Disparity Map for Stereo Images Using Image Segmentation and Correlation Based Matching

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ABSTRACT

Stereo vision is an imaging technique that gives us the 3D view of a image. It is area that deals with reconstruction of depth information from pairs of two dimensional images. Depth information of image is obtained from the Disparity map which is one of the key problems in 3D computer vision. We are finding Disparity map by using color image segmentation and different correlation based matching techniques like Sum of Squared Differences (SSD), Sum of Absolute Differences (SAD), Sum of Hamming Distance (SHD) and Normalized Cross Correlation (NCC). Mean-shift algorithm based segmentation method is applied for segmenting the input images into regions. The obtained experimental results demonstrate that the performance of segment based matching is competitive and the final disparity maps are close to the ground truth data.

Keywords: *Correlation, Disparity, Ground Truth, Matching, Stereo Images.*

1. INTRODUCTION

Stereo vision is an imaging technique that can provide full 3D field of view measurements in an unstructured and dynamic environment. Cameras are horizontally aligned in a stereo vision system. A set of 2D images is given as inputs to a stereo vision system. The main focus of stereo computer vision is extraction of 3D information from stereo images. To obtain the 3D information, knowledge of view properties and feature points between views are needed. To find these points for natural scenes is very hard. As an object moves closer to the cameras, the relative position of the object will change, and the positions in the images will move away from each other. In this case, we can calculate the distance of the object by calculating its relative positioning in the two images. This distance between positions of the same objects in two images is known as disparity. One of the key problems in 3D computer vision is computation of disparity map.

1.1 Stereo Vision

Stereo vision refers to the problem of determining the three-dimensional structure of a scene from two or more images taken from distinct viewpoints. Given two camera images, it is possible to determine three-dimensional location, if it is possible to identify the image locations that correspond to the same physical point in space from both the camera images. The aim of a stereo vision system is to retrieve depth information of a scene from two images which are taken from slightly different viewpoints.
It consists of five main steps:

- Calibrating the cameras
- Acquiring stereo images
- Rectifying the stereo images
- Finding pixel correspondences (Stereo Matching)
- Triangulating the pixel correspondences

Image rectification is a pre-processing step for stereo correspondence. This stage makes use of the calibration between the two cameras and epipolar geometry to transform the images so that their scanlines are aligned. This simplifies the stereo correspondence search from 2D to 1D.

The stereo matching stage is concerned with finding corresponding pixels between the two stereo images. After finding the corresponding pixels, the disparity of a pixel is determined. Stereo correspondence is a challenging problem in stereo vision.

1.2 Stereo Matching

Stereo matching is the correspondence problem in which we have to find the corresponding point of left image in right image. Given Two images of an object we can find its depth map, volumetric map, 3D map by using stereo matching. We can find the stereo matching using correlation based similarity measure or by using feature based similarity measure. The correlation based matching process involves computation of the similarity measure for each disparity value, followed by an aggregation and optimization step. Since these steps consume a lot of processing power, there are significant speed-performance advantages to be had in optimizing the matching algorithm.

1.3 Disparity Map

Stereo disparity is the measure of difference in position between correspondence points of two images. Depth information is obtained by the Disparity function. As depth information is a function of disparity and geometry of the object on image.

Disparity Map [1] is obtained after the stereo matching and gives us the information about the depth. Disparity map is used to find the 3D view of the image by giving disparity map to the OpenCV. Disparity map may be Dense or Sparse depending on the method used for the stereo matching as correlation based matching give dense map while feature based matching gives sparse map.

2. CORRELATION BASED STEREO MATCHING

Correlation based matching typically produces dense depth maps by calculating the disparity at each pixel within a neighborhood. This is achieved by taking a square window of certain size around the pixel of interest in the reference image and finding the homologous pixel within the window in the target image, while moving along the corresponding scan line. The goal is to find the corresponding (correlated) pixel within a certain disparity range d ($d \in [0, ...,d_{max}]$) that minimizes the associated error and maximizes the similarity[2]. The images can be matched by taking either left image as the reference (direct matching) or right image as the reference (reverse matching).

