Road Surface Estimation using a Piecewise Linear Function in v-Disparity

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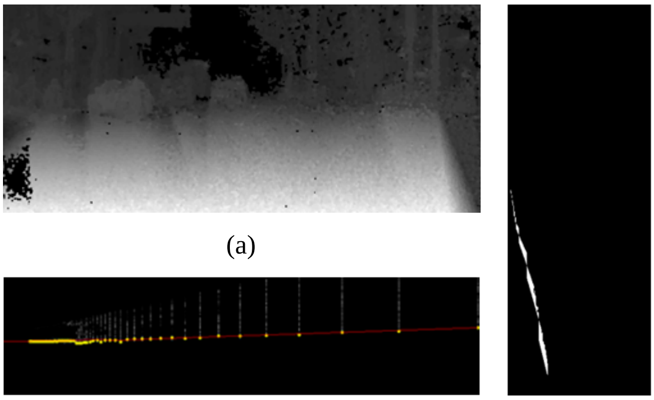
Abstract: In this paper we proposed an algorithm to estimate a road surface for a vehicle. Our method utilized a picewise linear function in v-disparity space directly to reduce time consumption without transformation of real-world coordinates. For robust algorithm, we implement a series of image processing procedures. u-disparity is used for filtering obstacles which disturb candidates extraction step of a road surface. v-disparity is used for extraction of a road surface candidates and estimation of a road surface. We separate regions from v-disparity and implement a line fitting algorithm independently. Experimental results show that our method estimates a road surface model successfully.

1. Introduction

The ultimate goal of the field of a vehicle provides users with an autonomous vehicle. An autonomous vehicle have to detect its surroundings in order to recognize its environment. Road surface is a key environment for an autonomous vehicle as well as for advanced driver assistance systems. Therefore, the estimation method of road surface has been researched based on various information. Depth information which is one of the various information could estimate a road surface. The depth-based road surface estimation method classifies the way that depth image is manipulated directly and the way that depth image is transformed to real world coordinates and implement road surface estimation in world coordinates[1-4]. In addition to these different sources, a lot of methods assume that a road surface is a planar, therefore the road surface could modeled in a single straight line in the past[5]. Recently, a number of road surface methods consider an undulating road that consists of uphill and downhill to improve a performance of road surface modelling[6-8]. But estimated road surface model based on world coordinate could make the problem when the model transforms to depth image coordinates. Fig 1.(c) shows that many depth ranges have the same height of image. It is possible to have the problem such as stixel-based object detection[9].

In this work, we perform a series of image processing procedures. For filtering perpendicular obstacles which disturb road surface estimation, we manipulate u-disparity. v-disparity is utilized for a road surface candidate extraction and estimation of a road surface using a piecewise linear function. Interval estimation is designed to compensate the previous step problems.

The remaining portions of this paper are organized as follows. In Section 2, we explain the proposed method, In Section 3, provide experimental results, we conclude in Section 4.



(a) (b) (c)

Figure 1. (a) Depth image based on stereo camera (b) result of road surface estimation in world coordinates (c) transformation estimated result of road surface from world coordinates to v-disparity space.

2. Proposed method

In this section, we explain the proposed method. The proposed method consists of three parts: (1) point sampling for road surface candidates, (2) implementation of a piecewise linear function for estimation of a road surface, (3) interval estimation for resolution of the problem that occur in step of estimation of a road surface. In following, there three parts will be addressed in detail.

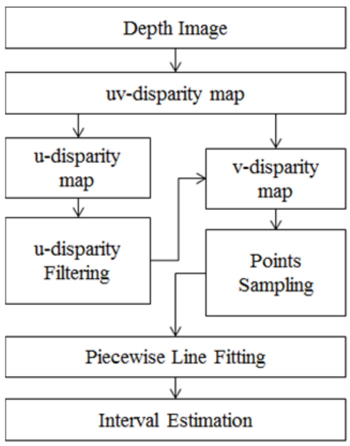


Figure 2. Flowchart of proposed method.

