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Moving Object Classification using Horizontal Laser Scan Data

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***Abstract*— Motivated by two potential applications, i.e. enhancing driving safety and traffic data collection, a system has been developed using a single-layer horizontal laser scanner as the major sensor for both localization and perception of the surroundings in a large dynamic urban environment. This research focuses on a classification method, that given a stream of laser measurements, classify the moving object into either a person, a group of people, a bicycle or a car. In this research, a number of features are defined after examining the property of data appearance. A classification method is proposed after examining the likelihood measures between each pair of feature and class. Experimental results are presented, demonstrating that the algorithm has efficiency with respect to both driving safety and traffic data collection in highly dynamic environment.**

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 the intelligent vehicle might be close to other moving objects, so high accuracy is required for understanding the state of each object. The other application involves collecting detailed traffic data such as the motion trajectories of cars, bicycles, and pedestrians for control and traffic analysis. In this latter application, it is important to associate the perceptions of local surroundings with a global coordinate system, and the traffic data are required to achieve a certain level of global accuracy.

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 [2,21] or monocular video camera [10], a laser scanner [3,11,14], or through sensor fusion [4,9]. A good survey to the recent contributions can also be found in [5,15]. Monitoring the front 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 highly-accurate perception are both required. Vu [16] and Weiss [18] performed online calculation of an occupancy map to detect objects that entered an object-free zone. This idea can be traced to the pioneering work by Wang [17]. Many research efforts can also be found in the famous DARPA urban challenge[1].

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There have been further research efforts to collect traffic data using probe vehicles. Most of these use GPS (Global Positioning System) to find the speed and trajectory of the probe vehicle and assume that these parameters somehow reflect the current traffic conditions of the road. Some probe vehicles have environmental sensors to monitor the surroundings, such as video cameras, laser scanners, and radar. Subsequent data processing is still a great difficulty. Gandhi [6] developed a system platform to detect, classify and log the surrounding vehicles using a video camera. Gao [7] proposed a method using a laser scanner to identify surrounding vehicles and correct GPS errors.

In our previous research [22,23], a system was developed using a one-layer horizontally profiling laser scanner as the major sensor for both localization and perception of the environment, where a laser-based SLAM (Simultaneous Localization And Mapping) in a dynamic environment was proposed, and the problem was formulated as a SLAM with object tracking and classification as follows.

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

Give a sequence of laser measurements $z_{0:k}$, a sequence of GPS observation, and a sequence of control inputs $u_{0:k}$, the problem is to estimate the current state of vehicle pose x_k, moving objects y_k, seed objects s_k (i.e. the objects that have not been discriminated to be static or mobile), and map m composed by the data of static objects. A framework of the system can be found in Figure 1. The general idea behind the system was that the detected objects should be classified in a spatial-temporal domain. In this way, after an object is detected, it was tracked until the system can classify the object into either a static or moving object with certainty.

This paper is an extension to our previous work, where the focus is on classifying the moving objects y_k that are extracted from the laser scan data. When given a sequence of laser measurement of a moving object, the purpose is to discriminate the moving object into either a person, a bicycle, a group of people (briefly "group") or a car (including the bus, the truck and so on), considering normal urban scenery.

There have been researches addressing on the classification of moving objects in a traffic scene using a laser scanner, e.g. [3,19]. There have also been researches that fusing a laser scanner with a video camera for such a purpose [8,12,13,20]. Normally, laser data are used to obtain knowledge, such as the size and the speed of the object, as the input of a previously trained classifier. However, the estimation of an object size from an instance measurement might be erroneous due to the always existing occlusions either from the other objects or the object itself. This also happens in

