degrade with such illumination associated problems and have high quality range bearing measurements, which are important in safe driving.

Laser measurement systems (LMS) have been gaining popularity in robotics community in the past decade. The application areas range from, obstacle detection [1], navigation [2], localization [3], map building [4] and simultaneous localization and map building (SLAM) [5]. There is also literature on the utilization of LMS for automotive applications ranging from, vehicle detection [6], road boundary detection [7], SLAM [8] and moving object tracking [9]. In all applications, the LMS stands as a high reliable sensor, which motivates us for further exploitation.

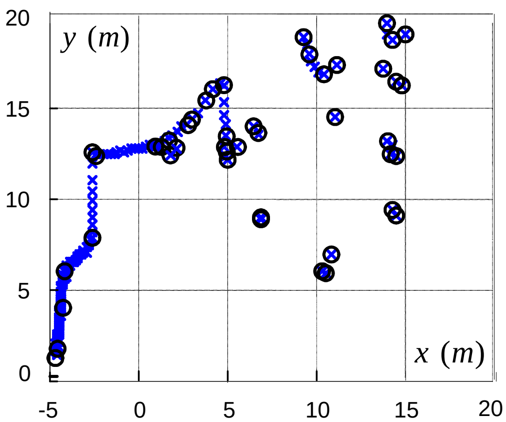
In Section II, a road boundary detection and tracking methodology is described. Section III provides the extensive work on simultaneous localization and mapping with detection and tracking of moving objects. Section IV summarizes the paper indicating future directions.

II. ROAD BOUNDARY DETECTION AND TRACKING

Road boundary detection and tracking is an important aspect in safe driving as it can be used to identify drivable and non-drivable areas and subsequently generate road departure warnings. There is an extensive amount of literature on camera based road boundary detection methods using visual features [10-16]. All those camera based systems suffer the camera specific problems due to illumination problems. One way to overcome this is to use another sensor modality (and may fuse with camera based observations). In this section, an alternate way of extracting road boundaries using LMS sensor is described. One way of detecting road boundaries using LMS is to analyze the range/bearing data corresponding to the road surface as in [17]. The performance can be adversely affected by road camber and spurious data due to the presence of water puddles. Another way of extracting road boundaries are to use features alongside the road, such as reflective posts [18] and guard rails and posts [19]. Disadvantages can be the non-existence of such regular features in most road scenarios. These problems can be overcome by extracting vertical curb edges defining the road boundaries.

A. *Road boundary detection*

Especially in urban environments, road boundaries are defined by curbs. Detection of these vertical curb surfaces is feasible with a front mount, tilted down LMS. Therefore, in this application the LMS was mounted in front of the vehicle, with a small tilt angle, which allows the laser beam to intersect the pavement, curb and road surfaces at 10-15m ahead. Since the LMS scans in a plane, its intersection with other planar surfaces such as vertical curb surfaces give rise to straight lines (see Fig.1. (a)). In the plot, data in between x = -3m and x = 5m correspond to the road surface and curbs. It is to be noted that there is a bank on the left hand side of the road and scatter of data on the right hand side are due to trees, poles and other man-made structures. Ideally the data corresponding to the road surface should be a single straight line, however due to the cylindrical nature of the road surface, the data forms a "V" shape. The LMS data belonging to straight lines can be segmented and line parameters (mid point of the line segment in Cartesian coordinates and the orientation of the line with respect to the x- axis: $\{x, y, \phi\}$) can be extracted using a Kalman filter based approach [7] (see Fig. 1). Then, these lines can be fed to a bank of filters [7] to detect the line segments corresponding to the vertical surfaces of the curbs (see Fig. 1(b)).



(a) *Crosses:* laser data, *circles:* detected discontinuity points for data segmentation

(b) Line segments corresponding to vertical curb surfaces

Fig.1. Curb detection using LMS data

B. Road boundary tracking

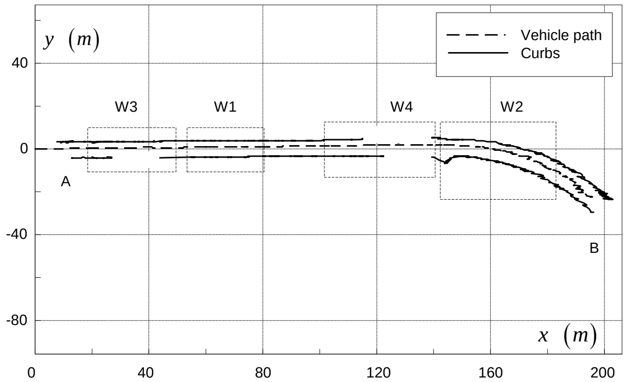
Now, the road boundaries can be perceived as trajectories of line segments evolved with time, which can be observed by the LMS on the moving vehicle. Tracking of these line segments (vertical surface of the curbs) is nontrivial due to the maneuvering nature and the presence of clutter due to various structures. Therefore, an adaptive state estimation technique using a multiple model approach is proposed.

