The 2010 IEEE/RSJ International Conference on
Intelligent Robots and Systems
October 18-22, 2010, Taipei, Taiwan

Online Road Surface Analysis using Laser Remission Value in Urban Environments

Teppei Saitoh and Yoji Kuroda
Meiji University, Department of Mechanical Engineering,
1-1-1 Higashimita, Tama-ku, Kawasaki, Kanagawa, Japan
Email: {tsaitoh, ykuroda}@isc.meiji.ac.jp

***Abstract*— This paper describes the novel road surface analysis using reflectivity of a laser scanner in structured outdoor environments. The proposed approach makes estimation of road surface conditions robust by using information of remission value as reflectivity of a laser that much less depends on brightness of color or ambient lighting than passive camera. Our method can be applied to various structured outdoor environments by online estimating distributions of the remission value from the road surface. This article shows that the method is successfully verified with accuracy of approximately 99% at both (i) the testing course of the 2009 Real World Robot Challenge which is known as "Tsukuba Challenge" and (ii) our university campus.**

***Index Terms*— Self-Supervised Learning, Reflectivity of Laser, Robot Maps, Structured Environments.**

I. INTRUDUCTION

RECENTLY, there are a lot of researches making a vehicle autonomous whom objectives are to improve safety of driving or detecting obstacles. Defense Advanced Research Projects Agency (DARPA) of United States organized "DARPA Grand Challenge" in 2004 and 2005 [1][2]. In addition, "DARPA Urban Challenge" was organized in 2007, which is a competition for autonomous vehicles achieving various predefined missions in urban environments [3]. On the other hand, "Real World Robot Challenge" which is known as "Tsukuba Challenge" has been organized since 2007 in Japan [4]. This challenge has required that robots have to drive along a predefined course autonomously in structured environments of Tsukuba city in Japan. Travel distance of the course that robots have to go is approximately 1 km. Pedestrians and other mobile robots exist in the course, because the course is not organized for this challenge. Robots have to arrive at a predefined goal within 2 hours although driving speed of robots is restricted at 4 km/h.

There are more difficult factors than that of DARPA Grand Challenge or Urban Challenge to accomplish the mission in the urban environments organized in 2009 Real World Robot Challenge. The driving course consists of diverse fields. In Urban Challenge, the area where robots drive is mostly paved road, which is less changed basically. Therefore, simple recognizing drivable surface algorithm such as detecting curbs or centered line is enough to accomplish the mission in the challenge. In Grand Challenge, recognizing the terrain geometrical hazards of the road works well in a desert environment. However, the conditions of the driving course in Tsukuba Challenge are not constant as

Fig. 1. Structured outdoor environment in Tsukuba. Road surfaces where a robot should go through are not uniform

shown in Fig. 1. A robot has to recognize hazardous object that are vegetation, boulevard trees, structures and curbs, which have non-uniquely shapes and are in various areas. Especially, the environment shown in right top figure of Fig. 1 makes the perception more complex problem. The problem in this environment of the figure is that robots are forbidden to drive into the vegetation. Drivable region, which is defined as traversable by organizers, is only center area. In this situation, it is difficult for a robot to recognize boundaries by using like a laser scanner according to the shape, because there are no clear boundaries such as steps between vegetation and center drivable area. Additionally, there are also drivable areas that have a lot of materials or colors (like textured paving block) in the course, and advanced decisions have to be required.

In this paper, novel road identification using a laser sensor is proposed. The approach can classify drivable regions from both of geometrical and non-geometric features by a laser. In order to classify and estimate road surface conditions, range measurement and remission value of a laser scanner are used. This approach with probabilistic analysis allows to recognize drivable region in uneven color fields like shown in left top or right bottom pictures of Fig. 1 without supervised learning or prior information. In addition, using remission value like color information is able to reduce fatal error of map integration by road vibration noise in driving. This paper shows road surface analysis results in the 1 km course of Tsukuba Challenge 2009 as an outdoor structured environment to show effectiveness of the proposed approaches. Another experimental result is shown in approximately 500 m course of our university campus, and lower false positive error of the road surface estimation is accomplished in both experimental results in comparison to other road surface analysis methods.

II. Related Works

A lot of drivable road detection have been studied. Detecting obstacles or map building using geometrical information from 2D or 3D laser scanners is effective [5][6]. Generally, 3D laser scanner is used to detect low obstacles like curbs in a road. However, estimating accurate road region continuously requires accurate robot pose estimation. Thrun et al. have proposed Probabilistic Terrain Analysis (PTA) in DARPA Grand Challenge. This algorithm is able to recognize hazardous regions in spite of not requiring high accurate pose estimation and to correct pose error affected by road noise [10]. Considering error of pose estimation and laser measurement probabilistically, it can remove estimation error of false positive hazardous steps on road. In vegetation like shown in Fig. 1, however, this approach cannot recognize drivable road surface that has even height of road boundary between vegetation and general road.