2.1 Sum of Absolute Differences (SAD)

Sum of Absolute Differences (SAD) is one of the simplest of the similarity measures[3][4]. It is calculated by subtracting pixels within a square neighborhood between the reference image and the target image followed by the aggregation of absolute differences within the square window[5], and optimization with the winner-take-all (WTA) strategy. If the left and right images exactly match, the resultant will be zero. SAD is obtained by,

$$SAD = \sum_{(i,j)\in W} |I_1(i,j) - I_2(x+i, y+j)| \qquad \text{………………..} (1)$$

Disparity maps for different sets of stereo images is obtained by using SAD algorithm and the obtained Disparity map is shown in Fig. 1, Fig. 2, Fig. 3 and Fig. 4 along with the set of stereo images and ground truth Disparity map.

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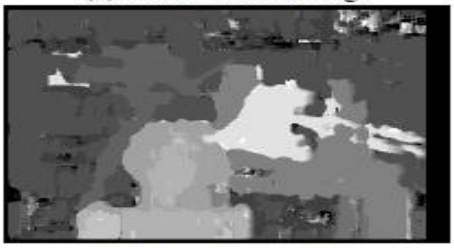
(a) Tsuksuba Left Image

(b) Tsuksuba Right Image



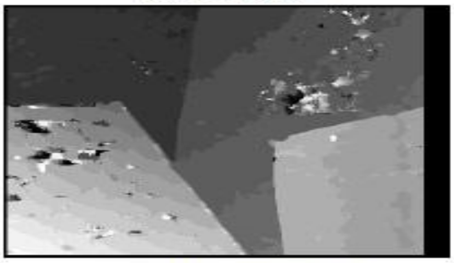
(c) SAD Disparity Map

(d) Ground Truth Disparity Map

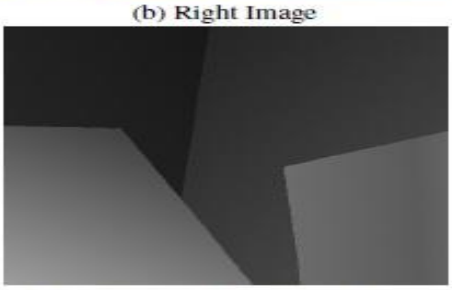
Figure 1 Disparity Map for Tsukuba Stereo Images

(a) Left Image

(b) Right Image



(c) SAD Disparity Map

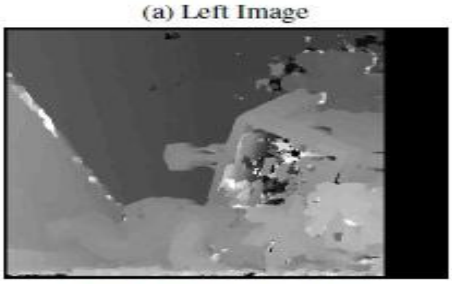


(d) Ground Truth Disparity Map

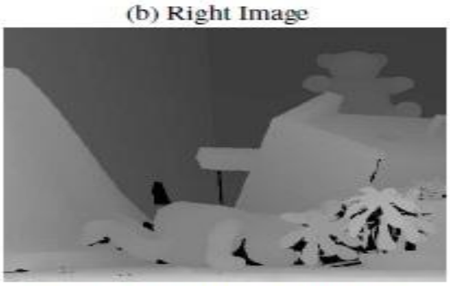
Figure 2 Disparity Map or Venus Stereo Pair