1) Track formation and termination: The initial tracks corresponding to the curbs can be formed using the detected line segments in the above section. Although, these initial tracks are sufficient for various road scenarios, there can be a little possibility that those are due to some other structures, but not curbs. Therefore, these initial tracks are used to form tentative tracks and ideas from the integrated probabilistic data association (IPDA) [23] with sequential probability ratio test (SPRT) [24] are used for track confirmation and termination. In track confirmation, the initial tracks are considered tentative until the log likelihood ratio (LLR) is higher than a predefined threshold. On the other hand, when the LLR is below a predefined threshold the track is terminated.

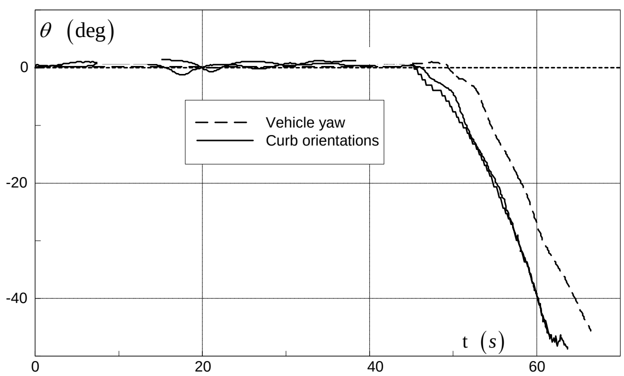
2) Track maintenance: The Interacting Multiple Model (IMM) is capable of tracking highly maneuvering targets in clutter [25]. A primitive approach in handling clutter is to use the global nearest neighbor data association, which merely seeks the single most likely hypothesis and use Interacting Multiple Model Global Nearest Neighbor Filter (IMMGNNF). However, the performance of a tracking filter with cluttered data can be improved by using all-neighbor data association methods rather than using a single most likely hypothesis as in GNN. One way of incorporating all neighbors is to use probabilistically weighted all neighbors as in Probabilistic Data Association (PDA). Therefore Interacting Multiple Model Probabilistic Data Association Filter (IMMPDAF) algorithm [24,26] based method is used for track maintenance.

The robustness of the IMMPDAF algorithm for curb tracking was evaluated experimentally using a car-like vehicle [7]. The vehicle was driven at a speed of $4ms^{-1}$ in a test site, which has straight road segments, bend, right road branching and a x-intersection. The test site is hilly consisting of more than 10^o slopes. Fig. 2 shows the curb tracking results using the IMMPDAF in various road scenarios including straight road segments, bend, right road branching and x-intersection.

Fig. 3 (a) shows consecutive Laser data corresponding to the window, *W1*, in Fig. 2 (a), which is a straight road segment. Fig. 3 (b) shows the laser data corresponding to the window, *W2*, of Fig. 2 (a). It is a right turn. Window, *W3*, in Fig. 2 (a) corresponds to a right road branching. The laser data refers to that segment of the road is as shown in Fig. 3 (c). It is to be noted the loss of laser data on the right hand side of the road. That is because of the unavailability of a curb on the right hand side of the road and also because of the downward inclination of the branched road. In this portion of the road, the right hand side track is terminated (see Fig. 2) due low LLR. With the track termination, the IMMPDAF simply predicts until it finds a new observation. Once it finds an observation, it goes through a series of filters [7] namely, orientation filter, neighborhood filter and road width filter before a tentative track is initiated. Then sequential probability ratio test is carried out for track confirmation. Fig. 3 (d) shows the laser data referring to the window, *W4*, in Fig. 2 (a). It is corresponding to an x- intersection where there are no curbs present on both sides of the road. As seen from Fig. 2, both tracks were being deleted during the x-intersection and both were reinitiated after the x-intersection showing the robustness to target loss and reappearing.