Therefore, low height vegetation recognition by a laser range sensor has been researched [7][8][9]. [7][8] are classification approaches that analyze distribution of geometrical information measured by laser sensors. [9] uses hidden Markov model to separate vegetation and road surface from variance of height information acquired from lasers. These approaches have same problems of pose estimation error while a robot drives. Therefore, they are done in a robot stopping by using 3D laser scanner. There are researches using both of vision sensor and laser scanner to detect not only general obstacles but low vegetation [11][12]. Moreover, H. Dahlkamp et.al have proposed a mapping technique by integrated vision sensor and laser scanner [13]. The approach has advantages of higher speed capturing 3D geometrical measurements than stereo reconstruction with maintaining advantage of vision system. However, it is hard to keep reliability of image processing for recognitions, because circumjacent brightness of a robot is easy to changes in outdoor environments according to weather or time of day. Moreover, a lot of factors, which have various color objects such as tree, stack, curb, vegetation, structures and so on in the outdoor environments dealt with this research, make the reliability reduce.

In order to cover the shortcomings of vision sensor for the brightness, several researches have introduced remission value as a reflectivity of laser sensor to recognize road surface conditions [14][15][16]. Remission value, which is a reflectivity of laser sensor, has advantages that remission value is hard to be affected from circumjacent brightness and road surface condition such as night time or rainfall [14]. Therefore, the remission value can be used as more reliable information than that of color information of vision.

In [14], SLAM algorithm utilizes a map based on the remission value to perform map-closing loop. An approach using vision, laser measurement and its remission value has been proposed, which analyze geometry and color information of structured objects to classify the area into several semantic labels [15].

Fig. 2. Testbed Mobile Robot named INFANT. INFANT means INtegrated Foundations for Advanced Navigation Technology.

The approach of [16] is closest to our approach has been proposed. In this algorithm, surface terrain is classified into road or vegetation by this approach in structured environment. The laser remission is modeled as a function of distance, incidence angle and material with self-supervised learning. However, road surface is classified into only two labels that are road and vegetation by learning a model of vegetation. The system uses Support Vector Machine to learn the model, which needs off-line learning previously. In our research, the system can classify the surfaces into several classes with self-supervised learning while the robot drives. Therefore, our system needs no prior information of the environments or learning.

III. Map Building

In this research, road surface analysis of drivable region is performed using geometrical 3D point information and remission value as a reflectivity of a laser. In order to acquire 3D point cloud around a mobile robot, 3D points of road surface are captured by a laser scanner fixed on the robot and integrated by time series in the robot driving. The mobile robot used in this research is shown in Fig. 2.

A. Remission Value of Laser Scanner and its Calibration

Reflectivity of a laser (remission value) is employed in order to robustly recognize a road where low positioned obstacles lie down such as vegetation or curbs neighbored with even or lower step. Each beam of a laser returns not only distance measurement but its remission value as a reflectivity. The remission value indicates observation according to reflectivity of materials hit for the beam. Thus, the value represents the object's information closed to intensity of color. Compared with vision, the remission value can be used as more reliable information like intensity of color because the value is hard to be affected from outdoor weather or brightness [14]. Figure 3 shows an example snapshot of 3D point cloud acquired at night. The color indicates remission value of a point. The bright color shows strong reflectivity.

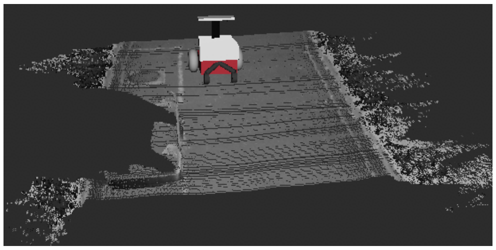


Fig. 3. 3D point cloud acquired at night. The points are colored by the laser remission value. Manhole is shown in the left of the robot.

It is shown that white line and manhole on the road can be observed by the remission value even if in night.

The remission value has a characteristic of reduction of the value in proportion to the distance. Therefore, the value has to be calibrated by related to the observed distance. In this paper, the value is calibrated by following expression made from several experiments.

$$\gamma^{i*} = \frac{\gamma^i}{k_\gamma \exp(-r^i/\beta_\gamma)} \tag{1}$$

Where, γ^i is a observed remission value, k_γ and β_γ are positive constants. r^i is a measured distance. We set $k_\gamma = 3500$, $\beta_\gamma = 10000$ as a result of sensor calibration in this paper. This equation makes the remission value normalized to [0 1].

B. Map Representation

Hazardous region, which means obstacles or where a robot cannot entry, may be able to be detected by information of the height or remission value. Though, it is difficult to estimate condition of the point on road from acquired 3D points directly. In this paper, squared 2D grid map is employed to deal with the area as an approximated patch at $x - y$. The condition of the area at $x - y$ is computed from points that fall into the patch whom size is expressed as ϵ. Each patch contains the height z at $x - y$, remission value γ and updating time t. The representative remission value γ at $x - y$ is a mean of the values that falls into the patch. The height z contains two values as maximum and minimal of the heights of the points. In this paper, the size of a patch is set to 15 cm × 15 cm.