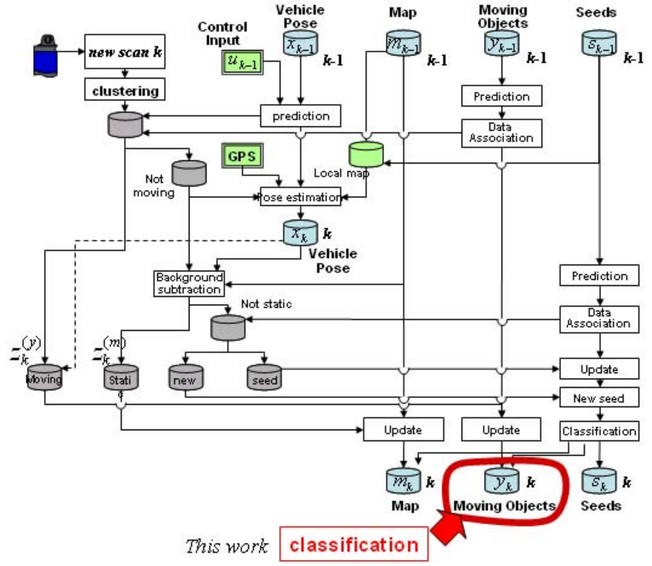

Fig. 1. A framework of SLAM with moving objects' detection and tracking

the estimation of speed. An accurate estimation of speed always relies on an accurate estimation of the object's center point or specific feature points, for example, which is very vulnerable in the case of occlusion. In addition, most existing approaches address on the classification of car and people using laser data, while, we have not found any one that considers the case such as a group of people, and few on the bicycle, which are common in a populated environment.

In this research, we first develop an object model to describe the objects in normal urban scenery. We examine all the features that could be extracted from a sequence of laser measurements, then examine their discriminative properties, i.e. the likelihood functions. Finally, we propose a classifier based on a supervised training on a set of selected features. This paper is organized as follows. The object model and feature extraction are discussed in section 2. A classifier is proposed in section 3. Experimental results and discussions are given in section 4, followed by conclusions and future works in section 5.

II. FEATURES FOR CLASSIFICATION

We consider normal urban scenery, where the moving object such as person, a group of people, bicycle and car (including bus and truck) exists. In order to classify a moving object, the features such as object size and speed are always used. Here we discuss a special feature in laser measurement that is discriminative in classification.

A. Data Appearance

Figure 2 shows a typical laser scan that highlights the data features of different kinds of objects.

1) Car: The data appearance of a car varies dramatically as its relative position and direction to sensor changes. A number of cars are captured in Figure 2, demonstrating some typical data appearance of cars in a horizontal laser scan. A car might be measured on one or two neighboring sides, so the laser points look like one or two orthogonal edges. We call each edge an "axis". In the case that only the rear or front side of a car is measured, a motion vector that is vertical to the extracted axis, could be detected through inter-frame differential, making up an additional axis. According to the maximal axes that could be extracted from an instance measurement of the object, we characterize a car as a two-axis object.

2) Bicycle: As for a bicycle, except the cases when it is measured only on its rear or head, where no obvious axis could be detected from the cloud of data, the laser points can be fit on a line that is parallel to the objects' motion vector(see Figure 2). Therefore, we characterize a bicycle as a one-axis object.

3) Person: In the case a person, its data appearance do not change dramatically considering an average range error ($3cm \sim 10cm$) in laser scanning. The data looks like a point cloud, no obvious axis can be extracted. Therefore, we characterize it as a zero-axis object.

4) Group: In a populated environment, it is common to have groups of people (i.e. people walk in a crowd, briefly "group"). The data always have a variety of appearances and their shape changes non-rigidly. In some cases, an edge that is either parallel or vertical to its motion vector could be extracted. And occasionally, two axes might also be detected. Therefore, a group might be characterized as either a one-axis object or a two-axis one, which brings much confusion in classification.

However, axes number is only one data feature to characterize the object. From an instance laser scan, the axes of an object might be partially measured. Moreover in many cases, it is hard to tell whether the axes are partially measured or not. Besides axes number, there are other axis-associated features that could be exploited in the classification of different objects. In the followings, we define object models and the features that are used in classification.

B. Object Model

In this research, the classes of moving objects are defined in a hierarchical structure as shown in Figure 3. At the first layer, moving objects are divided into three groups, zero-axis, one-axis, or two-axis objects. At the second layer, some detailed models are defined to achieve a more accurate classification. Here, we give explicit model definitions to person, bicycle and car as shown in Figure 4, and they can be expanded according to the moving objects to be classified. We do not give specific model definition to the class of group. It belongs to the "others" in Figure 3.

