Obstacle and Free Space Detection Based on U-V-Disparity
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Keywords: Obstacle detection, Free space detection, U-V-disparity, Stereovision.

Abstract. This paper presents a novel method for obstacle and free space detection for intelligent
vehicles by using U-V-disparity of stereovision. The U-V-disparity map is generated by calculating
the histogram of the disparities with regards to the row and column. The obstacles and road surface
appear as various straight lines in the U-V-disparity maps. By detecting these lines and reconstructing
them back to the initial disparity map, obstacles can be located and measured. The free space is
extracted from the subtraction of the obstacle disparity map obtained from the U-disparity from the
initial dense disparity map. The experimental results show that the proposed methods can efficiently
detect obstacle and free space.

Introduction
Obstacle and free space detection are important for intelligent vehicles. Stereovision is one of the core
technologies for this purpose. This paper presents a novel method for obstacle and free space
detection by using U-V disparity.

Many studies have been conducted for obstacle detection by using stereovision. Huang et al. [1]
proposed a position-based obstacle segmentation method by using stereovision’s 3-dimensional
reconstruction capability. A bird’s-eye-view image (depth map) was generated from the disparity
image, and objects were segmented in the depth map in terms of their positions. The image was also
separated into multiple layers according to the distances. Obstacles were further segmented in these
layered images to give a better and reliable result. Franke et al. [2, 3] employed stereovision in
interpreting urban traffic scene. In [2], 3-D point clouds representing 3-D object models were
computed by analyzing image sequences in both space and time, i.e., by fusion of stereo vision and
tracked image features. In [3], the quotient of the optical flow and the depth obtained from
stereovision was used as constraint for a robust and powerful detection scheme. In [4], moving
obstacles were detected from the difference between the mixed flow and the ego-motion flow by
integrating stereovision and optical flow. The works in [5, 6, 7] also developed stereovision systems
for autonomous vehicles or robots to enable real-time obstacle avoidance.

As another stream, the U-V-disparity was also adopted for obstacle detection. Labayrade et al. [8]
firstly proposed the construction of the “V-disparity” map, where the road-related line and the
obstacles located above the road can be extracted. Fu et al. [9] proposed a complete "U-V-disparity"
concept that can be used to classify a 3D road scene into relative surface planes and characterize the
features of road surfaces, roadside structures and obstacles. Ref. [10] acquired positions of the
obstacles under various road conditions by using U-V-disparity map. The advantage of this method is
positions of the obstacles can be obtained regardless of some restrictions on road conditions. Musleh
et al. [11] proposed a visual ego motion estimation system, where obstacles were detected by
matching the disparity values between U-disparity map and V-disparity map.

U-V-Disparity
Geometric Model of Stereovision. Fig. 1 shows a general stereo camera set-up and the
relationship between camera coordinate system (Xc, Yc, Zc) and world coordinate system (Xw, Yw, Zw).
The two cameras have been calibrated and mounted on the vehicle with parallel optical axes. Their
horizontal co-axis is parallel to the ground plane. $\theta$ is the pitch angle, $h$ is the height of the cameras above the ground, $b$ is the baseline distance, and $f$ is the focus length of the cameras.

![Diagram of camera and world coordinate systems](image)

Figure 1. The relationship between camera coordinate system and world coordinate system.

The transformation between the world coordinate system $(X_w, Y_w, Z_w)$ and image coordinate system $(U, V)$ with regard to the projection of the optical center assumed to be at the center of the image can be expressed by:

\[
\begin{align*}
U_w &= f \frac{X_w + b/2}{Z_w + b/2} \\
V &= f \frac{-Y_w}{Z_w + b/2}
\end{align*}
\]

The disparity $\Delta$ can be deducted as:

\[
\Delta = u_z - u_r = f \frac{b}{Z_w + b/2}
\]

The detailed derivation can be found in [9].

**Projection of 3D Planes in U-V-Disparity Maps.** In a driving environment, objects can be divided into two categories. The first category is the obstacles vertical to the ground plane, including vehicles, pedestrians, trees and roadside constructions, which can be abstracted as the vertical planes. The second one is the road surface, which can be abstracted as the horizontal plane. The road plane is regarded as the horizontal plane and can be described as Eq. 3 in the world coordinate system:

\[
Y_w = h.
\]

The following equation can be derived by substituting Eq. 3 into Eq. 2. It indicates that a horizontal plane in the world coordinate system will be projected as an oblique line in the V-disparity domain.

\[
\frac{h}{b} \Delta = f \sin \theta + V \cos \theta.
\]

Obstacles are abstracted as vertical planes, which can be described as:

\[
Z_w = p.
\]

The following equation can be derived by substituting Eq. 5 into Eq. 2. It shows that the vertical planes in the world coordinate system will be projected as straight lines in the V-disparity domain. With a pitch angle, vertical planes are projected as approximate vertical straight lines.

\[
\frac{f}{b} \Delta = f \cos \theta - V \sin \theta.
\]

**Formation of U-V-Disparity Map.** The disparity map $\Delta(U,V)$ can be obtained from the stereo matching. In the disparity map, the number of pixels with the same disparity values are counted for each row and column. The U-V-disparity map is formed as follows;
The formation of a V-disparity map: The row of the generated V-disparity map is the same to the row of the original disparity map \( \Delta(u,v) \). The column of the generated V-disparity map is the disparity value in the original disparity map \( \Delta(u,v) \). The number of the columns is the maximum disparity value. The gray value of the pixel \((u,v)\) in the generated V-disparity map is the number of pixels with disparity equal to \( \Delta \) in \( V \)th row.