IV. Self-Supervised Road Identification using Remission Value

A. Analysis for Drivable Road Surface

This section describes a classification method that road surface is drivable or not by using both of distance and remission value of a laser scanner. The drivable region can be acquired at time t with a local map m as following expression.

$$\frac{p(m_{xy} = 1 | m,\ z_{xy}\ \gamma_{xy}, \delta)}{\int p(m_{xy} = 1 | m,\ z_{xy}\ \gamma_{xy}, \delta) d\delta} > \pi_m \tag{2}$$

Where, $p(m_{xy} = 1 | m,\ z_{xy}\ \gamma_{xy}, \delta)$ indicates a probability that the area at $x - y$ is drivable for a robot when height z_{xy} and remission value γ_{xy} is observed. π_m is a threshold of the probability to decide that the area is drivable. $m_{xy} = 1$ means that the patch m_{xy} is drivable for a robot. δ is a variable to decide $m_{xy} = 1$. The denominator of left hand is a constant value to normalize the left hand side equation. The authors investigated structured outdoor fields where weaves drivable even height area and undrivable area. As a result, it is shown that the mixture fields can be divided effectively as following definitions.

1) Difference of heights z of neighbors' patches is larger than a certain constant and the difference of neighbors remission values γ is larger than a constant. Then, the region is defined as undrivable, because the area is made from differential materials and contains steps.
2) The region is able to be defined as undrivable but there are no steps, when difference of neighbors remission values γ is larger than a certain constant (this constant value is larger than one of the first definition).
3) The remission value γ in a patch is not identified as drivable by self-supervised learning, then, it is regarded that a robot has not to entry the area. Therefore, the area is defined as undrivable.

Under these definitions, numerator of left hand side of Eq. 2 is rewritten as follows.

$$\begin{aligned} p(m_{xy} &= 1 \mid m,\ z_{xy}\ \gamma_{xy}, \delta) \\ &= \big(1 - p(\Delta z_{xy} > \delta_z,\ \Delta\gamma_{xy} > \delta_{\gamma\alpha} \mid m)\big) \\ &+ \big(1 - p(\Delta\gamma_{xy} > \delta_{\gamma\beta} \mid m)\big) \\ &+ p(m_{xy} = 1 \mid\ m, \gamma_{xy}) \end{aligned} \tag{3}$$

Each term of right hand side of this equation corresponds to above definitions. δ_z, $\delta_{\gamma\alpha}$, $\delta_{\gamma\beta}$ are thresholds respectively, and they are defined as $\delta_{\gamma\alpha} < \delta_{\gamma\beta}$. Then, it is very important problem how to decide these thresholds as the parameters for accurate recognition. If $\delta_{\gamma\alpha}$ and $\delta_{\gamma\beta}$ were defined as constant values, wrong recognizing the area might occur on the various textured road which means the road has colored patterns. Additionally, when δ_z is set to large constant, low obstacles such as curbs could not be detected, or if δ_z is small, false positives would increase by pose estimation error caused by road noise. In this research, we propose a novel laser-based classification approach that is suited for decision of the thresholds for recognizing road surface in various outdoor environments by using self-supervised learning.

B. Geometrical Road Surface Estimation

The first term $p(\Delta z_{xy} > \delta_z, \Delta\gamma_{xy} > \delta_{\gamma\alpha} | m)$ of right hand side in Eq. 3 can be factorized as follows.

$$\begin{aligned} p(\Delta z_{xy} &> \delta_z, \Delta\gamma_{xy} > \delta_{\gamma\alpha} \mid m) \\ &= p(\Delta z_{xy} > \delta_z \mid m) p(\Delta\gamma_{xy} > \delta_{\gamma\alpha} \mid m) \end{aligned} \tag{4}$$

Factorized probabilities of geometrical hazard and undrivable regions decided by remission value can be considered independently. This paragraph describes the probability of right hand side first term $p(\Delta z_{xy} > \delta_z \mid m)$ that indicates hazardous probability estimated by geometrical definition.

A point that has lowest height in the area at $x - y$ with ϵ size is defined as $(X_t^i,\ Y_t^i,\ Z_t^i)$. The relationship between the point and the neighbors point $(X_u^j,\ Y_u^j,\ Z_u^j)$ is focused. Where, u is a time at a robot observing the data. Δz_{xy} is defined as $\left|Z_t^i - Z_u^j\right|$. A condition that the area is forbidden to entry for a robot is defined as following.

$$\left|Z_t^i - Z_u^j\right| > \delta_z \tag{5}$$

Thus, the area is decided to be undrivable when the difference of Z direction of neighboring points is larger than a certain constant value δ_z, and if the difference were smaller than the constant the region would be drivable.

However, a problem would be generated in detecting lower steps on field such as between road and curbs. The problem occurs due to error of robot's pose estimation required to integrate 3D points to make a local map. The bump estimation error on ordinary positive road surface would cause to take off robot navigation from drivable road surface. In order to overcome this problem in this research, we employ Probabilistic Terrain Analysis (PTA) proposed by Thrun et al. [10]. PTA can prevent road hazard errors caused by pose estimation error effectively by probabilistic approach.

Thus, probability that bump between neighbors' points with ϵ exceeds a threshold δ_z is able to be calculated with normal distribution as

$$p\left(\left|Z_t^{i*} - Z_u^{j*}\right| > \delta_z\right) > \pi. \tag{6}$$

Where, π is the error probability threshold. We set $\delta_z = 3$ cm with π=0.05 (10%) in this research. This equation is detailed in [10].

C. Road Surface Classification using Remission Value

Right hand side of Eq. 3 and right hand side of Eq. 4 contain terms calculated by remission value. However, each distribution by remission value acquired from an outdoor field is different definitely by depending on the environment. For this reasons, it is hard for the classification to be adapted to the changing environment when thresholds $\delta_{\gamma\alpha}, \delta_{\gamma\beta}$ for remission value in Eq. 3 and Eq. 4 are constant values. Therefore, these thresholds have to be adaptable for changing environment. In addition, it is desirable to be able to identify low height hazard such as vegetation as undrivable region only to use remission value. However, supervised learning can not be employed to be adapted for massive situation of changing environment for the road surface classification. We propose the novel road surface classification method with self-supervised learning for decision of the thresholds. This approach can identify drivable road surface by analysis and classification of the remission value distribution that a local map includes.

Left picture (a) of Fig. 4 shows example snapshots of a local map colored by remission values in vegetation and road. White points indicate strong remission values, and darker points mean weak values. Difference of remission values appears clearly in this environment that consists of only two elements vegetation and road. On the other hand, environment shown in Fig. 4 (b) of right side consists of hedge, dirt, braille block and also fallen leaves. It is difficult to detect positive road surface or definite boundaries from like this environment including the complex distribution of remission value. Figure 5 shows histograms of remission value that the environments shown in Fig. 4 (a) and (b) include. The histogram in top of Fig. 5 indicates definite difference of remission values between vegetation and road. Meanwhile, each distribution shown in histogram of field (b) in bottom of Fig. 5 spreads widely around hedge, dirt, braille block and fallen leaves. We note that it is not suit for the distribution of remission value to be classified by constant thresholds in like this environment. Therefore, we propose that remission value distribution of a local map is analyzed and classified into several distributions. In this approach, an acquired distribution is approximated as mixture of gaussian distribution by using *Expectation Maximization* (EM) algorithm [17].

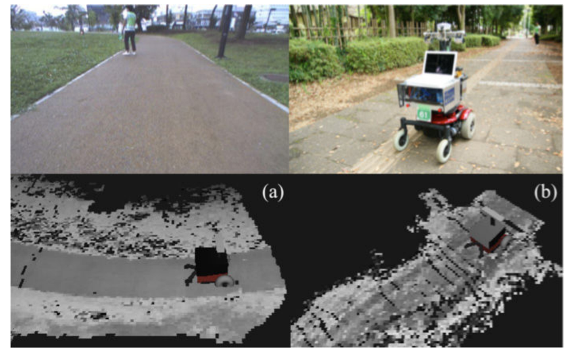


Fig. 4. Example of ground surface map of remission value of laser.

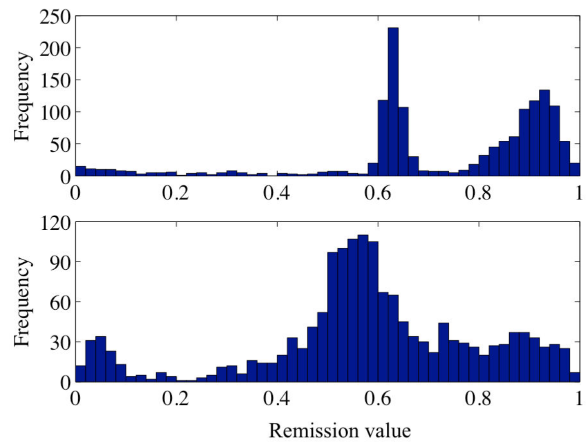


Fig. 5. Histogram of ground surface of laser in the fields. Top histogram is in field (a) and bottom is in field (b).