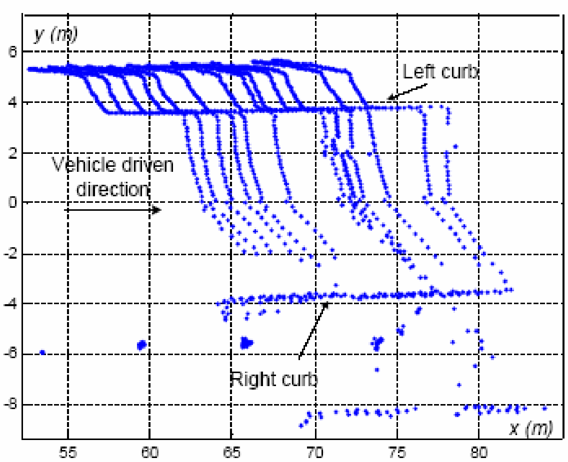


(a) Position tracking

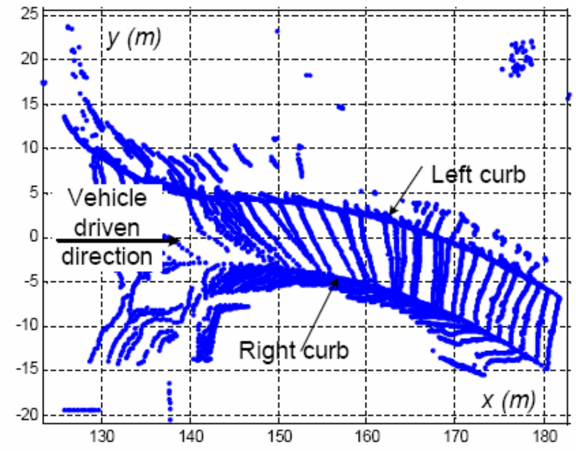


(b) Orientation tracking

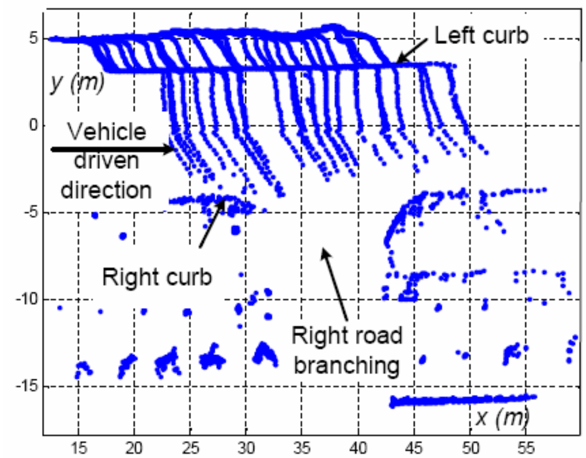
Fig. 2 Experimental curb tracking results using IMMPDAF



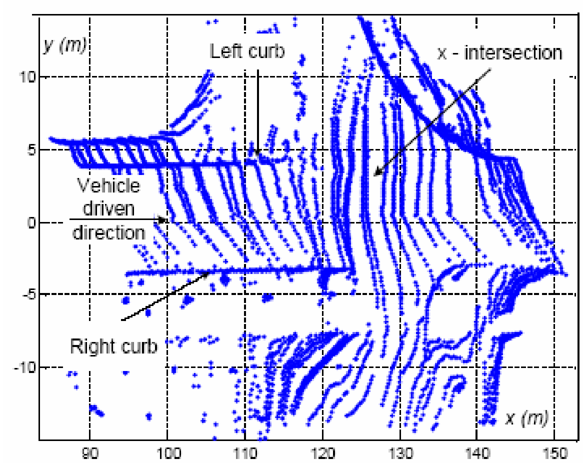
(a) Laser data corresponding to *W1* of Fig. 2 (a)



(b) Laser data corresponding to *W2* in Fig. 2 (a)



(c) Laser data corresponding to *W3* in Fig. 2 (a)



(d) Laser data corresponding to *W4* in Fig. 2 (a)

Fig. 3. Laser data corresponding to windows, *W1*, *W2*, *W3* and *W4*.

III. Simultaneous Localization and Mapping with Detection and Tracking of Moving Objects

In this section, we explain Simultaneous Localization and Mapping (SLAM) with Detection and Tracking of Moving Objects (DATMO) intuitively and describe the practical algorithms for accomplishing SLAM with DATMO from a ground vehicle at high speeds in crowded urban areas using laser scanners and odometry.

In order to detect and track moving objects by using sensors mounted on a moving ground vehicle at high speeds, a precise localization system is essential. It is known that GPS and DGPS often fail in urban areas because of urban canyon effects, and good inertial measurement systems (IMS) are very expensive. If we can have a stationary object map in advance, the map-based localization techniques can be used to increase the accuracy of the pose estimate. Unfortunately, it is difficult to build a usable stationary object map because of temporary stationary objects such as parked cars. Stationary object maps of the same scene built at different times could still be different, which means that we still have to do online map building to update the current stationary object map.

SLAM allows robots to operate in an unknown environment and then incrementally build a map of this environment and concurrently use this map to localize robots themselves. Over the last decade, the SLAM problem has attracted immense attention in the mobile robotics literature, and SLAM techniques are at the core of many successful robot systems. However, we have shown that SLAM can perform badly in crowded urban environments because of the static environment assumption [8]. Moving objects have to be detected and filtered out.

DATMO problem has been extensively studied for several decades. Even with precise localization, it is not easy to solve the DATMO problem in crowded urban environments because of a wide variety of targets [9].