The formation of a U-disparity map: The column of the generated U-disparity map is the same to the column of the original disparity map \( \Delta(u,v) \). The row of the generated U-disparity map is the disparity value in the original disparity map \( \Delta(u,v) \). The number of the rows is the maximum disparity value. The gray value of the pixel \((u,v)\) in the generated U-disparity map is the number of pixels with disparity equal to \( \Delta \) in \( U \)th column.

Implementations and Experiments

Obstacle Detection Using U-V-disparity

In summary, an obstacle appears as a horizontal line in the U-disparity map and a vertical line in the V-disparity. The length of the horizontal line represents the width of the obstacle while the length of the vertical line represents the height of the obstacle. The road surface appears as an oblique straight line in the V-disparity map. Furthermore, the obstacle-related lines intersect the road-related line. The distance of the obstacle depends on the disparity. The bigger the disparity is the closer the obstacle is. By detecting these lines in U-V-disparity map, obstacles with their position and size can be determined. The detection procedure is shown on a sample image pair selected from the KITTI database as follows:

1. Figure 2. shows the left and right image captured from a traffic scene. The disparity map is calculated from the stereo matching algorithm detailed in [1]. It is preprocessed to remove the noise and enhance the contrast. The processed disparity map is shown in Figure 3.

2. The V-disparity is constructed using the method presented in section 2.3, as shown in Fig. 4. It is processed by using Hough transform to detect the road-related line and the obstacle-related lines. Fig. 5 shows the V-disparity map followed by Hough transform. The intersection points give the position of the obstacles in Y direction. The length of the vertical lines gives the height.

3. The U-disparity is constructed using the method presented in section 2.3, as shown in Fig. 6. The horizontal lines are detected by Hough transform in Fig. 7, which indicates the width of the obstacles.
(4) Obstacles are sorted according to their coordinates and matched between the results obtained from U and V disparity maps according to their disparity values. A vertical line in V-disparity is matched to the horizontal line in U-disparity map with the same disparity value. Accordingly, the location and size of the obstacle can be determined, as marked in Figure 8.

(5) The detected obstacles can be reconstructed into 3D world coordinates system by using the binocular stereo imaging principle.

**Free Space Detection Using U-Disparity.** The road plane with eliminated vertical planes (obstacles) can be regarded as free space. Because points in the U-disparity map are majorly caused by obstacles and contain very little road points (road disparity spreads out in any column), we can use a threshold to remove the road points and binarize the U-disparity map. And then the disparity map only containing obstacles, called obstacle disparity map, can correspondingly be extracted from the initial disparity map according to the binarized U-disparity map. Subtraction of the obstacle disparity map from the initial dense disparity map will generate the disparity map only containing free space, which is called the free-space disparity map.

The free space detection algorithm is as follows;
(1) The disparity map is generated by stereo matching as same as Fig. 3.
(2) The U-disparity map is generated as shown in Fig. 7.
(3) The gray value of the pixel \((U, \Delta)\) in the U-disparity map is the number of pixels with disparity equal to \(\Delta\) in \(U\)th column. Because the road surface spreads out in Y direction, the gray value of road pixels in the U-disparity map is tiny and the U-disparity can be easily binarized using a threshold to remove the road points. Correspondingly, the obstacle disparity map can be extracted from the dense disparity as shown in Fig. 9, which is also processed by using the morphological closing operation to remove small patches caused by the in-continuity.
(4) The free-space disparity map can be obtained by subtracting Fig. 9 from Fig. 3. The result is shown in Fig. 10. It represents the disparity map only containing the free space.

(5) Correspondingly the free space can be mapped into the original image as shown in Figure 11., The free space can be also reconstructed into 3D world coordinates system by using the binocular stereo imaging principle.
Experiments have been conducted on the image sequences presented in the KITTI database. The results show the proposed method is capable of detecting obstacles and free space in most cases with a detection rate of 90%.

**Conclusion**

Two algorithms including obstacle detection using U-V-disparity and free space detection using U-disparity map are presented in this paper. The U-V-disparity map is generated by calculating the histogram of the disparities with regards to the row and column. The first algorithm locates obstacles by detecting corresponding lines in the U-V-disparity maps and reconstructing them back to the initial disparity map. The second algorithm extracts the free space from the subtraction of the obstacle disparity map from the initial dense disparity map. The experiments demonstrate that the proposed methods can efficiently detect obstacles and free space. The system is implemented in a PC quipped with a 2.40-GHz Intel Dual Core i5 processor and 4GB of RAM. The implemented system also meets the real-time requirement.

**Acknowledgement**

This research was financially supported by the National Science Foundation of China (Grant No. 61374197).

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