Enhanced Disparity Computation for ADAS Applications

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Abstract: Many of ADAS applications such as pedestrian and vehicle detection are using stereo vision. By computing the well-known disparity the range of objects ahead of the car can be determined. According to the computed range, it is possible to identify whether this object is in a collision position or not. Based on the chain code algorithm a new disparity computation method is introduced. The proposed method enhances obviously the delivered disparity values as well as the object segmentation results by integrating the segmentation into the disparity assignment step.

1 Introduction

Basically a 3D point can be reconstructed using a stereo vision system through the determination of the difference between its projections (disparity) in both left and right images [1, 2, 11]. Therefore stereo vision offers a visual and passive method concerning the determination of obstacle distance from the car in driver assistance systems, moreover the 3D reconstruction of the car surrounding area can be effectively achieved.

Due to the geometry and optics of each camera, which are assumed to be calibrated, both stereo images are rectified in order to get the standard stereo geometry, where the epipolar lines are coinciding the image scan lines [12, 16, 13]. The disparity estimation, or stereo matching, is considered as the more difficult processing step. Usually a small neighborhood around the pixel of interest in one stereo image is correlated within a predefined search window in the other image using one of the famous similarity measures. This correlation costs much computing time, in addition to, it fails at non-textured image patches. Recent literature contains many approaches, which had dealt with the problem of finding the corresponding pixel in the other stereo image. In general these approaches can be divided into area-based [3, 4, 5, 6, 7, 8] and feature-based [14, 15] approaches.

The proposed approach in this paper introduces a contribution to overcome the drawbacks of the conventional stereo matching approaches. Relying on the well-known chain code (freeman code) [10], which was developed to describe the object boundaries in an image, the corresponding pixel in other stereo image is searched.

This chain code-based disparity assignment strategy has improved remarkably the reliability of the estimated disparities as well as the object segmentation results. By implementing the segmentation procedure within the disparity estimation one, object segments are separated due to the estimated disparity value, i.e. due to their postures in the 3D space. Furthermore, this strategy produces a sparse disparity map requiring less computing time over a map produced by using a traditional feature-based approach. These advantages make the proposed algorithm to be a suitable disparity computation algorithm for an object segmentation using stereo vision in many of ADAS fields like pedestrian protection.

In this paper the results of applying the algorithm on a pedestrian scenario are demonstrated.

2 Chain Code-Based Disparity Assignment

The key idea of our approach is to integrate the object segmentation, which is conventionally performed afterwards, into the disparity assignment step by exploiting the pixel orientation. Pixel orientation describes the contribution of the considered pixel to the local orientation in a small neighborhood. Accordingly, pixels can be identified as horizontal edges, vertical edges, diagonal edges, and corners as shown in figure.1.

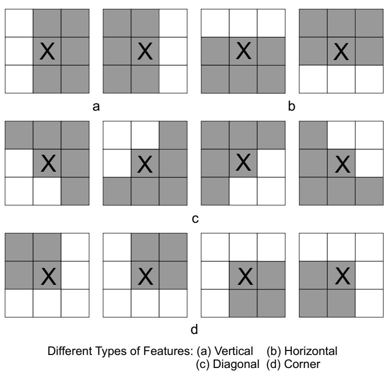

Figure 1: Available Feature Types

In order to extract feature pixels due to their orientation, the so called LOC-Operator (Local Orientation Coding) is used [9]. This filter takes a 3x3-neighborhood around each pixel and compares the grey values of the surrounding pixels with this of pixel of interest. Each pixel gets a logical one (1) if the difference exceeds a predefined threshold otherwise it gets a logical zero (0). The resulting bits within the considered neighborhood are coded using one of the coding schemes depicted in figure.2 below. The encoded orientation *C(m,n)* is mathematically computed using the following form:

$$C(m,n) = \sum_{i=-1}^{+1} \sum_{j=-1}^{+1} U[p(m+j,n+j) - p(m,n) - threshold]. \qquad (1)$$
$$K(i,j)$$

where $U(z)$ is the unite step function, p the grey value and $K(i,j)$ the used coding schema.