C. Feature Definition

Suppose there are totally m laser points measured on the moving object at scan k, two orthogonal axes are extracted from them. Among the m laser points, m_v corresponds to the vertical axis and m_h corresponds to the horizontal one. d_{ik} is the residual from laser point i to its corresponding axis, either vertical or horizontal. Let v_k denotes inter-frame

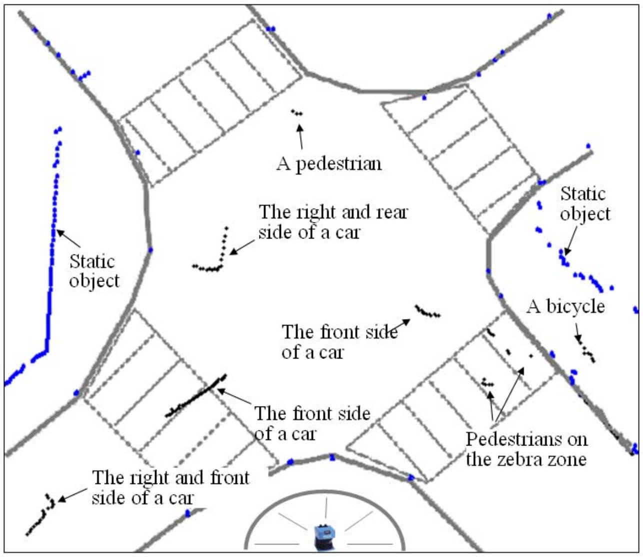

Fig. 2. Some typical data appearance of different kinds of objects in a laser scan. The road boundaries and zebra zones are hand draws in order for a better understanding.

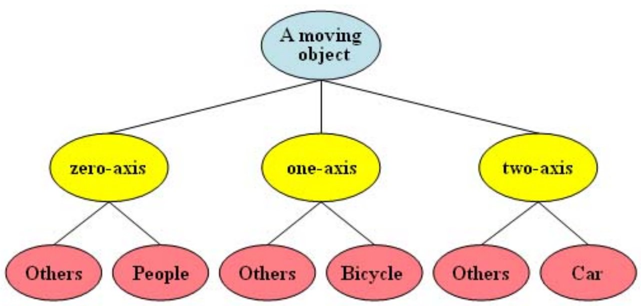

Fig. 3. A hierarchical structure of object classes

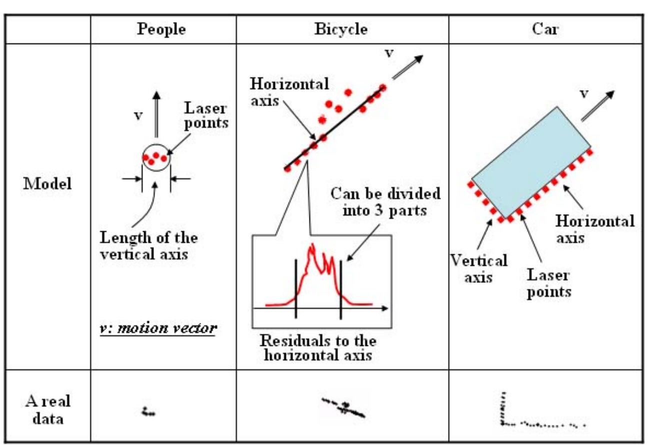

Fig. 4. The object models for car and bicycle

speed of the object at scan k, $\bar{v}_k$ be an averaged value at scan k after a smoothing procedure on v_k, $\bar{v}$ be the average speed during the measurement. Let $l_k^{(h)}$ denotes the length of horizontal axis, $l_k^{(v)}$ the vertical axis, $l_k^{(d)}$ diameter of the laser points. In addition, in the case of a bicycle, as has been defined in object models, the laser points might be segmented into three parts based on the residuals to the horizontal axis. Normally, residuals are high in middle parts, but low on two sides. Let $\bar{D}_k$ represents the averaged residual of middle part, and $\bar{d}_k$ for the two sides. We define the following features for classification.