(a) Left Image

(b) Right Image

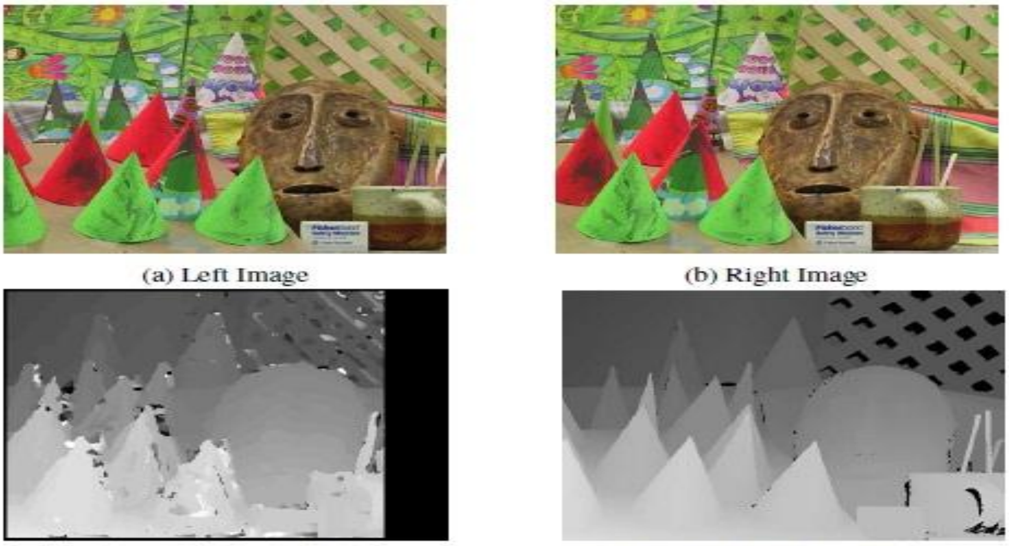


(c) SAD Disparity Map



(d) Ground Truth Disparity Map

Figure 3 Disparity Map for Teddy Stereo Pair



(a) Left Image (b) Right Image

(c) SAD Disparity Map (d) Ground Truth Disparity Map

Figure 4 Disparity Map for Cones Stereo Pair

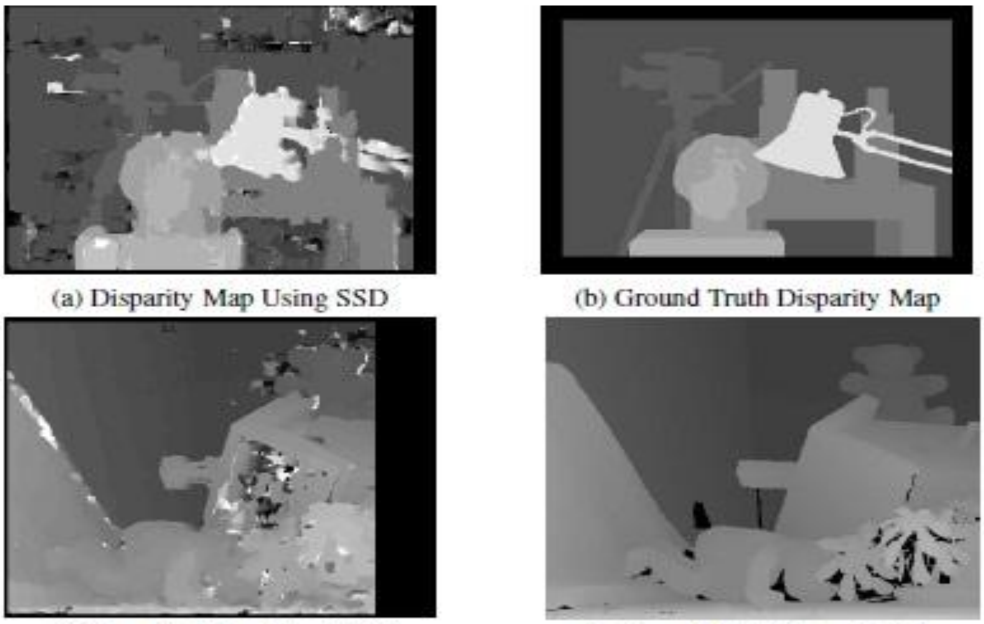
2.2 Sum of Squared Differences (SSD)

In Sum of Squared Differences (SSD), the differences are squared within a square neighborhood between the reference image and target image. After that the aggregation of absolute squared differences within the square window is done. Because of large number of multiplication operations in SSD algorithm, it has a higher computational complexity compared to SAD algorithm. SSD is obtained by,

$$SSD = \sum_{(i,j)\in W} \left|\left(I_1(i,j) - I_2(x+i, y+j)\right)^2\right| \qquad \text{.........................} (2)$$

Where W is the window size taken in that particular set of stereo images. I2 is the reference image in which we are searching for the corresponding match of a pixel in image I1.