When cameras are used to detect moving objects, appearance-based approaches are widely used and moving objects can be detected no matter whether they are moving or not. If laser scanners are used, feature-based approaches are usually the preferred solutions. Both appearance-based and feature-based methods rely on prior knowledge of the targets. In urban areas, there are many kinds of moving objects such as pedestrians, animals, wheelchairs, bicycles, motorcycles, cars, buses, trucks and trailers. Velocities range from under 5 mph (such as a pedestrian's movement) to 50 mph. When using laser scanners, the features of moving objects can change significantly from scan to scan. As a result, it is very difficult to define features or appearances for detecting specific objects using laser scanners.

Both SLAM and DATMO have been studied in isolation. However, when driving in crowded urban environments composed of stationary and moving objects, neither of them is sufficient. The simultaneous localization, mapping and moving object tracking problem aims to tackle the SLAM problem and the DATMO problem at the same time. Because SLAM provides more accurate pose estimates and a surrounding map, a wide variety of moving objects are detected using the surrounding map without using any predefined features or appearances, and tracking is performed reliably with accurate robot pose estimates. SLAM can be more accurate because moving objects are filtered out of the SLAM process thanks to the moving object location prediction from DATMO. SLAM and DATMO are mutually beneficial, as shown in Fig. 4. Integrating SLAM with DATMO would satisfy both the safety and navigation demands of safe driving. It would provide a better estimate of the robot's location and information of the dynamic environments, which are critical to driving assistance and autonomous driving.

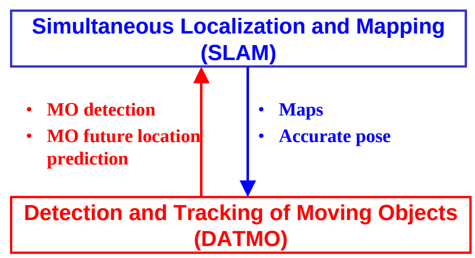


Fig. 4: SLAM with DATMO

Although performing SLAM and DATMO at the same time is superior to doing just one or the other, the integrated approach inherits the difficulties and issues from both the SLAM problem and the DATMO problem. In the following subsections, we will describe the implementation of SLAM with DATMO from a ground vehicle at high speeds in crowded urban areas using laser scanners and odometry. The experimental data were collected with the Navlab11 vehicle. One SICK LMS221 and two SICK LMS291 laser scanners were mounted in various positions on Navlab11, performing horizontal or vertical profiling. The range data were collected at 37.5 Hz with 0.5 degree resolution. The maximum measurement range of the scanners is 81m.

A. Detection and tracking of moving objects in crowded urban areas

In order to accomplish moving object tracking in crowded urban areas, three key issues have to be solved: detection, data association, and moving object motion modelling.

1) Detection: Recall that detection of ground moving objects using feature- or appearance-based approaches is infeasible because of the wide variety of targets in urban areas. In [8], the consistency-based detection and the moving object map based detection was proposed for robustly detecting moving objects using laser scanners.

2) Cluttered Environments: In the tracking literature, there are a number of techniques for solving data association in the cluttered such as multiple hypothesis tracking (MHT) approaches and joint probabilistic data association (JPDA) approaches. In addition to the MHT approach, we use geometric information of moving objects to aid data association in cluttered scenes because of the rich geometric information contained in laser scanner measurements. Fig. 5 shows a result of multiple vehicle detection and data association. Five different cars were detected and associated over 11 consecutive scans. This result demonstrates that our detection and data association algorithms are reliable even with moving objects 60 meters away. Additionally, the visual image from the tri-camera system illustrates the difficulties of detection using cameras.

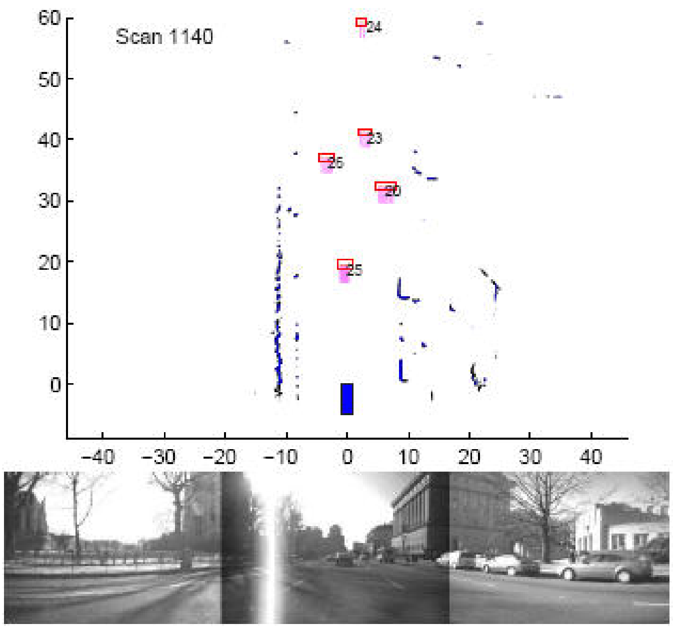


Fig. 5: Multiple vehicle detection and data association. Rectangles denote the detected moving objects. The segment numbers of the moving objects are shown.