Feature	Definition
y_1	$\frac{1}{n \cdot \|\bar{v}\|} \sum_{k=1}^{n} \|v_k - \bar{v}\|$
y_2	$\frac{1}{n \cdot \|\bar{v}\|} \sum_{k=1}^{n} \|\bar{v}_k - \bar{v}\|$
y_3	$max\{l_k^{(v)}\}$
y_4	$max\{l_k^{(h)}\}$
y_5	$max\{l_k^{(d)}\}$
y_6	$\bar{v}_k$
y_7	$\frac{1}{m_v} \sum_{i=1}^{m_h} d_{ik}$
y_8	$\frac{1}{m_h} \sum_{i=1}^{m_v} d_{ik}$
y_9	$\frac{\bar{d}_k}{\bar{D}_k}$

Features y_{1-5} reflect global tendencies of the moving object along the measurement, and y_{6-9} are the features estimated at each instance measurement.

D. Feature Extraction

Given a stream of laser measurements, features y_{1-9} are extracted as follows.

For any instance measurement z_k, a K-L transform is conduct on the laser points. According to the number of obvious axes that are detected, the laser points of z_k are further fitted to extract the edges on each side. Meanwhile, a speed vector v_k is estimated based on inter-frame data matching. It is compared with the extracted edges, in order to decide the horizontal axis $L_k^{(h)}$, the vertical axis $L_k^{(v)}$, their length $l_k^{(h)}$, $l_k^{(v)}$, and the residuals $\{d_{ik}\}$. If any of the axis is not detected, the corresponding values are set to be invalid.

Features y_{1-9} are calculated based on the valid values that are extracted from in-frame and inter-frame estimations on $\{z_k\}$. In the case of features y_{1-6}, valid estimations can be obtained for all the objects. However, the estimation of y_{7-9} is related with the axis number of the object, so it is not valid for all the objects. For example, y_8 is valid if the object is a two-axis object, and the vertical axis is measured.

III. CLASSIFICATION

A. Training for Likelihood Measures

For each pair of object class (c_j) and feature (y_i), a likelihood measure $\lambda_{c_j}(y_i)$ is defined telling the probability

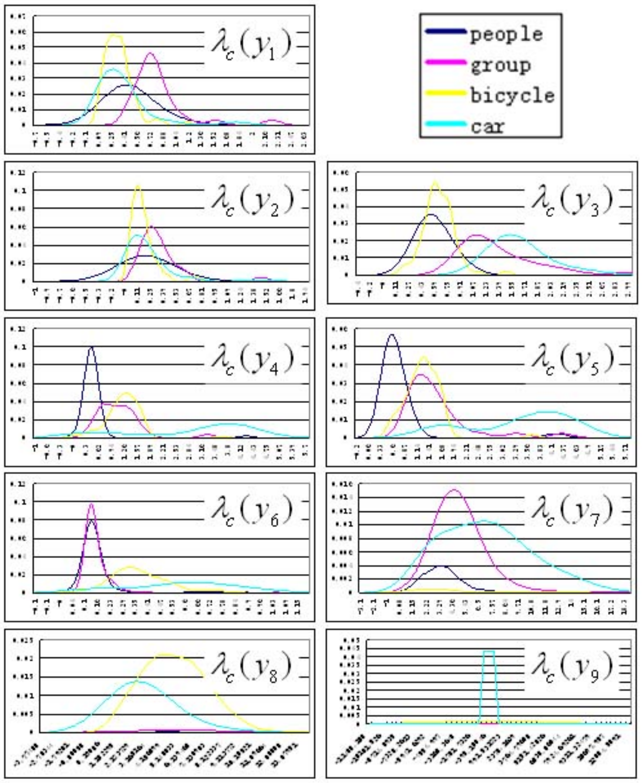

Fig. 5. The likelihood functions $lambda_{c_j}(y_i)$

of making a feature observation y_i when the object class c_j is known. In this research, all the likelihood measures are generated based on a supervised training using a set of real experimental data. They are demonstrated in Figure 5. The likelihood measure $\lambda_{c_j}(y_i)$ is basically a normalized histogram using the valid estimations y_i with respect to c_j. Here we need to mention a special handling for implementation. As has mentioned above, invalid estimations happen to the features y_{7-9}. These are also counted in our likelihood measures. Based on the training data, we calculate the ratio of invalid estimation y_i with respect to c_j, denoted by $P_{inv}(y_i|c_j)$. The ratios are shown below.

