

# Disparity Estimation by a Real Time Approximation Algorithm

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## Abstract

This paper presents an approximation real time algorithm for estimating the disparity of the stereo images. The approximation is achieved by shrinking the left and right of original images. According to this method (i) left and right images have been shrunked three times, (ii) the disparity image is computed from the shrunked left and right images to reconstruct the disparity image and extrapolate the disparity image to retrieve the original image size. The computational time of proposed algorithm is less than the existing methods, approximately real time and requires less memory space. This method is applied on the standard stereo images and the results show that it can easily reduce the computational time of about **76.34 %** with no appreciable degradation of accuracy.

**Keywords:** Stereo Matching, Quantization, Approximation, Stereo Corresponding, Disparity, Sum of Absolute Differences, Normalized Correlation.

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## 1. INTRODUCTION

The difference in the coordinates of the corresponding pixels is known as disparity, which is inversely proportional to the distance of the object from the camera. Stereo correspondence is a common tool in computer or robot vision, essential for determining three-dimensional depth information of object using a pair of left and right images from a stereo camera system. For of a pixel in the left image, its correspondence has to be searched in the right image based on the epipolar line and maximum disparity. Stereo correspondence or disparity is conventionally determined of matching windows of pixels by using Sum of Square Differences (SSD), Sum of Absolute Difference (SAD) or normalized correlation techniques.

Window-based stereo correspondence estimation technique is widely used due to its efficiency and ease of implementation. However, there is a well-known problem in the selection of an appropriate size and shape of window [1, 2]. If the window is small and does not cover enough intensity variation, it gives erroneous result due to low signal to noise ratio. If, on the other hand, the window is large, it includes a region where the disparity varies or discontinuity of disparity happens, then the result becomes erroneous due to different projective distortions in the left and right images. Pixels that are close to a disparity discontinuity require windows of different shapes to avoid crossing the discontinuity. Therefore, different pixels in an image require windows of different shapes and sizes.

To overcome this problem, many researchers proposed adaptive window techniques using windows of different shapes and sizes [3-7]. In adaptive window technique, it requires comparing the window costs for different window sizes and shapes, so the computation time is relatively

higher than that of fixed window based technique. For example, in the references 6 and 7 the authors used a direct search over several window shapes to find the one that gives the best window cost. Beside gray scale stereo images, the use of color stereo images brings a substantial gain in accuracy with the expense of computation time [8].

The better classifications have presented by Scharstein and Szeliski[11] and many new methods have been proposed here. Primarily matching algorithms can be classified with respect to sparse output and dense output. Feature based methods that based on segments or edges between stereo images result sparse output. Such type of output has the limitations both speed and accuracy due to their disadvantages causes it dreadful for many applications. Dense matching algorithms are divided into local and global ones.

Local methods are also known as area based stereo matching that can perform better speed compare to global methods. According to this, disparity is being calculated at a point in a fixed window. Global methods are also known as intensity or energy based stereo matching that can perform better accuracy compare to local methods. According to this method, the global cost function is reduced as minimum as possible. This cost function synthesizes image data and smoothness terms. Besides these some algorithms are not fallen into above mentioned two categories. