A framework for detecting road curb on-line under various road conditions

Jian Liu, Huawei Liang and Zhiling Wang

Abstract—Quick and accurate understanding of the ambient environment is critical in the development of the intelligent vehicle. As the most important element consisting the ambient environment, road curb detecting is a fundamental and vital work for the development of intelligent vehicle. In this paper, a framework was presented to detect the road quickly and robustly using the velodyne lidar, which provides a massive and unstructured information of the environment in the format of point cloud. Three-sigma rule in the field of error processing and reliability theory was adopted to detect road curb which adapts various road condition. After then, the point cloud was grided and outlier points were removed. Lastly, by utilizing the road continuous information, a search method consists of eight search templates was utilized to search the road curb automatically. The framework we presented has been proved to be able to detect straight or curve road curbs robustly and quickly in most road conditions automatically. Compared to the former works, this paper detects the the road curb depending on a adaptive threshold, which means it can be adaptive to different road conditions. Besides, the search model is adaptive to the changing of the road curb direction, which improve the search speed and increase the road curb detection average accuracy.

I. INTRODUCTION

Autonomous driving technology is developing very fast these years. One of the most important aspects in autonomous driving technology is to understand the environment around the vehicle, which is consisted of pedestrians, vehicles, road curbs, trees, etc. Among these, detecting road curb automatically is a fundamental topic in intelligent vehicle. On the one hand, the curb itself is a very important element consisting the environment. On the other hand, as the delimiter of the drivable area, a precisely detected curb can be used to reduce the search scope and much less attention needs to be paid to the objects outside the road curb, which have much less influence on driving decision making.

There are many sensors can be used for road curb detecting such as video sensors, laser sensors, etc. Kluge [1] managed to extract road curvature and orientation from image. Y.shin [2] used a 1D laser scanner for curb detection. Siegemund [3] modelled the road as a conditional random field using dense stereo vision which can only detect the obvious road curb

This work was supported by The National Nature Science Fund Project (61005091, 91120307 and 91320301).

Jian Liu is with the Department of Automation, University of Science and Technology of China, Hefei, China and Institute of Advanced Manufacturing Technology, Hefei Institutes of Physical Science, Chinese Academy of Science, Hefei, China. fdlj@mail.ustc.edu.cn

Huawei Liang is with the Institute of Advanced Manufacturing Technology, Hefei Institutes of Physical Science, Chinese Academy of Science, Hefei, China.

Zhiling Wang is with the Institute of Advanced Manufacturing Technology, Hefei Institutes of Physical Science, Chinese Academy of Science, Hefei, China.

with the elevation larger than 20cm. The drawback of all the above methods is the false positive rate due to information absence caused by the drawback of their sensors and the complexity of modelling the three dimension world from the lower dimension information.



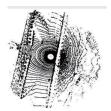






Fig. 1. The tested car and the point cloud examples obtained by the velodyne

A more informative data can be obtained by the Velodyne 3D-LIDAR scanner, which can produce an accurate description of the local environment in the format of pointcloud. Fig.1 shows the test cars and some point clouds obtained by the Velodyne 3D-LIDAR scanner which is widely used in modelling the ambient environment. Poullis [4] presented a framework in modelling the surrounding which is composed of segmentation, boundary extraction and 3D modeling. Jiping Liu [5] proposed a framework to extract the individual of tree crowns using point cloud data which is also composed of several steps:slop filter filtering, non-ground segmentation, tree points clustered. Frédéric Bosché [6] used point cloud to extract plane. The method mentioned above can only be used for off-line processing since their methods contained large numbers of iteration.

As the objects in the ambient environment vary from cars to trees, they may have totally different features, leading to the selection of feature vector and classification need to take into consideration of many factors, which is the one of the main reasons for the time-consuming of the methods mentioned above. In this research, since the attention was focused on the road curb detection, only features of the road curb needed to be taken into consideration to accelerate the process time to meet the need of on-line processing. Curb detection on-line is a hot problem which has not been tackled well and many works has been done on this subject

yet. Ganqiang Zhao [7] proposed a method to solve this problem whose result was impressive. However, there are two problems need to be considered further. Firstly, the paper set a threshold of 25cm for curb judgement which may cause the leak detection of the road curb. Secondly, the paper used a particle filter to detect the curb, which is time-consuming. Wentao [8] extracted the road by projecting the 3D data onto the ground plane, in which the ILP features and the elevation information were applied to extract the road. However, as same as [7], a presupposed range of 10cm to 15cm road height was set for the curb-detecting. Yang [9] estimated the road curb by calculating the maximum elevation difference, point density and slope change in a moving window to be compared with the presupposed threshold to search the road curb, which can make full use of the local information but still had the same shortcomings of fixed threshold as mentioned above. Alexandre Hervieu [10] detected the curb taking angular distance to ground normal map as the feature which is filtered by the Kalman filter to obtain the road curve. The feature value was modelled probabilistic with the mean value of 20, which is not suitable for the case in which the elevation changes slowly. Similarly, Kalman filter was also applied in Yeonsik [11], in which 3-dimensional data was projected onto the horizontal plane and the Hough transform-based method was used to detect the curb point. Elöse [12] detected the curb stone by analyzing the gradient computed over the ground segment. They registered the road axes to the point cloud, by which the curb and road segments were ordered and connected. Identifying ground points by the lowest peak of the elevation histogram is not always practical since it includes points belonging to the bottom of the objects lying on the floor level like, poles, tree trunks and pedestrian feet. Goulette [13] analyzed the histogram of each scan line to detect ground points where the ground is a horizontal plane with a high point density. They refined the segmented ground by utilizing a fuzzy logic algorithm. However, the road in realty can not be modelled as a pure horizontal plane which is slope.

A new framework for road curb detection fitted for both the rural road and urban road, especially for those whose road condition is not very well and curb is not obvious, is proposed in this paper. Firstly, the cloud data was directly parsed from the packet file sent by the Velodyne 3D-LIDAR. Secondly, a probability model was proposed to model the road as a stationary random field where the concept of gross error in error processing and reliability theory was applied to model the road curb. According to this model, the elevation difference was applied to find the road curb. Thirdly, since the road condition is complex and consists of obstacles such as cars, pits, etc., which will affect the road detection in the actual situation, a search algorithm implemented by eight templates was taken to extract the road curb by utilizing the continuous information contained in the road curb pattern.

The remainder of this paper is organized as follow:in section 2 some basic concepts in the field of error processing and reliability theory and its application in this paper were discussed and used to detect the obstacles, which consists of

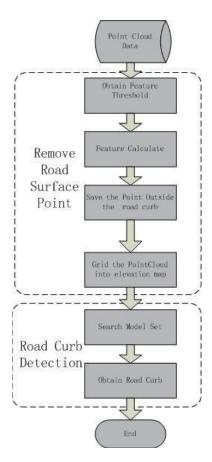


Fig. 2. Road with different variance

the vehicles, trees, curb and so on. In section 3, implementation details are presented for further filtering considering the continuity information since the largest difference between the road curb and other obstacles is the continuity in one direction. At last, some experiment results obtained in our work will be presented in section 4. The whole procedure is shown in Fig .2

II. OBSTACLE DETECTING

As different roads have different road irregularity, the threshold cannot be fixed to decide whether the point belongs to the the additive noise or the road edge. Here a method of a vary threshold where the threshold will be decided by the road irregularity is proposed by applying the error types in the theory of the error processing and reliability to model the road

The error is classified into systematic error, random error and gross error in error processing and reliability theory. Systematic error is the bias caused by some significant factors which exist persistently and will lead to the situation where the value of many separate measurements differ significantly from the actual value of the measured attribute regularly. The random error is the bias caused by some random reasons whose influence on the measurement are much less than the systematic error. As the random error is hard to be modelled accurately, the random error is modelled probabilistic, which follows Gaussian distributions and the

mean value is zero. Gross errors are bias deviating far from the known or accepted value which are usually caused by the mistake and should be get rid of. As for the application of the three error types in the modelling of the road environment, the road curb is modelled as the gross error since its elevation with the road surface is distinct, while the two slope, which is formed by the fact that it's a bit higher in the middle of the road, and additive noise on the slope plane is modelled as the systematic error and random error respectively.

The HDL-64E LiDAR sensor was used to model the surround environment in our experiment, which can get 64 points at each rotary position and 2160 positions in one circle and can spin at rates ranging from 300 RPM (5 Hz) to 1200 RPM (20 Hz). The sensor models the surrounding environment using the polar coordinate system which was translated into cartesian coordinate system in our research.