D. EM Algorithm

EM algorithm is a representative approach to search probabilistic parameters to maximize log likelihood of probabilistic variables for observations. In this research, EM algorithm is used to estimate probabilistic variables of the distribution of remission value that a local map has as a mixture of gaussian distribution. Thus, remission value distribution $\Gamma_t =$

$\{\gamma_1 \dots \gamma_j\}$ of a map m that a robot has at time t is defined as following:

$$p(\Gamma_t \mid \alpha, \mu, \Sigma) = \sum_k^K \alpha_k N(\Gamma_t \ ; \ \mu_k, \ \Sigma_k) \tag{7}$$

Where, K is a number of gaussian distribution to approximate. $\alpha = \{\alpha_1 \dots \alpha_K\}$ is a mixture proportion of the distribution but there is constrained condition $\sum_i^K \alpha_i = 1$. $\mu = \{\mu_1 \dots \mu_K\}$, $\Sigma = \{\Sigma_1 \dots \Sigma_K\}$ means mean and variance of approximated gaussian distribution, respectively. Using maximum likelihood estimation, parameters to maximize following log likelihood function are estimated for EM algorithm.

$$\begin{aligned}&\log p(\Gamma_t \mid \alpha, \mu, \Sigma)\\ &= \sum_n^N \log \sum_k^K \alpha_k \frac{1}{\sqrt{2\pi\Sigma_k}} \exp\left\{\frac{-(\gamma_n - \mu_k)^2}{2\Sigma_k}\right\}\end{aligned} \tag{8}$$

Where, N is a number of observation data. This estimation is computed by two steps, which are E-Step and M-Step, for estimating maximum likelihood.

a) E-Step: E-Step computes conditional expectation of likelihood function on the parameters now estimated. Expectation $Q(\theta)$ for parameters $\theta = \{\alpha, \mu, \Sigma\}$ is to

$$Q(\theta) = \sum_n^N \sum_k^K p(k \mid \gamma_n; \theta) \log N(\gamma_n; \mu_k, \Sigma_k). \tag{9}$$

Where, $p(k \mid \gamma_n; \theta)$ means posterior probability of parameter k. The probability is given by following expression based on Bayes' theorem.

$$p(k \mid \gamma_n; \theta) = \frac{N(\gamma_n; \mu_k, \Sigma_k)\alpha_k}{\sum_k^K N(\gamma_n; \mu_k, \Sigma_k)\alpha_k} \tag{10}$$

b) M-Step: From solved posterior probability $p(k \mid \gamma_n; \theta)$, means μ, variances Σ and mixture proportion α of mixture of gaussian distribution are solved. Means μ, variances Σ and mixture proportion α are respectively given by:

$$\begin{aligned}\mu_k &= \frac{\sum_n^N p(k \mid \gamma_n; \theta)\gamma_n}{\sum_n^N p(k \mid \gamma_n; \theta)}\\ \Sigma_k &= \frac{\sum_n^N p(k \mid \gamma_n; \theta)(\gamma_n - \mu_k)^2}{\sum_n^N p(k \mid \gamma_n; \theta)}\\ \alpha_k &= \frac{1}{N} \sum_n^N p(k \mid \gamma_n; \theta).\end{aligned} \tag{11}$$

E. Road Surface Classification

Distribution of remission value that a map has is classified into K gaussian distributions from estimated mixture of gaussian $\Theta = \{\theta_1 \dots \theta_K\}$. Fig. 6 shows an example result of mixture of gaussian approximating the histogram of distribution shown in top of Fig. 5. Here, a number of classes to approximate the distribution is set to $K = 3$. This classification approach and each distribution of remission value are used to compute Eq. 3.

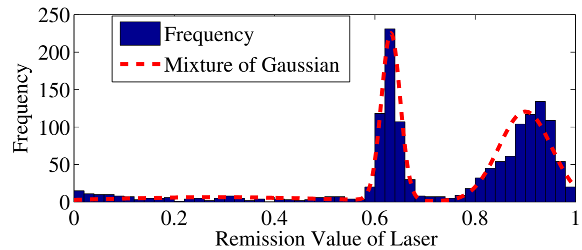


Fig. 6. Histogram of remission value of laser in field (a). The red dashed line shows fitted mixture of gaussian function.

First, the drivable probability $p(m_{xy} = 1 \mid \ m, \gamma_{xy})$ of the third term in Eq. 3 is estimated from classified each distribution. The condition $m_{xy} = 1$ is defined as area where a robot currently drives. Mean of remission value in the patch currently occupied by the robot is expressed as γ_{ro}, and the probability $p(m_{xy} = 1 \mid \ m, \gamma_{xy})$ is computed by

$$\begin{aligned}p(m_{xy} = 1 \mid \ m, \gamma_{xy}) &= p(\gamma_{xy} = \mu_{ro} \mid \ \Gamma_t, \gamma_{ro}, \theta)\\ &= \exp\{\frac{-(\gamma_{ro} - \mu_{ro})^2}{\Sigma_{ro}}\}.\end{aligned} \tag{12}$$

Where, μ_{ro} and Σ_{ro} indicate mean and variance of drivable region class selected from γ_{ro}. The drivable class is decided by γ_{ro} using maximum likelihood estimation.

Secondly, it is shown to compute $p(\Delta\gamma_{xy} > \delta_\gamma \mid m)$ of second term of Eq. 3 and right hand side in Eq. 4. When remission values in nearby area belong to same class, the difference of the value is modeled as following.

$$\gamma_t^{i*} - \gamma_u^{j*} \sim N\big(0, \Sigma_\gamma^{1/2}\big) \tag{13}$$

Thus, the probability that the values in nearby area belong different class is given by

$$p\big(\gamma_t^{i*} \neq \gamma_u^{j*}\big) > \pi_\gamma \tag{14}$$

Where, π_γ is an error probability of remission value error. In this research, $p(\Delta\gamma_{xy} > \delta_{\gamma\alpha} \mid m)$ is set to $\pi_{\gamma\alpha} = 0.159(68\%)$. $p(\Delta\gamma_{xy} > \delta_{\gamma\beta} \mid m)$ is $\pi_{\gamma\beta} = 0.05(10\%)$. Therefore, $\delta_{\gamma\alpha}$ and $\delta_{\gamma\beta}$ are expressed as $\delta_{\gamma\alpha} = 1\sigma_\gamma$ and $\delta_{\gamma\beta} = 1.64\sigma_\gamma$, and expressed as follows.

$$\begin{aligned}p(\Delta\gamma_{xy} > \delta_{\gamma\alpha} \mid m) &\sim (\gamma_t^{i*} - \gamma_u^{j*})^2 &> \Sigma_\gamma\\ p(\Delta\gamma_{xy} > \delta_{\gamma\beta} \mid m) &\sim (\gamma_t^{i*} - \gamma_u^{j*})^2 &> 1.64^2\Sigma_\gamma\end{aligned} \tag{15}$$

Where, Σ_γ indicates variance of remission value of the drivable region class computed by EM algorithm, and $\sigma_\gamma^2 = \Sigma_{ro}$.

Σ_{ro} is computed by executing analysis of remission value distribution by EM algorithm at every calculation step in driving. The classification and the thresholds are decided adaptively in the environment. In this paper, a number of classification is set to $K = 3$. This classification number was decided by experimental investigation, and it is enough to represent the distribution. Initial values of means and variances at time $t = 0$ are set to $\{0.0, \ 0.5, \ 1.0\}$ and $\{0.05, \ 0.05, \ 0.01\}$, respectively. Initial mean and variance

Fig. 7. Example snapshots of experimental fields in our university campus (A) and Tsukuba Challenge course (B).

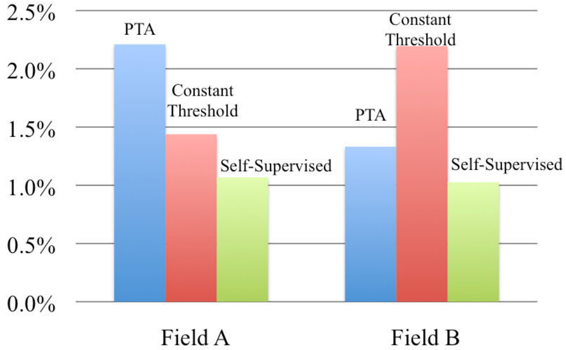


Fig. 8. Comparison of false positive rate of PTA and our approaches.

at time t to compute EM algorithm use the previous value calculated at time $t-1$ assumed as that the distribution of remission value of a local map would not abrupt change. After computing Eq. 3, the area is judged as drivable or not by Eq. 2. In this paper, π_m in right hand side of Eq. 2 is defined as 0.55 (55%).

V. Experiments

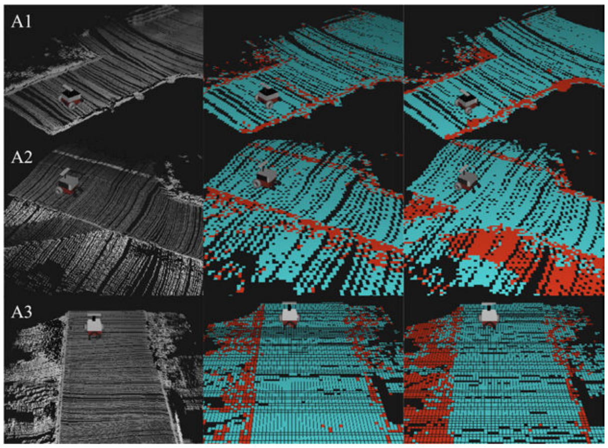
Our approach has been implemented and evaluated in several environments in order to show the effectiveness. The experiments are demonstrated in two outdoor structured environments, our university campus (Field A) and whole course of Tsukuba Challenge (Field B). Figure 7 shows example snapshots of experimental fields. Field A in our university campus includes paved road, curbs and little vegetation. Another experimental Field B has hedge, dirt, braille block, also fallen leaves and low vegetation, which indicates diverse textured environment. A robot that is used in this experiments goes at approx. 0.5 m/s speed. Total travel distances of the robot in both of our university and Tsukuba course are 533 m and 1037 m, respectively.