Disparity map for different sets of stereo images using SSD algorithm is shown in Fig. 5.



(a) Disparity Map Using SSD (b) Ground Truth Disparity Map

(c) Disparity Map Using SSD (d) Ground Truth Disparity Map

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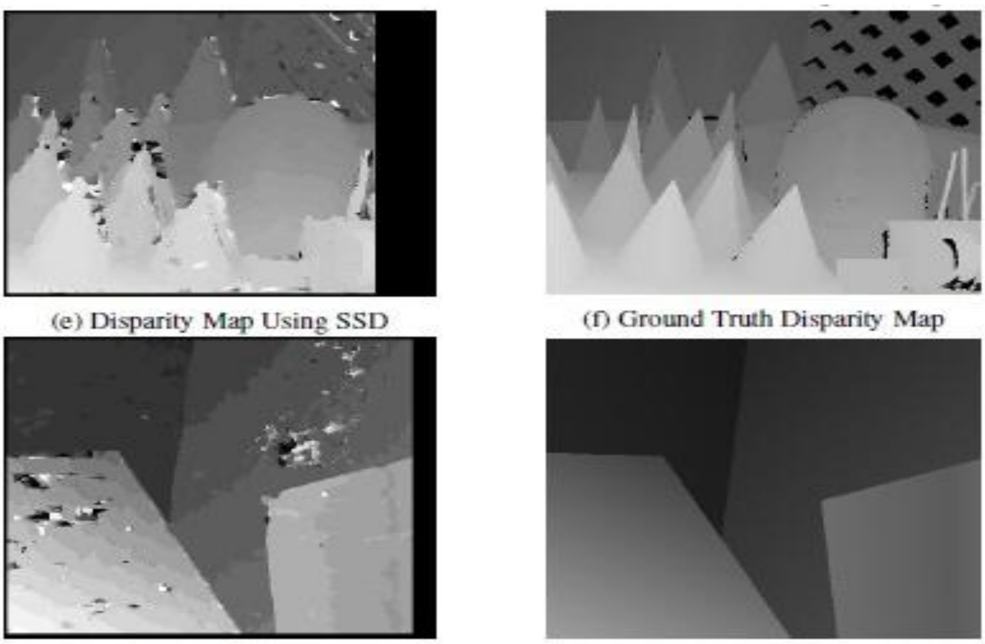


(e) Disparity Map Using SSD
(f) Ground Truth Disparity Map
(g) Disparity Map Using SSD
(h) Ground Truth Disparity Map