Fig. 6 shows a result of pedestrian detection and data association where object 19, 40, and 43 are detected pedestrians, object 17 is a detected car and Object 21 is a false detection. Without using features or appearances, our algorithms detect moving objects based on motion. Fig. 7 shows a result of bus detection and data association.

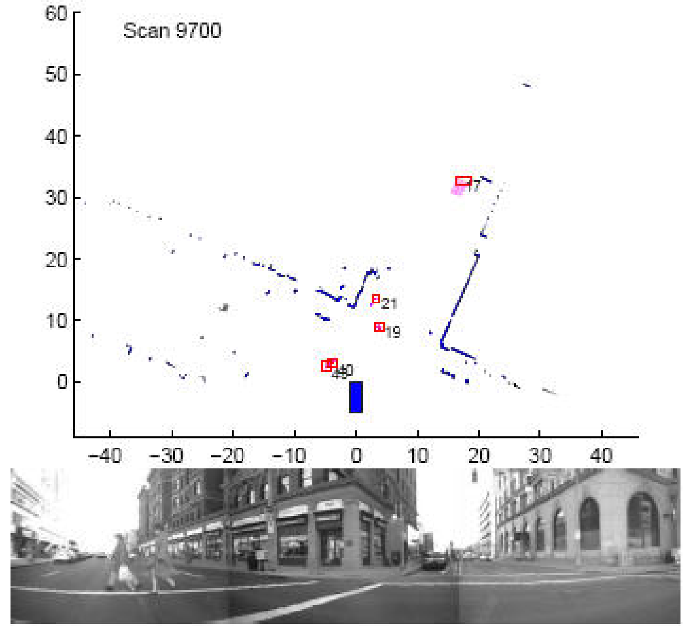


Fig. 6: Pedestrian detection and data association.

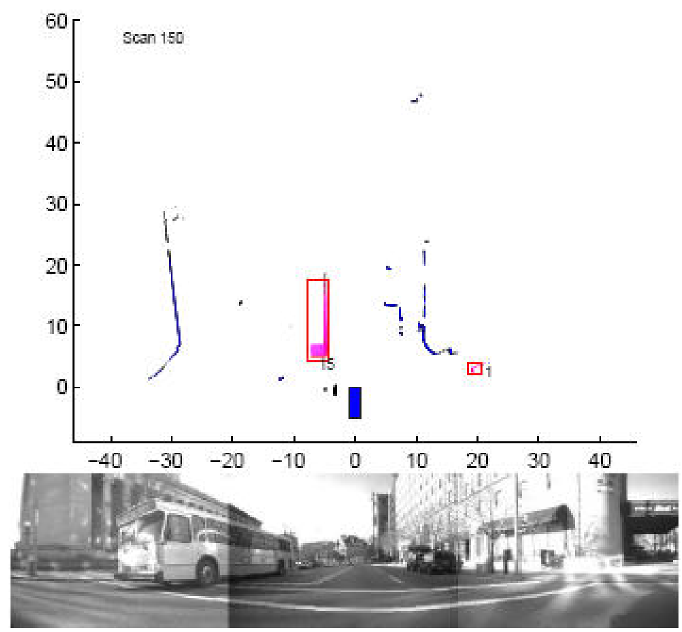


Fig. 7: Bus detection and data association.

3) Motion Modeling: In SLAM, we can use odometry and the identified robot motion model to predict the future location of the robot, so that the SLAM problem is an *inference* problem. However, in DATMO neither *a priori* knowledge of moving objects' motion models nor odometry measurements about moving objects is available. In practice, motion modes of moving objects are often partially unknown and time-varying. Therefore, the motion modes of the moving object tracking have to be learned online. In other words, moving object tracking is a *learning* problem.

In the tracking literature, multiple model based approaches have been proposed to solve the motion modeling problem. Compared to air and marine target tracking, ground moving object tracking is more complex because of more degrees of freedom (e.g., move-stop-move maneuvers). In [21], we present a stationary motion model and a move-stop hypothesis tracking algorithm to tackle this issue.

B. City-sized Simultaneous Localization and Mapping

Over the last decade, the SLAM problem has attracted immense attention in the mobile robotics literature. SLAM involves simultaneously estimating locations of newly perceived landmarks and the location of the robot itself while incrementally building a map. The web sites of the 2002 and 2004 SLAM summer schools provide a comprehensive coverage of the key topics and state of the art in SLAM. In this section, we address two key issues to accomplish city-sized SLAM: representation and revisiting.