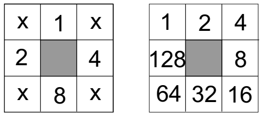

Figure 2: N4 and N8 Coding Schemes

For the purpose of avoiding multi-pixel-wide features, which may negatively affect the next processing step, a simple thinning procedure is afterward performed. In this procedure the labeled feature pixel is eroded, if it is succeeded with a similar label-pixel in the direction orthogonally to the labeled direction. For example if the found pixel represents a horizontal edge (figure 3), all the labels are deleted vertically, if these represent also a horizontal edge.

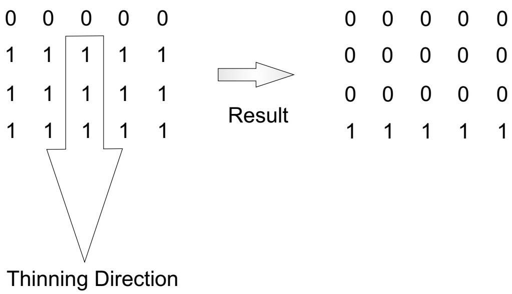

Figure 3: Thinning Example

Next disparity values of both corners and start points of one-dimensional features are computed by correlating a neighborhood round them using the SAD (Sum of Absolute Differences) as similarity measure. The computed disparities are then ensured using left-to-right consistency check. These start pixels (corners and start points) and their disparities are the core of the next step, which handles the search for the corresponding pixel and consequently the disparity value assignment in other stereo image.

Round each start pixel in one stereo image considering its disparity value a chain code-based search for the next feature pixel is performed. To the new found feature pixel the disparity value is assigned, if the same pixel (feature pixel with similar orientation) in other stereo image can be found. Then the new found feature pixel becomes the core of a new search and so forth until opposing another start pixel, there the new disparity value must be taken into account. Figure.4 below shows an example of this method applied on a horizontal edge.

The resulting segments, which are belonging to the same object, must be then grouped together depending on their estimated disparity.

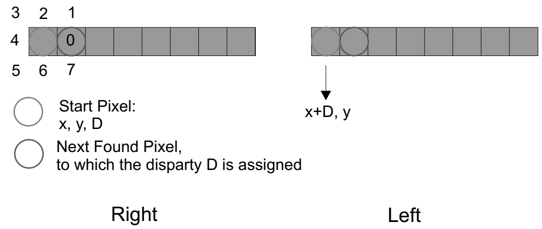

Figure 4: Example of Chain-code Based Disparity Assignment

3 Results

In driver assistance systems pedestrians can be observed as 2D objects. To 2D objects points that are lying at the same distance from stereo rig are belonging, i.e the disparity inside such objects is constant. Figure.5 shows one stereo image of a real pedestrian scenario and the resulted sparse disparity map using the already introduced algorithm. The stereo images are acquired by means of our stereo system, which consists of two cameras beside each other separated with base length of 20 [cm], each of them has 14 [mm] focal length and 7.4 [μm] wide square pixel. The camera calibration matlab toolbox [13] is implemented to rectify the provided images. Disparity values are encoded in term of false colors shown aside.

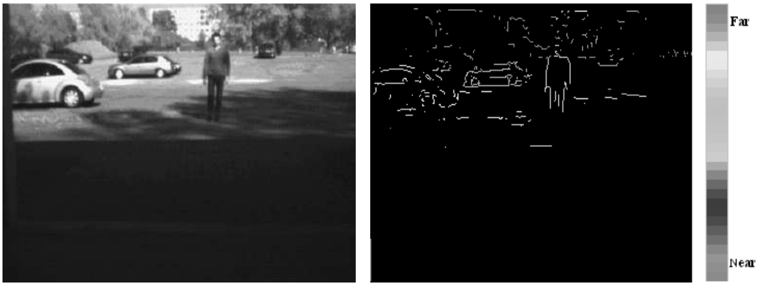

Figure 5: One Stereo Image of a Pedestrian, The Resulted Disparity Map

4 Conclusion and Further work

The constitution of start pixels, which are considered as the decisive points of the disparity variation, enables object segments separation according to the assigned disparity. Furthermore it increases the reliability of the assigned disparities and thus helps the avoidance of the well-known ambiguity problem, which can be specifically encountered at image horizontal edges. Moreover the new disparity estimation method offers the on-line applicability over the traditional stereo matching approaches because fewer correlations are required. Therefore the development of this disparity estimation strategy for recognition and detection of 3D objects is also thought. 3D objects are such objects, which are spreading into the 3D space, i.e. pixels that are belonging to those objects, are lying in different disparity layers.

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