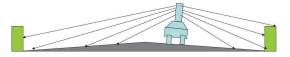


Fig. 3. the work functional picture

Instead of calculating the gradient in X direction and Y direction, the elevation change was simply calculated in the direction of laser beams in each rotation position, in which way the information in the packet sent by the lidar can be utilized to accelerate the process time. The circle was divided into 360 equal sections in peripheral direction in which average point obtained by each laser beam was calculated to eliminate the random error caused by the lidar. The obtained points were stored in a two-dimension array, in which the row direction represented the information of the 64 points obtained in one direction that was stored in the order from the inside to the outside while the column direction represented the 360 positions in one circle. For every 64 points position information $(x_i, y_i, z_i), i = 1...64$ retrieved in one rotation position, the surface points were removed in the following steps:

As the systematic error was modelled linearly, the systematic error can be eliminated by using the elevation difference instead of elevation. Calculate the elevation difference and the distance projected in the X-Y plane between the neighboring point as follows:

$$Dif_i = |z_{i+1} - z_i| \tag{1}$$

$$Distance_i = \sqrt{(x_{i+1} - x_i)^2 + (y_{i+1} - y_i)^2}$$
 (2)

 Since the beams projected onto the road surface are not parallel and vary in angle with the Z axis, the height difference between the neighboring point varies even in the slippy surface, which can be eliminated by normalizing the height difference with the distance projected in the X-Y plane in the following equation:

$$NormDif_i = \frac{Dif_i}{Distance_i} \tag{3}$$

• To decide whether one point belongs to the road curb point or the road surface point, the history information of the former point sequence need to be obtained, which was expressed in the form of the average and the variance of normalized height difference of the former point sequence and can help us to decide depending on the road condition. If the deviation of the normalized height difference of this point with the average normalized height difference of the former sequence was lager than the triple of the variance of normalized height difference of the former point sequence, the point was classified as the road curb and saved. If the deviation of the normalized height difference of this point with the average normalized height difference of the former sequence was smaller than the triple of the variance of the normalized height difference of former point sequence, the point was classified as the road surface and removed. The average and the variance of the normalized height difference of former point sequence was calculated as follows:

$$Average_n = \frac{\sum_{i=0}^{i=n-2} NormDif_i}{n-1}$$
 (4)

$$Var_n = \frac{\sum_{i=0}^{n-2} (NormDif_i - Average_n)^2}{n-1}$$
 (5)

• Since the obstacles that are too far away from the car have little influence on the car driving, a space distance filter was taken on the point cloud, which covered a square of 100m*100m and was grided into 512*512 pixels. To obtain more information in the direction of car advancement, which is better for the decision making, the car was placed on (256,100). The pixel value was binarized depending on the number of points that had been grided to the pixel. If the number was bigger than 10, the pixel value was set as 255 which can be regarded as an obstacle, otherwise, the pixel value was set as 0.

After the process above, the points belong to the road surface has been removed, while the points that represent the obstacles remains. The result is shown in the middle column in Fig.5.

III. ROAD CURB DETECTION

There were many other obstacles such as cars, pedestrians, etc. on the road which were classified as road curb since the height difference satisfied the rule adopted above. A further step to extract the road curb was taken by utilizing a search algorithm with eight search models presented as shown in Fig.4, which represented the eight search direction.

The search started at (256,0), which is the middle pixel at the top of picture and the position of the car's vertical projection on the top of the image. To detect the right lane and the left lane, the search was done both in right direction and left direction. The search was done from the top to the bottom firstly, and from the middle to the side lastly. If the search started with the middle to the side firstly and ended

with the top to the bottom lastly while it happened that the road lane was absent in the top of the picture, the search may start at the position that was out of the road which would cause the false detection of the road curb since the points outside the road curb had not been removed and formed a false road curb. Once the value of a pixel equaled 255 during the search, the model 1 was applied to search for its neighborhood. If the value of another pixel was found equaling 255, it means that the former point may be a point that can be classified as the road curb and should be pushed into the vector that contained the points been classified as the road curb. Otherwise search was continued using the model in the sequence of 2,8,3,7,4,6,5, which changed 45 degree away from the origin direction per time both in the direction clockwise and anticlockwise, until the pixel was found equaling 255 or all the model had been used without finding a pixel equaling 255. If a pixel equaling 255 was found, the point was set as the new searching starting-point and the eight search direction model was applied to search for the next possible road curb point. However, as history information was preferred to be utilized to accelerate the searching speed, a counter on the search direction continuous times was created. If the number of the points detected continuously in a fixed direction, which was different from the current direction, was bigger than the specific threshold, it means that the road direction has been changed. To accelerate the search speed, the search was started at the new direction and changes 45 degree away from the new direction per time both in the direction clockwise and anticlockwise until a pixel was found or all the models had been used. If a pixel had been found, it was set as the start point and do as mentioned above. Otherwise, the number of the point was calculated that had been classified as the road curb. If the number was bigger than the threshold, the search was stopped and one road curb was found. This process is shown in algorithm 1.

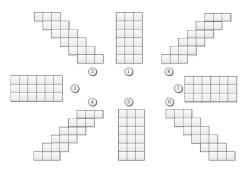


Fig. 4. Eight search models for road curb searching

According to the algorithm mentioned above, DetectNextPt((x,y),Model) means finding next closest pixel whose pixel value is 255 using the model Model which represents one search direction to be saved as a road curb point. The result is shown in the right column in Fig.5.

IV. EXPERIMENT RESULT

The algorithm mentioned above was tested on our intelligent vehicle. The processor used for processing the lidar

```
Algorithm 1 [(x_i, y_i)|_{i=1}^{N_s}, isDetect] = DL((x, y), Model)
```

Input: (x,y)Search start point, Model which model in the eight models to be used

Output: $(x_i, y_i)|_{i=1}^{N_s}$: the point sequence that has been detected, isDetect: whether the road lane is found

```
for m=0 \rightarrow 4 do
  NewModel \leftarrow model + (m+1)/2 * (-1)^{m+1}
  if newModel > 7 then
     newModel \leftarrow newModel - 8
  end if
  if newModel < 0 then
     newModel \leftarrow newModel + 8
  [(x_0, y_0), isPtDetect] \leftarrow \mathsf{DetectNextPt}((x, y), newModle)
  if isPtDetect then
     save the (x_0, y_0) in the (x_i, y_i)|_{i=1}^{N_s}
     PointCount + +
     if newModel==Model then
       ModelCount + +
     else
       ModelCount \leftarrow 1
     end if
     if ModelCount > ChangeDirectionThreshold
       DetectLine((x_0, y_0), NewModel)
     else
       DetectLine((x_0, y_0), Model)
     end if
  end if
end for
if PointCount > POINTTHRESHOLD then
  return [(x_i, y_i)|_{i=1}^{N_s}, true]
  return [null, false]
```

data was $Core^{TM}$ i7-3610QE Processor, whose process frequency can be speeded up to 3.3G Hz and the cache is 6M. The time complexity for the presented algorithm is O(n) while the time complexity for those algorithm bases on iteration is O(n^2), which contributes to the possibility for the on-line processing where the frequency of the packet sent by the velodyne lidar is 15Hz and the average time for processing a single frame is about 15ms.

The driving track formed a square, during which the road condition and the road curb type varied. The road conditions contained straight road, lean road, crossroad, etc. Meanwhile, the road curb was formed by stones, bushes, grasses, trees, etc. The stone curb is the most common case in the urban environment, which is easy to be detected as it's continuous and the elevation difference is obvious. However, the condition is more complicated in the rural environment since the road edge may be defined by trees,

end if

bushes, etc., where the curb may be discontinuous and the height difference is not big enough. So it's much more difficult to detect the road in the rural area since the road condition in the rural area is more irregular.

The result is shown in Fig. 5. The first row of Fig. 5 is the most simple case in which shows a straight road. It is shown in the right picture in the first row of of the Fig. 5 that the road curb is extracted out. It is shown that a car is driving at the left side of the car at the left picture of first row of Fig. 5 which is not removed in the middle of the first row of Fig. 5 since the elevation difference of the car satisfied the condition as the elevation difference was applied to extract the road curb. But when the model was applied to search the road curb, the car points were removed because of their discontinuity with the road curb points. The second row of Fig. 5 shows the result conducted on a more complicated situation which shows that the road is discontinuous and oblique. As the information of former search direction was employed, it was easy to distinguish whether the discontinuity was caused by the obstacles or by the discontinuity of the road curb itself. With the combination of the usage of the eight models, the search speed and the accuracy rate increased. It is shown in the origin picture that because the inside trees are absent in the a stretch of the road, the outside trees are defined as the road edge. But when the trees appear inside, as the information of the road direction was employed, the road curb was defined with the inside trees again. The third row of the Fig.5 shows that two parterres in the middle of the road were combined and defined as a road edge though they are seperated. Even though the parterre is not the road curb in true sense, this satisfy the practical application since the vehicle should drive in its own lane. The fourth row of Fig.5 demonstrates the case that the height difference between the road curb and the road surface is not obvious. The reason that the road curb can not be extracted precisely shown in the middle picture is that the height differences of the the points belong to the road point change slowly but are bigger that the threshold calculated by the road surface. As the former information was taken into consideration by using direction-change template, the extracted road curb reflects the road curb in the reality in general. Some attention should be paid that the points looks like the noise in the middle of the road is not the noises but caused by three cars in this case.