Feature	Person	Group	Bicycle	Car
y_7	0.8891	0.4331	0.9749	0.1865
y_8	0.9909	0.9595	0.4968	0.6572
y_9	0.9995	1	0.9322	0.9988

In order to count the invalid estimations, a normalization is conducted on $\lambda_{c_j}(y_i)$ to meet the following condition.

$$P_{inv}(y_i|c_j) + \int \lambda_{c_j}(y_i)dx = 1 \tag{2}$$

Given a feature estimation y_i, if it is a valid value, the probability $P(y_i|c_j)$ is calculated using a Parzen window.

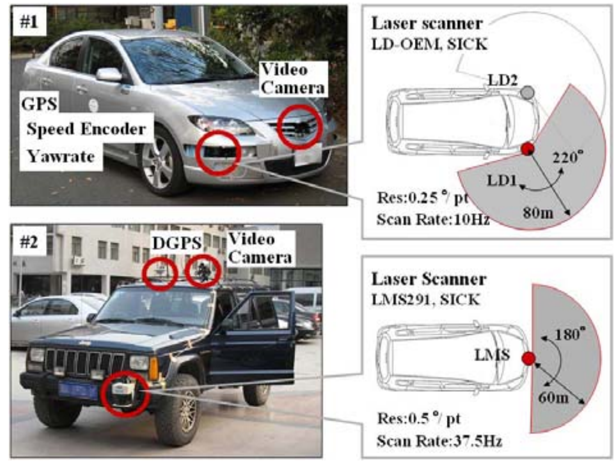

Fig. 6. The test-bed vehicles and their sensor configurations

However, if y_i is an invalid value, the probability $P(y_i|c_j)$ is set to $P_{inv}(y_i|c_j)$.

B. Classification Method

Given a stream of laser measurements $s = \{z_{k1}, ..., z_{kn}\}$ from scan k_1 to k_n, and a set of features $\{Y_1, ...Y_9\}$ extracted s, where $Y_i = y_{i,k1}, ..., y_{i,kn}$ are the set of y_i that are extracted from z_{k1} to z_{kn}, the objective is to classify a moving object into a certain class c_j, where c_j might be either a person, a group, a bicycle or a car. The problem is formulated as follows.

$$c_j = \arg\max_j P(c_j|Y_1, ..., Y_9) \tag{3}$$

According to Baysian rule, it can be parsed to

$$c_j = \arg\max_j \{P(c_j) \cdot \Pi_{i=0}^{9} P(Y_i|c_j)\} \tag{4}$$

Where, $P(c_j)$ is a prior that is trained previously using experimental data. $P(Y_i|c_j)$ is calculated as follows assuming that $\{y_{i,k}|k_1 \le k \le k_n\}$s are independent measurements. Here, the reason for us to take root n is to reduce the influence from the different stream lengths.

$$\begin{aligned} P(Y_i|c_j) &= \sqrt[n]{P(y_{i,k1}, ..., y_{i,kn}|c_j)} \\ &= \sqrt[n]{\Pi_{k=0}^{n} P(y_{i,k}|c_j)} \end{aligned} \tag{5}$$

IV. EXPERIMENTAL RESULTS

We present a set of experimental results on the classification of moving objects, and examine the possibility of improving driving safety and traffic data collection in a large populated environment.

A. Sensor and Data Configuration

Figure 6 shows the test-bed vehicles used in this study. Sensor configurations of the test-bed vehicles are slightly different, but their functions are similar and their data are

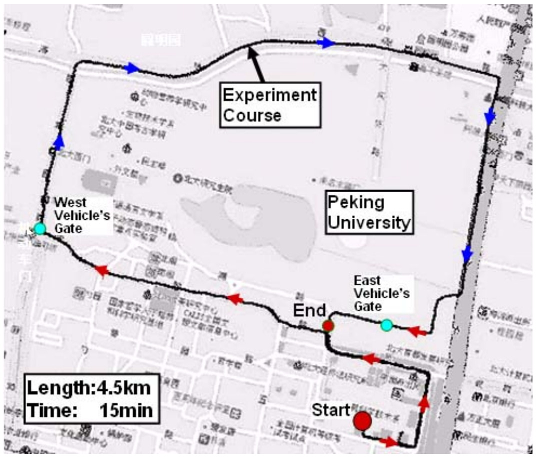

Fig. 7. Experimental Course

processed using the same approaches. The following experiment exploits data are collected using the test-bed #2, where a laser scanner (LMS291 from SICK) is mounted at the front of the vehicle, monitoring a wide angle (180 degrees, and 0.5 degree/point) of the vicinity with a scan rate about 37.5Hz. The data is downsized to 10Hz in processing considering the performance and computation efficiency. Also, a video camera is mounted and calibrated with the laser scanner. In this research, they are used to examine and visualize the results of laser-based processing. In the future, we will fuse both sensors to achieve higher intelligence and accuracy. Here, we need to make it clear that the experimental results demonstrated below are achieved in an off-line mode shortly after the data collection. The trajectories of moving objects as well as their data streams with respect to a global coordinate system are first extracted using the system of our previous development as shown in Figure 1. A detailed description to the processing and results can be found in [23]. Given the measurement streams of each moving object, our focus here is to classify each moving object into a person, a group, a bicycle or a car.

B. Experimental Course

The experimental course is shown in Figure 7, 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 the campus is very crowded with pedestrians, bicycles, and parked cars. The course outside the campus is also very dynamic, composed of a number of intersections and crowded roads. Among all the data sets that we have collected, this is the most challenging one.

C. Training and Classification

There have been totally 227 trajectories of moving objects extracted using the system of our previous development. Among them, 58 trajectories are individual person, 27 are groups of people, 65 are bicycles and 77 are cars. The ground truth values are counted from the calibrated video images. Among the 227 trajectories, 170 (75%) of randomly selected trajectories are used in training procedure, leaving the rest 57 trajectories for test. Based on the training samples, a set of likelihood measures with respect to each pair of class and feature are obtained. They are demonstrated in Figure 5. The prior $P(c_i)$ of each class is assigned to the ratio of the objects in training sample set.

TABLE I
CLASSIFICATION RESULTS

Class	Samples for Training	Samples for Test	Correct Classification	Accuracy Ratio
$Person$	44	14	13	93%
$Group$	22	7	6	86%
$Bicycle$	49	16	16	100%
Car	57	20	19	95%
$Total$	170	57	54	95%

Figure 8 demonstrates some of the results. Thirteen pairs of results are presented, where the first ten pairs are correct classification, the last three are wrong results. Each pair contains a screen capture of the processing program on laser scans, and a back-projection of the laser processing results onto the corresponding video image for visualization and evaluation.

Laser points of the moving objects are shown as red dots in both video and laser results. They are detected and tracked using the system developed previously. Based on the stream of laser points, the moving objects are classified and the results are represented using frames of different colors in video result, using characters in laser results. Red frame and the character 'P' associated with an ID of the moving object represents person, green frame and character 'G' represent a group of people, water-blue frame and character 'B' represent a bicycle, purple frame and character 'C' represent a car. Accuracy of the classification is counted by an operator looking at the back-projected result on video image. It is summarized in Table 1.

One of the major reasons for a wrong classification is the erroneous laser points extracted from the previous processing. These can be reasoned from the wrong classification results in Figure 8. Result #11 shows a person walks close to another object, and mis-recognized as a group. The reason for it is, when an object gets near to another, their laser points might be merged to one cluster, which tends to be mis-recognized as a bigger one. Result #13 shows a bus mis-recognized as a group. The reason for it is that the laser points on bus are divided into two in clustering procedure, which are mis-recognized as two smaller objects. On the other hand, Result #12 show a group of people mis-recognized as a car. Laser scanner measures a contour line of the object at a certain plane. Based on the limited