Figure 8 shows false positive rate detected on the drivable region by road surface classification in our approach and other methods. Other approach results as comparisons that are computed by PTA that we implemented but no parameter training (hand tuning) [10] and approach with constant thresholds ($\delta_{\gamma\alpha} = 0.08, \delta_{\gamma\beta} = 0.15$) are also shown. Failure rate in the figure is defined as a ratio of false positive for total area where a robot travels. The false positive means phantom obstacles in originally traversable area.

The result shows that the rate of PTA approach has a larger error of 2.2% than the other approaches in Field A that has hazardous low curbs. This result indicates that it is hard to separate pose estimation error by road noise vibration and detecting low centimeters curbs even if PTA is introduced. On the other hand, analytical result of constant threshold approach using constant thresholds is given lower false positive of 1.5% than that of PTA approach. Because the experimental field consists of uniform paved road make the remission value analysis easy even if our self-learning is not introduced. In Field B, however, it is difficult to classify the road surface that is not uniform condition using constant threshold method as constant thresholds for remission value analysis. Thus, the false positive of the result increases to 2.2%. Moreover, false positive of PTA approach in Field B including a few low curbs tends to decrease to 1.3%. Each advantage for environments can be shown in these results of PTA or constant threshold method. However, it is shown in Fig. 8 that lowest false positives in these approaches are able to be given by our approach with self-supervised learning. This result shows that our approach is adaptable for the road identification in the outdoor environments.

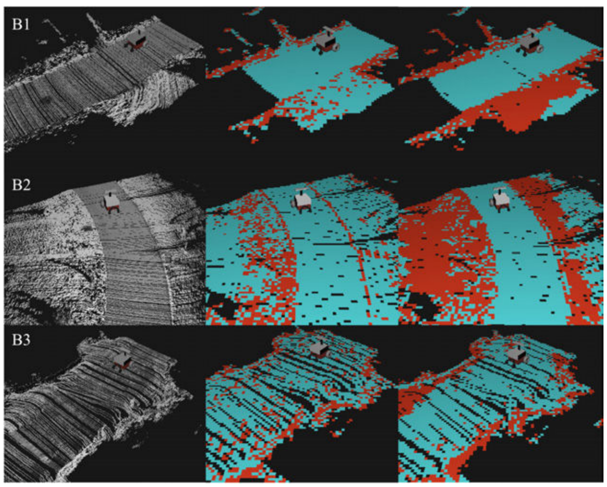
Figure 9 shows sample snapshots of classification results in Field A of our university campus. Red patches mean undrivable area for a robot, and blue patches indicate drivable. Figure 9 (a) indicates 3D point cloud colored by remission value acquired from laser data. Figure 9 (b) and (c) represent road surface analytical results by constant threshold methods and our self-supervised approach, respectively. Figure A1 (b) (center top picture) in Fig.9 shows that false positive of undrivable region is generated vertically on road by pose estimation error. On the other hand, accurate road surface analysis is accomplished in the figure A1 (c) without false positive even if pose estimation would be caused. In the results shown in figure A2 (b) and A3 (b) in Fig. 9 where both sides of the robot are vegetation area, only boundary lines can be detected by constant threshold method. However, our approach results shown in figure A2 (c) and A3 (c) achieve accurate road surface estimation that left side whole area returning strong remission value is able to be recognized as undrivable area.

Figure 10 shows sample snapshots of classification results in Field B of the course of Tsukuba Challenge. Figure B2 (b) shows that only boundary lines can be detected by constant threshold method in the field where both sides of the robot are vegetation area (Fig. 7). Our approach result (c) indicates that appropriate road identifications, which whole vegetation area is classified as undrivable region, are able to be achieved. In addition, figure B3 shows accurate estimation in the area where has a lot of fallen leaves is also given by our approach even if the fallen leaves makes. There are a lot of fallen leaves or dirt area in the figure B3, which makes the distribution of remission value not uniform. The results of the figure B3 (b) shows a lot of false positives caused by detecting wrong region with different remission value from that of road due to constant thresholds of constant



(a) 3D point cloud (b) constant threshold (c) self-supervised

Fig. 9. Comparison of terrain analysis result in Field A



(a) 3D point cloud (b) constant threshold(c) self-supervised

Fig. 10. Comparison of terrain analysis result in Field B

threshold method. However, analytical results B3 (c) shows effectiveness of our approach that fewer false positive is generated than results of B3 (b) by calculating distribution of the remission of road including fallen leaves.