1) Representation: Even with an advanced algorithm to deal with computational complexity, most SLAM applications are still limited to indoor environments or specific environments and conditions because of significant issues in defining environment representation and identifying an appropriate methodology for fusing data in this representation. For instance, feature-based approaches have an elegant solution by using a Kalman filter or an information filter, but it is difficult to extract features robustly and correctly in outdoor environments. Grid-based approaches do not need to extract features, but they do not provide any direct means to estimate and propagate uncertainty and they do not scale well in very large environments. In [22], we addressed the representation related issues in detail and describe a hierarchical object based representation for overcoming the difficulties of the city-sized SLAM problem.

2) Revisiting: Given correct revisiting or loop detection, SLAM can build a globally consistent map regardless of the size of the map. In order to obtain correct data association in the large, most large scale mapping systems using moving platforms are equipped with expensive state estimation systems to assure the accuracy of the state estimation. In addition, independent position information from GPS or aerial photos are used to provide global constraints. Without these aids, the accumulated error of the pose estimate and unmodelled uncertainty in the real world increase the difficulty of loop detection. For dealing with this issue without access to independent position information, our algorithm based on covariance increasing, information exploiting and ambiguity modelling is presented in [21]. Fig. 8 shows a raw dataset collected from the Navlab11 test-bed. Fig. 9 shows the results from our SLAM with DATMO algorithms, which demonstrate that it is indeed feasible to accomplish city-sized SLAM.

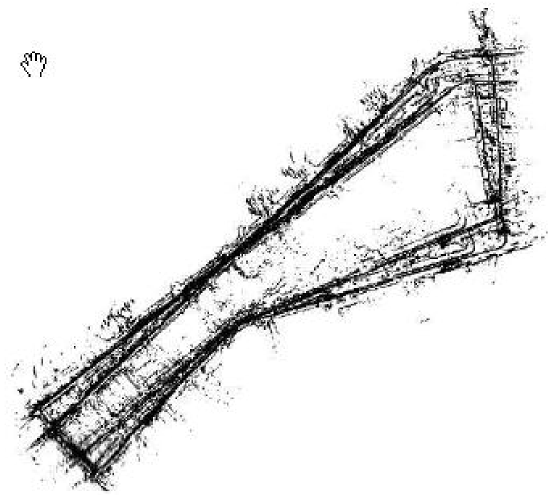


Fig. 8: Raw data from the Navlab11 testbed. This dataset contains ~36,500 scans and the travel distance is ~5 km.

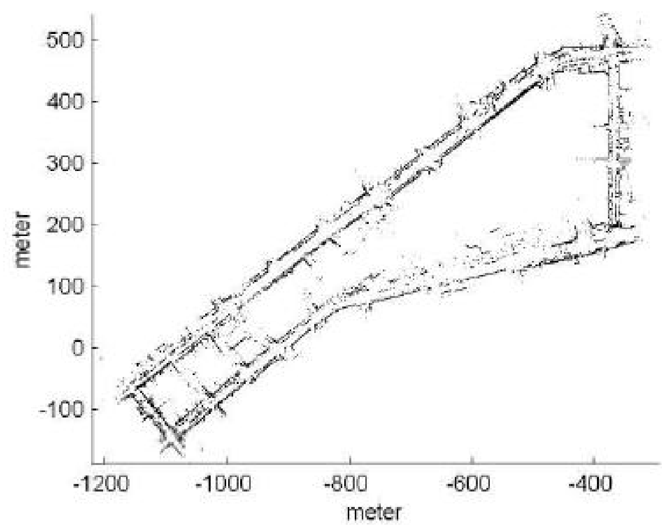


Fig. 9: Results of SLAM with DATMO. A globally consist map is generated and measurements associated with moving objects are filtered out.

In order to build 3-D (2.5-D) maps, we mounted another scanner on the top of the Navlab11 vehicle to perform vertical profiling. Accordingly, high quality 3D models can be produced in a minute. Fig. 10 and Fig. 11 show the 3-D models of different objects such as buildings and parked cars. These precise 3-D models can be very useful to applications of civil engineering, architecture, landscape architecture, city planning, etc.

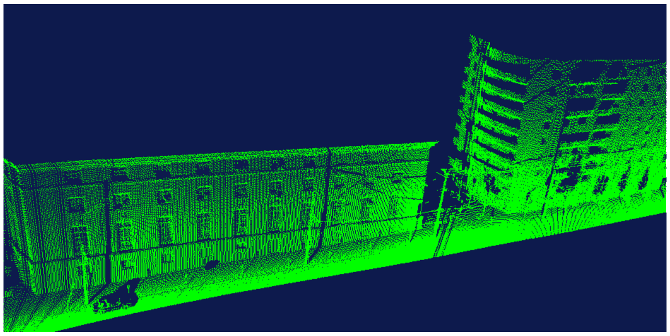


Fig. 10: 3-D models of buildings.

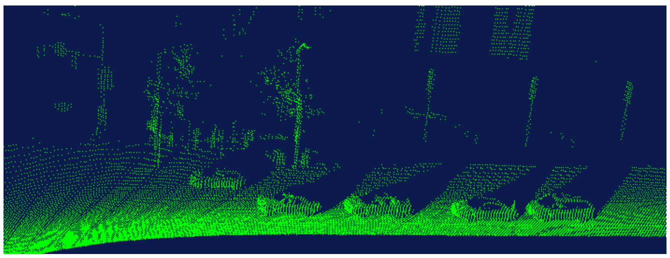


Fig. 11: 3-D models of parked cars.

C. 2-D Environment Assumption in 3-D Environments

Although the formulations derived in [20] are not restricted to two-dimensional applications, it is more practical and easier to solve the problem in real-time by assuming that the ground is flat. But can algorithms based on the 2-D environment assumption survive in 3-D environments? For most indoor applications, this assumption is fair. But for applications in urban, suburban or highway environments, this assumption is not always valid. False measurements due to this assumption are often observed in our experiments. One is from roll and pitch motions of the robot, which are unavoidable due to turns at high speeds or sudden stops or starts. These motions may cause false measurements such as wrong scan data from the ground instead of other objects. Additionally, since the vehicle moves in 3-D environments, uphill environments may cause the laser beam to hit the ground as well (see Fig. 9).

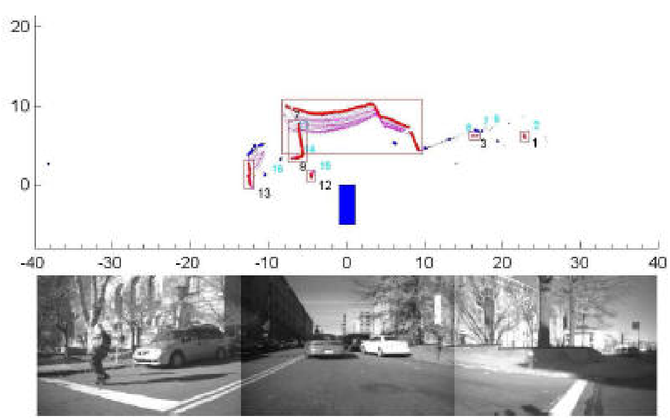


Fig. 12: False measurement from an uphill environment.

In order to accomplish 2-D SLAM with DATMO in 3-D environments, it is critical to detect and filter out these false measurements. Our algorithms can detect these false measurements implicitly without using other pitch and roll measurement. First, the false measurements are detected and initialized as new moving objects by our moving object detector. After data associating and tracking are applied to these measurements, the shape and motion inconsistency will tell us quickly that these are false measurements. Also these false measurements will disappear immediately once the motion of the vehicle is back to normal. The results using data from Navlab11 show that our 2-D algorithms can survive in urban and suburban environments. However, these big and fast moving *false alarms* may confuse the warning system and cause a sudden overwhelming fear before these false alarm are filtered out by the SLAM with DATMO or SLAM with GO processes. Using 3-D motion and/or 3-D perception sensors to compensate these effects should be necessary.

IV. Discussion and Future Work

In this paper we have detailed methodologies for understanding the environment using only LMS as a perception sensor. The LMS was used for road boundary extraction and temporal tracking. The experimental results showed it is robust to various road scenarios. The LMS based SLAM and DATMO showed amazing and convincing results in a city environment. A major problem of SLAM due to the presence of moving objects was successfully overcome by utilizing the information from DATMO. Most importantly SLAM and DATMO were treated in a unified manner rather than separate treatments as in the literature. Issues related to experimenting in 3-dimensional environments with 2-dimensional assumptions were also addressed.

Up to now we have discussed about favorable properties of LMS as an automotive sensor, however it has failure modes and limitations too. For example, LMS may not be capable of detecting glass or black objects. Further, LMSs are not sufficient to fully understand a complex urban scene. For instance, lane markings, traffic signs and lights can not be recognized using an LMS. Therefore, it is suggested to utilize heterogeneous sensor fusion methodologies for further improving the robustness.

In the map building, we have shown our ability to build precise 2.5 dimensional models of several street blocks. However, the real world is indeed four-dimensional, three dimensions for space and one dimension for time. Therefore, it is suggested to build 4 dimensional maps for better understanding the environment.

V. ACKNOWLEDGMENT

The authors would like to thank people in the Navlab group of Carnegie Mellon University for their helps on collecting data. The authors would also like to thank the group working on GenoME test bed at the School of EEE, Nanyang Technological University, Singapore. The on-going project is supported in part by the ARC Centre of Excellence program, funded by the Australian Research Council (ARC) and the New South Wales State Government.

VI. REFERENCES

[1] G Foux, M Heymann, A. Bruckstein, 'Two-dimensional robot navigation among unknown stationary polygonal obstacles', IEEE Trans on Robotics and Automation, 1993 9 (1) 96 – 102

[2] D Dedieu, V Cadenat, and P Soueres, 'Mixed camera-laser-based control for mobile robot navigation', IEEE/RSJ Int Conf Intelligent Robots and Systems, 2000,1081–1086.