Fig. 8. Classification results

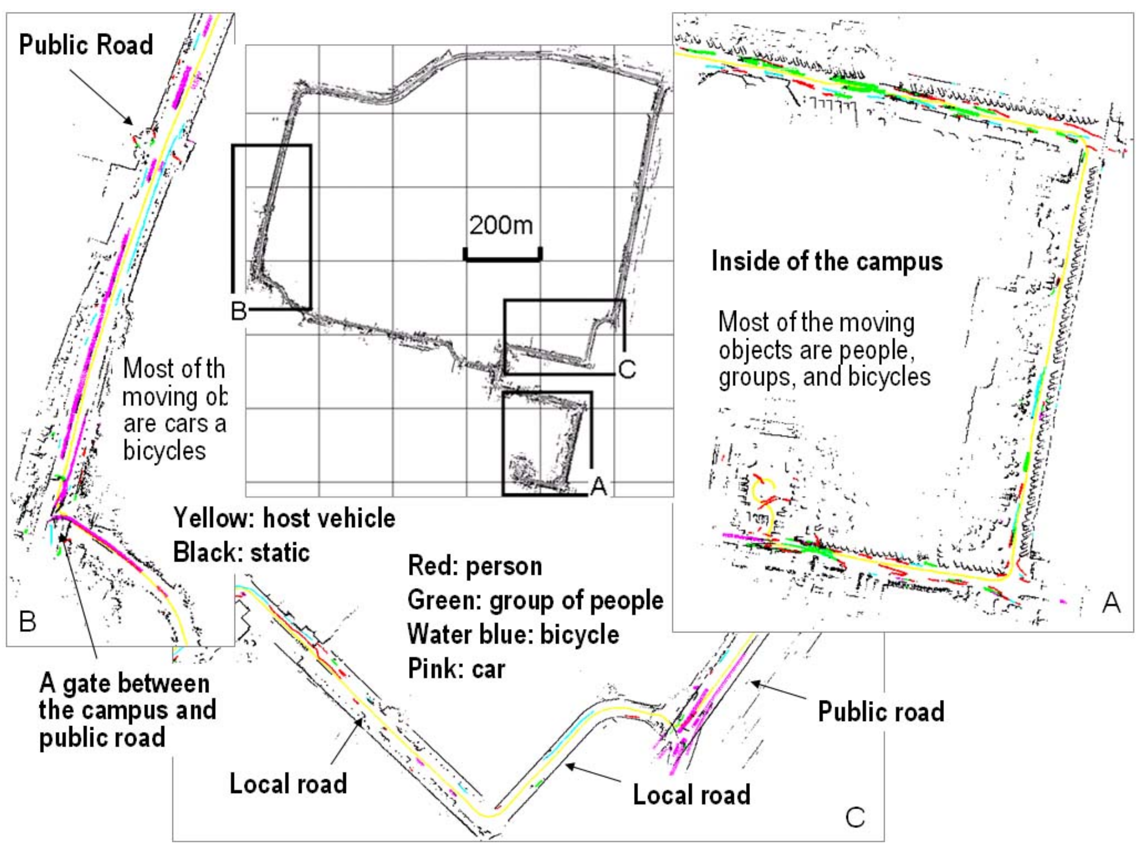

Fig. 9. A map demonstrating the classification results. Laser points of the moving objects are projected onto the map with a certain color representing their class.

information, it is difficult to tell the difference between them with a car of slow speed. In order to reduce such erroneous classification, a fusion of laser scanner with other kind of sensors, such as video camera, is important.

Figure 9 demonstrates a final map containing all the moving objects that are captured during the run. The results of simultaneous localization and mapping have been presented in [22,23]. Here, we present the classification results by projecting the laser points of moving objects onto the map with a certain color. Color definition is consistent with that of Figure 8, where red represent for single person, green for group, water-blue for bicycle, and pink for car. Three parts of the map are enlarged. Sub-map "A" is inside of the campus, where many people, groups, and bicycles exist. Sub-map "B" is outside of the campus, where cars and bicycles are the major moving objects. In Sub-map "C", the host vehicle run on a public road at first, and turned to a private road later. The difference of traffic volume on the roads is clearly presented by the map. It is also possible to generate a map for each class of objects using their speed, direction and so on, which demonstrate a possibility as an advanced probe vehicle for traffic data collection.

V. CONCLUSIONS AND FUTURE WORKS

Motivated by two potential applications, i.e. enhancing driving safety and traffic data collection, a system have been developed using a single-layer horizontal laser scanner as the major sensor for both localization and perception of the surroundings in a large dynamic urban environment. This research focus on a classification method, that given a stream of laser measurements, classifies the moving object into either a person, a group of people, a bicycle or a car. In this research, a number of features are defined after examining the property of data appearance. The relationship (i.e. likelihood measure) between each pair of feature and class are examined, followed by a classification method. Experimental results demonstrated that the algorithm has efficiency with respect to both driving safety and traffic data collection in highly dynamic environment.

However in future, the algorithms are necessary to be examined using on-line systems. Also, a fusion with video image will be addressed to improve classification accuracy..

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