V. CONCLUSION

A new framework to detect the road curb is proposed in this article, which is robust and fits for most road conditions. By applying the concept of systematic error, random error and gross error in error processing and reliability theory, the algorithm makes use of the information contained in the point cloud data itself to derive the adaptive height difference threshold used for detecting the road curb, which makes it adaptive to different types of road curbs, such as bushes, trees, stone road curbs, etc. The privileged direction to detect the next point is obtained by the statistics of the history information, which makes the search speed accelerated and

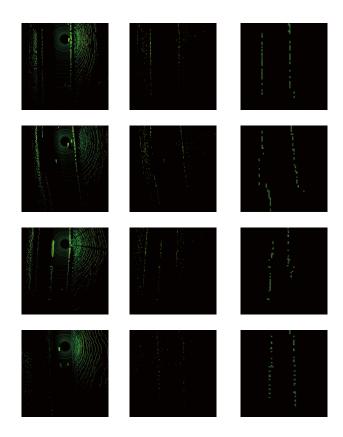


Fig. 5. Example with experimental results.

accurate rate improved. The algorithm proved to be robust and fast in the mostly continuous road curb conditions. But in those cases where the continuous information can not be utilized to detect all the lines in picture which represent the road curb, such as the crossroad, leak detection of the road curb occurs. The crossroad curb detection is a key issue to be addressed in the future work.

REFERENCES

- K. Kluge, "Extracting road curvature and orientation from image edge points without perceptual grouping into features," in *Intelligent Vehicles' 94 Symposium, Proceedings of the*. IEEE, 1994, pp. 109–114
- [2] Y. Shin, C. Jung, and W. Chung, "Drivable road region detection using a single laser range finder for outdoor patrol robots," in *Intelligent Vehicles Symposium (IV)*, 2010 IEEE. IEEE, 2010, pp. 877–882.
- [3] J. Siegemund, D. Pfeiffer, U. Franke, and W. Förstner, "Curb reconstruction using conditional random fields." in *Intelligent Vehicles* Symposium, 2010, pp. 203–210.
- [4] C. Poullis, "A framework for automatic modeling from point cloud data," *Pattern Analysis and Machine Intelligence, IEEE Transactions* on, vol. 35, no. 11, pp. 2563–2575, 2013.
- [5] J. Liu, J. Shen, R. Zhao, and S. Xu, "Extraction of individual tree crowns from airborne lidar data in human settlements," *Mathematical and Computer Modelling*, vol. 58, no. 3, pp. 524–535, 2013.
- [6] F. Bosché, "Plane-based registration of construction laser scans with 3d/4d building models," Advanced Engineering Informatics, vol. 26, no. 1, pp. 90–102, 2012.
- [7] G. Zhao and J. Yuan, "Curb detection and tracking using 3d-lidar scanner," in *Image Processing (ICIP)*, 2012 19th IEEE International Conference on. IEEE, 2012, pp. 437–440.
- [8] W. Yao, Z. Deng, and L. Zhou, "Road curb detection using 3d lidar and integral laser points for intelligent vehicles," in Soft Computing and Intelligent Systems (SCIS) and 13th International Symposium

- on Advanced Intelligent Systems (ISIS), 2012 Joint 6th International
- Conference on. IEEE, 2012, pp. 100–105.
 [9] B. Yang, L. Fang, and J. Li, "Semi-automated extraction and delineation of 3d roads of street scene from mobile laser scanning point clouds," ISPRS Journal of Photogrammetry and Remote Sensing, vol. 79, pp. 80-93, 2013.
- [10] A. Hervieu and B. Soheilian, "Road side detection and reconstruction using lidar sensor," in Intelligent Vehicles Symposium (IV), 2013 IEEE.
- IEEE, 2013, pp. 1247–1252.
 [11] Y. Kang, C. Roh, S.-B. Suh, and B. Song, "A lidar-based decisionmaking method for road boundary detection using multiple kalman filters," *Industrial Electronics, IEEE Transactions on*, vol. 59, no. 11, pp. 4360-4368, 2012.
- [12] E. Denis, R. Burck, and C. Baillard, "Towards road modelling from terrestrial laser points," International Archives of Photogrammetry, Remote Sensing and Spatial Information Sciences, vol. 38, pp. 293-298, 2010.
- [13] F. Goulette, F. Nashashibi, I. Abuhadrous, S. Ammoun, and C. Laurgeau, "An integrated on-board laser range sensing system for on-theway city and road modelling," ISPRS RFPT, 2006.