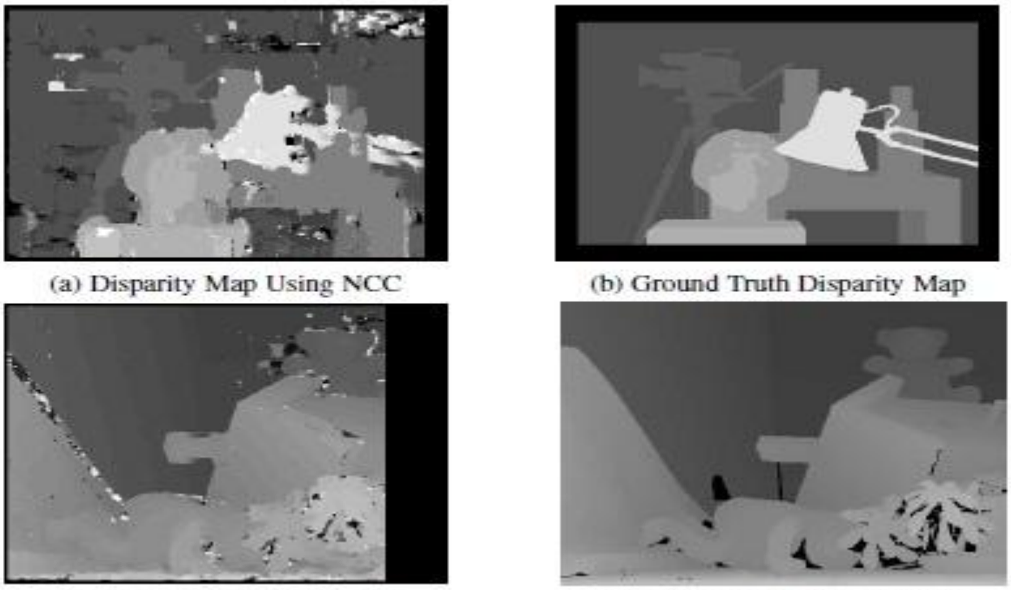
Figure 5 Disparity Map Using SSD

2.3 Normalized Cross Correlation (NCC)

Normalized Cross Correlation (NCC) involves a large number of multiplication, division and square root operations which makes it much more complex than SAD and SSD algorithms. As it involves numerous arithmetic operations, time taken by the NCC algorithm is much higher than the SAD and SSD algorithms. NCC is obtained by,

$$NCC = \frac{\sum_{(i,j)\in W} I_1(i,j)\cdot I_2(x+i,y+j)}{\sqrt{\sum_{(i,j)\in W} I_1^2(i,j)\cdot \sum_{(i,j)\in W} I_2^2(x+i,y+j)}} \qquad \ldots\ldots\ldots\ldots\ldots\ldots\ldots\ldots (3)$$

Disparity map for different sets of stereo images using NCC algorithm is shown in Fig. 6.



(a) Disparity Map Using NCC
(b) Ground Truth Disparity Map
(c) Disparity Map Using NCC
(d) Ground Truth Disparity Map

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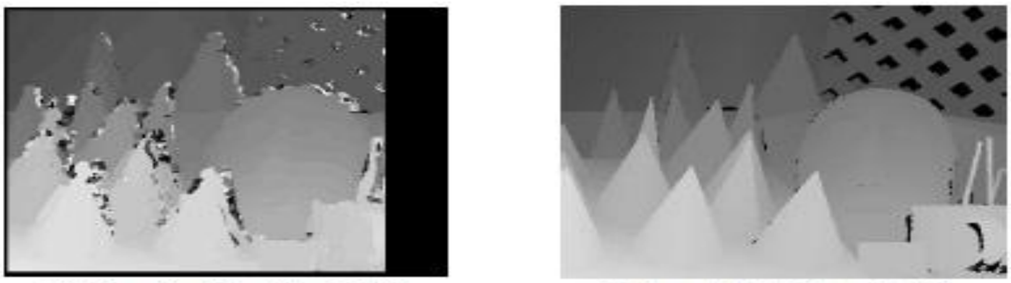
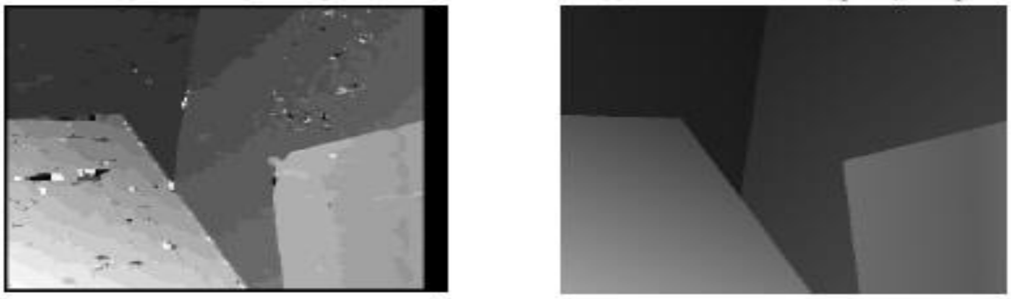