VI. Conclusion

In this paper, we proposed novel approach to road surface classification using the remission value of a laser scanner. Our approach using a laser is able to detect hazardous regions including not only geometrical hazard such as structures or curbs but undrivable area without geometrical information such as vegetation. The approach accomplished accurate road classification with fewer false positive using self-supervised learning of the distribution of the remission value of a map. This paper shows that the method is successfully verified with accuracy of approximately 99% at both our university campus and the testing course of Tsukuba Challenge.

References

[1] Thrun, S., Montemerlo, M., Dahlkamp, H., Stavens, D., Aron, A., Diebel, J., Fong, P., Gale, J., Halpenny, M., Hoffmann, G., Lau, K., Oakley, C., Palatucci, M., Pratt, V., Stang, P., Strohband, S., Dupont, C., Jendrossek, L.-E., Koelen, C., Markey, C., Rummel, C., van Niekerk, J., Jensen, E., Alessandrini, P., Bradski, G., Davies, B., Ettinger, S., Kaehler, A., Nefian, A., and Mahoney, P. (2006). "Stanley: The robot that won the DARPA Grand Challenge". Journal of Field Robotics, 23(9), 661-692.

[2] Urmson, C., Anhalt, J., Bartz, D., Clark, M., Galatali, T., Gutierrez, A., Harbaugh, S., Johnston, J., Kato, H., Koon, P., Messner, W., Miller, N., Mosher, A., Peterson, K., Ragusa, C., Ray, D., Smith, B., Snider, J., Spiker, S., Struble, J., Ziglar, J., and Whittaker, W. (2006). "A robust approach to high-speed navigation for unrehearsed desert terrain". Journal of Field Robotics, 23, 467-508.

[3] M. Montemerlo et al., "Junior: The Stanford entry in the Urban Challenge", Journal of Field Robotics, vol. 25, no. 9, Aug 2008.

[4] 2009 Real World Robot Challenge, http://www.ntf.or.jp/challenge/.

[5] W. S. Wijesoma, K. R. S. Kodagoda and Arjuna P. Balasuriya, "Road-Boundary Detection and Tracking Using Ladar Sensing", IEEE Transactions on robotics and automation, vol. 20, no. 3, 2004D

[6] P. Pfaff, R. Triebel, C. Stachniss, P. Lamon, W. Burgard, and R. Siegwart. "Towards Mapping of Cities". In Proceedings of the IEEE Internation Conference on Robotics and Automation (ICRA '07), Rome, Italy, April 2007.

[7] J. Macedo, R. Manduchi, and L. Matthies. "Ladar-based discrimination of grass from obstacles for autonomous navigation". In ISER 2000: Experimental Robotics VII, London, UK, 2001.

[8] J-F. Lalonde, N. Vandapel, D. Huber, and M. Hebert. "Natural terrain classification using three-dimensional ladar data for ground robot mobility". Journal of Field Robotics, 23(10):839 - 861, 2006.

[9] D.F.Wolf,G.Sukhatme,D.Fox, and W.Burgard, "Autonomous terrain mapping and classification using hidden markov models". In Proc. of the IEEE Int. Conf. on Robotics & Automation (ICRA), 2005.

[10] S. Thrun, M. Montemerlo, and A. Aron. "Probabilistic terrain analysis for high-speed desert driving". In Proc. of the Robotics Science and Systems Conference, 2006.

[11] D. Bradley, R. Unnikrishnan, and J. Bagnell. "Vegetation detection for driving in complex environments". In Proc. of the IEEE Int. Conf. on Robotics & Automation (ICRA), 2007.

[12] C. Wellington, A. Courville, and A. Stentz. "A generative model of terrain for autonomous navigation in vegetation". International Journal of Robotics Research, 25(12):1287-1304, 2006.

[13] H. Dahlkamp, A. Kaehler, D. Stavens, S. Thrun, and G. Bradski. "Self-supervised monocular road detection in desert terrain". In Proc. of Robotics: Science and Systems (RSS), Philadelphia, USA, 2006.

[14] Levinson, J. and Montemerlo, M. and Thrun, S. "Map-Based Precision Vehicle Localization in Urban Environments". Proceedings of the Robotics: Science and Systems Conference (RSS). Atlanta, USA. June, 2007.

[15] Paul Newman, Gabe Sibley, Mike Smith, *et. al*, "Navigating, Recognizing and Describing Urban Spaces With Vision and Lasers", The International Journal of Robotics Research OnlineFirst, July 21, 2009.

[16] Kai M. Wurm, Rainer Kümmerle, Cyrill Stachniss and W. Burgard, "Improving Robot Navigation in Structured Outdoor Environments by Identifying Vegetation from Laser Data", In Proc. of the IEEE/RSJ Int. Conf. on Intelligent Robots and Systems (IROS), 2009.

[17] Dempster, A., Laird, A., & Rubin, D., "Maximum likelihood from incomplete data via the EM algorithm". Journal of the Royal Statistical Society, Series B, 39, 1977.