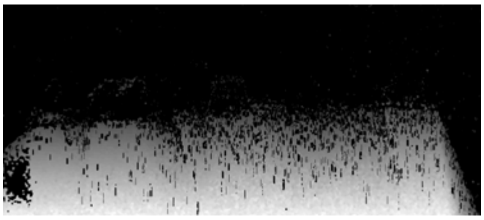
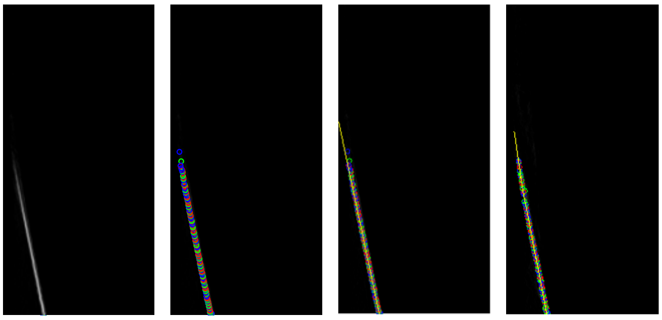


Figure 3. Filtering result in u-disparity



(a) (b) (c) (d)

Figure 4. (a) v-disparity (b) result of road surface candidate points extraction (c) result of single straight line fitting (d) result of piecewise line fitting.

2. 1 Road candidates sampling

We generate a u-disparity map in order to remove obstacles' depth information in original depth image before road candidate points sampling in v-disparity. Obstacles have more values than road surface in u-disparity, because basically obstacle stands perpendicularly. Fig 3. shows obstacle-filtered depth image.

Fig 4.(a) shows v-disparity map which is generated using filtered depth image for road candidate points sampling. Although a previous step could remove the obstacle's depth information, v-disparity has a lots of noises and small obstacle's depth information that could not filtered in u-disparity filtering step. We select the points of road surface candidate for more robust line fitting step, fig 4(b), the equation (1) that is proposed[7] is modified to apply v-disparity space directly as (2).

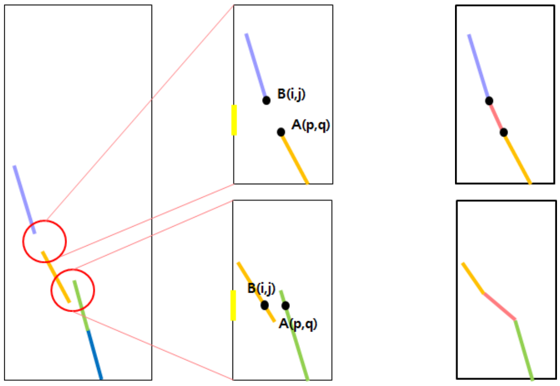
$$T_{sample}(Z) = W\frac{f}{Z}; \tag{1}$$

$$T_{sample}(D) = W\frac{D}{B}; \tag{2}$$

where Z and D are the real depth and disparity value, respectively; and f and B are the focal length and base line, respectively; and W is a minimum width of the road surface.

2. 2 Piecewise line fitting

In case of a planar road surface, it is possible to estimate the road surface model as a single straight line. However, for a non-planar road surface such as up hills or down slopes, it couldn't be modeled into a sing straight line. Therefore, we select a couple of sub-regions in v-disparity space based on real depth information calculated by the camera parameters and the disparity values. The line fitting method is implemented based on the road candidate points of the each sub-region independently.



(a) (b)

Figure 5. Interval estimation for resolution of the problems, (a) shows the problems and (b) shows resolved result.

2. 3 Interval Estimation

A piecewise linear function could make the two problems, fig 5. The previous step causes disconnection and overlapped case between the each estimated lines based on the height of the image coordinates. We resolve the problems by applying the equation (3) for the former case, and (4) for the latter case, respectively.

$$v = p + \left(\frac{DD}{EI}\right) \times D; \tag{3}$$

$$v = \left(\frac{i+p}{n}\right); \tag{4}$$

where v is the height of image coordinate. i and p are the height of each sub-region road model, and j and q are the depth value of each sub-region road model. n is the number of the overlapped road model's length. DD and EI indicate depth difference and empty interval between road models, respectively.

3. Experimental results

The experimental environment is a PC with Intel® Core™ i5-2500 CPU 750 @ 3.30GHz, image resolution is 1280 x 672. Depth images are generated using ELAS[10]. For results shown with our implementations, W was empirically determined to be 0.5m in sampling step, and depth range is separated to 4 sub-regions which have 0~5m, 5~10m, 10~15m, and 15~25m in piecewise line fitting step. Comparison of the road surface estimation using sing line fitting in v-disparity(Fig 4.(c)) and piecewise line fitting in each sub-region of v-disparity(Fig 4.(d)). Fig 6.(a) shows the result image of the road surface model transformed to depth image space. Fig 6.(b) and (c) show the results that the case of a planar road and a undulating road, respectively.

(a) (b) (c)

Figure 6. (a) Depth image of the estimated road surface (b) result of the planar road case (c) result of the uphill road case.

4. Conclusions

We proposed an algorithm to robustly estimate a road surface model based on a piecewise linear function and complementary interval estimation in v-disparity space. As shown in the experimental results, we could estimate an undulating road surface as well as a planar road surface.

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