(e) Disparity Map Using NCC (f) Ground Truth Disparity Map



(g) Disparity Map Using NCC (h) Ground Truth Disparity Map

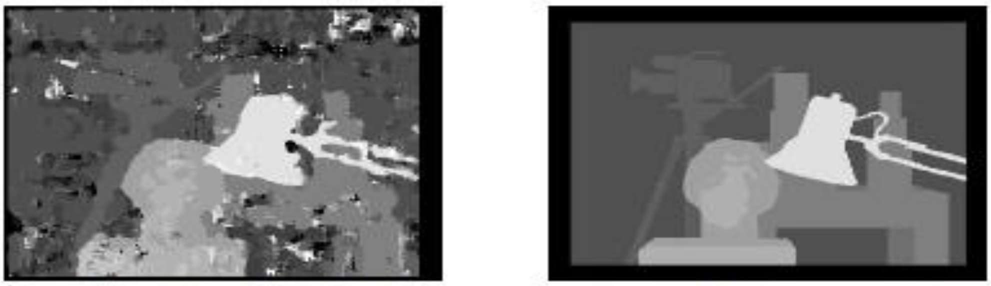
Figure 6 Disparity Map Using NCC

2.4 Sum of Hamming Distances (SHD)

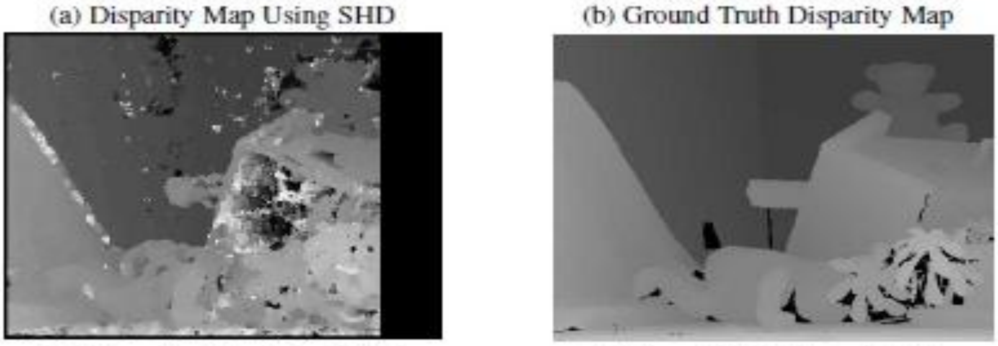
The Hamming distance between two strings of equal length is the number of positions at which the corresponding symbols are different. Firstly, bitwise-XOR of the values in left and right images is computed within a square window. Secondly, a bit-counting operation is performed which results in the final Hamming distance score. After bit-counting operation, the pixel with the minimum Hamming distance is selected as the best match for the corresponding pixel in search window. SHD is obtained by,

$$SHD = \sum_{(i,j)\in W} |I_1(i,j)\ \text{bitwiseXOR}\ I_2(x+i, y+j)| \qquad \ldots\ldots\ldots\ldots\ldots\ldots (4)$$

Disparity map for different sets of stereo images using SHD algorithm is shown in Fig. 7.