[3] J Neira, J D Tardos, J Horn, and G Schmidt, 'Fusing range and intensity images for mobile robot localization', IEEE Trans Robotics and Automation, 1999 15 76–84.

[4] R Madhavan, G Dissanayake, H Durrant-Whyte, 'Map-building and map-based localization in an underground-mine by statistical pattern matching', Proc of fourteenth Int Conf on Pattern Recognition, 1998 2 1744 – 1746.

[5] J A Castellanos, J M M Montiel, J Neira, J D Tardos, 'The SPmap: a probabilistic framework for simultaneous localization and map building', IEEE Trans on Robotics and Automation, 1999 15(5) 948 – 952.

[6] S Ono, M Kagesawa, K A Ikeuchi,, 'A probe car for parking-vehicle detection by using laser range sensor', IEEE Intelligent Vehicle Symposium, 2002 2 322 – 327.

[7] W S Wijesoma, K R S Kodagoda and A P Balasuriya, 'Road Boundary Detection and Tracking Using LADAR Sensing', IEEE Trans on Robotics and Automation , 2004 20(3) 456-464.

[8] C C Wang and C Thorpe, 'Simultaneous Localization and Mapping with Detection and Tracking of Moving Objects', IEEE Int Conf on Robotics and Automation (ICRA'02) 2002.

[9] C C Wang, C Thorpe and A Suppe, 'Ladar-Based Detection and Tracking of Moving Objects from a Ground Vehicle at High Speeds', IEEE Intelligent Vehicles Symposium (IV2003), 2003.

[10] D Pomerleau and T Jochem, 'Rapidly adapting machine vision for autonomated vehicle steering', IEEE Expert, 1996 11 19–27.

[11] E D Dickmanns and B D Mysliwetz, 'Recursive 3-D road and relative ego-state recognition', IEEE Trans Pattern Anal Machine Intell, 1992 14 199–213.

[12] M Bertozzi and A Broggi, 'GOLD: A parallel real-time stereo vision system for generic obstacle and lane detection', IEEE Trans. Image Processing, 1998 7 62–81.

[13] D A Pomerleau, 'Progress in neural network-based vision for autonomous robot driving', Proc. Intelligent Vehicles Symp., 1992, 391–396.

[14] K Kluge, 'Extracting road curvature and orientation from image edge points without perceptual grouping into features', Proc. Intelligent Vehicles Symp., 1994 109–114.

[15] K Kluge and S Lakshmanan, 'A deformable-template approach to lane detection', Proc. Intelligent Vehicles Symp., 1995 54–59.

[16] R Aufrère, R Chapuis, and F Chausse, 'A model-driven approach for real time road recognition', Int J Machine Vis Applicat, 2001 13. 93–107.

[17] H Cramer and G Wanielik, 'Road border detection and tracking in noncooperative areas with a laser radar system', Proc. German Radar Symp., Bonn, Germany, 2002 24–29.

[18] J Sparbert, K Dietmayer, and D Streller, 'Lane detection and street-type classification using laser range images', Proc. IEEE Intelligent Transportation Systems Conf., 2001 454–459.

[19] A Kirchner and T Heinrich, 'Model-based detection of road boundaries with a laser scanner', Proc. Int. Conf. Intelligent Vehicles, 1998 93–98.

[20] C C Wang, C Thorpe and S Thrun, 'Online Simultaneous Localization and Mapping with Detection and Tracking of Moving Objects: Theory and Results from a Ground Vehicle in Crowded Urban Areas', IEEE Int Conf on Robotics and Automation (ICRA'03), 2003.

[21] C C Wang., 'Simultaneous Localization, Mapping and Moving Object Tracking. Doctoral dissertation', Tech. report CMU-RI-TR-04-23, Robotics Institute, Carnegie Mellon University, 2004.

[22] C C Wang and C Thorpe, 'A Hierarchical Object based Representation for Simultaneous Localization and Mapping', IEEE/RSJ Int Conf on Intelligent Robots and Systems (IROS), 2004.

[23] D Musicki, R Evans and S Stankovic, 'Integrated probabilistic data association', IEEE Trans Automat Contr, 1994 39(6) 1237-1241.

[24] S Blackman and R Popoli, Design and Analysis of Modern Tracking Systems, Boston, Artech House, 1999.

[25] H A P Blom and Y Bar-Shalom, 'The interacting multiple model algorithm for systems with Markovian switching coefficients', IEEE Trans Automat Contr, 1988 33(8) 780-783.

[26] Y Bar-Shalom and X R Li, Multitarget-Multisenor Tracking: Principles and Techniques, Storrs CT: YBS Publishing, 1995.