(a) Disparity Map Using SHD (b) Ground Truth Disparity Map



(c) Disparity Map Using SHD (d) Ground Truth Disparity Map

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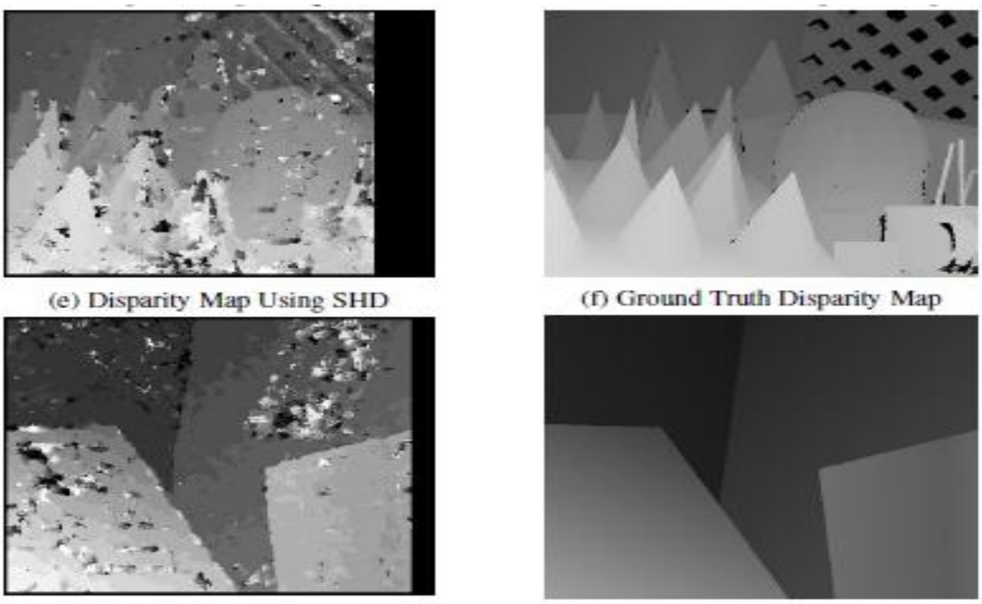


(e) Disparity Map Using SHD

(f) Ground Truth Disparity Map

(g) Disparity Map Using SHD

(h) Ground Truth Disparity Map

Figure 7 Disparity Map Using SHD

3. SEGMENTATION BASED STEREO MATCHING

Segmentation based stereo matching [6] is a technique for finding the Disparity map using the segmented image as a reference image. Firstly, pixel Disparity map of the stereo pair images is obtained by using sum of absolute intensity differences (SAD). Secondly, combine image information with the pixel disparities to get a cleaner Disparity map. This image information, used for filtering the Disparity map, is obtained from the segmented image. We combined image information with the pixel disparities to get a near ground truth Disparity map. First, we take the segmented image of the reference image obtained by the Mean-shift Segmentation[7][8]. After the Mean-shift segmentation, for each segment we look at the associated pixel disparities. In this project, we assign each segment to have the median disparity of all the pixels within that segment. This gives the final Disparity map which is close to ground truth Disparity map.

Disparity map for different sets of stereo images obtained by using segmentation based stereo matching is shown in Fig. 7. Table 5.1 given below gives the percentage of Bad Matching Pixel in different set of stereo images using different algorithms.

Table 1 Average Percentage Bad Pixels in Different Algorithms

Algorithm	Tsukuba	Venus	Teddy	Cones	Average % Bad Pixels
Segmentation based matching	1.98	0.74	11.7	8.48	5.72
SAD	12.89	9.20	26.44	19.22	16.93
SSD	15.70	10.24	29.34	24.80	20.02
NCC	10.56	5.28	20.63	14.87	12.83
SHD	9.24	4.77	23.39	18.48	13.97

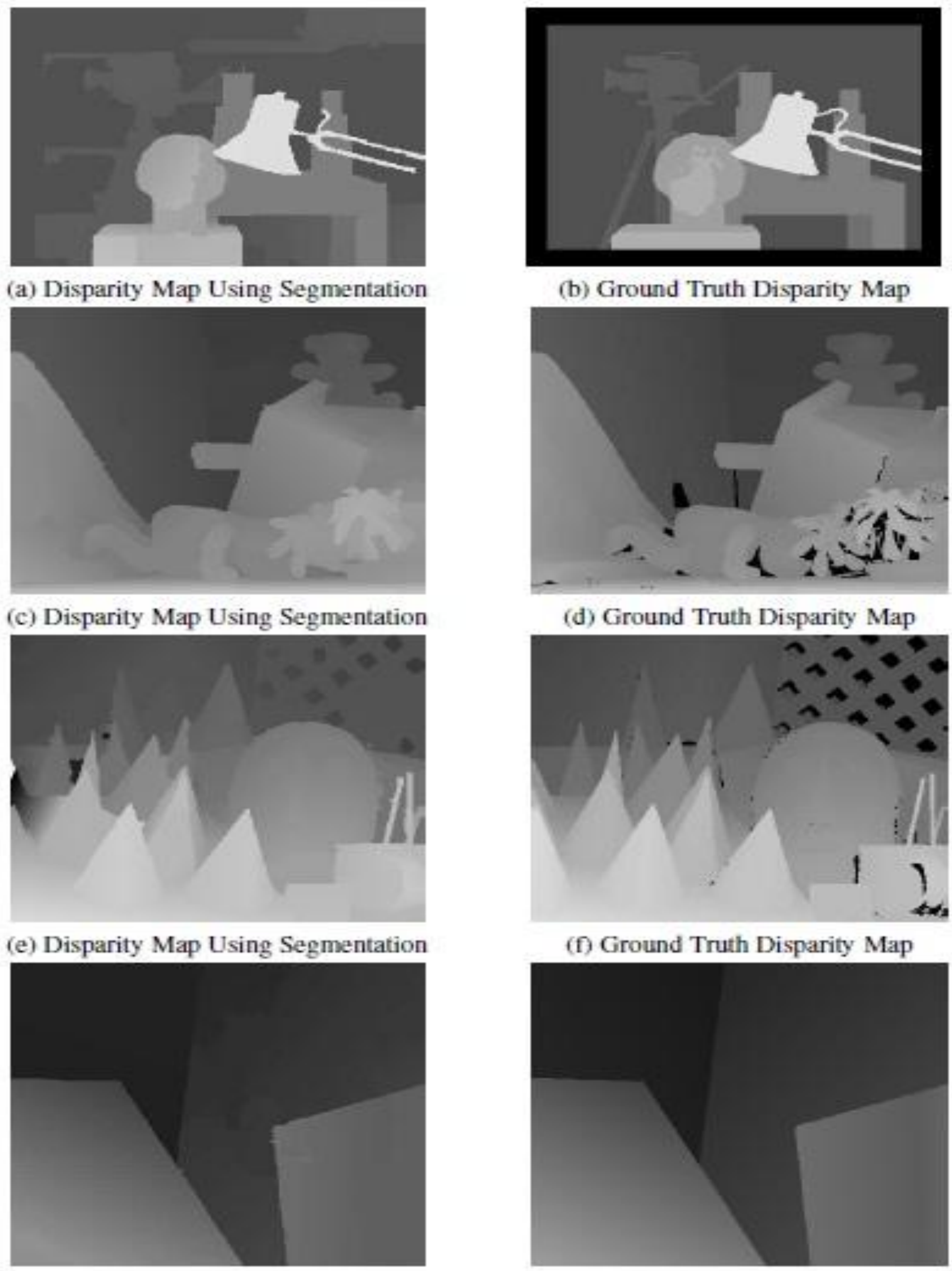
The average time (in seconds) for processing the images by the Correlation based stereo matching is given below in Table 2. This time is while implementing the particular technique (Left to Right matching) on Tsukuba images (384 × 288 image resolution, disparity range [0, 16], window size: (9×9)), on my machine using MATLAB. Result shows that the SAD based stereo matching is taking less time than other correlation based techniques.

Table 2 Time Taken by Different Algorithms

Algorithm	SAD	SSD	NCC	SHD
Time Taken	11.25	12.15	19.86	42.25

4. CONCLUSION

Result shows that the time taken to find the Disparity map using SAD is less than the other correlation technique. Also complexity of SAD is less so it is mostly used in real time systems, after optimizing, where high speed and less cost is required. Also, the segmentation based stereo matching is better than correlation based techniques in terms of accuracy. A segmentation based technique can be used in those stereo vision systems where high accuracy is required.



(a) Disparity Map Using Segmentation (b) Ground Truth Disparity Map
(c) Disparity Map Using Segmentation (d) Ground Truth Disparity Map
(e) Disparity Map Using Segmentation (f) Ground Truth Disparity Map
(g) Disparity Map Using Segmentation (h) Ground Truth Disparity Map

Figure 8 Disparity Maps Obtained Using Segmentation

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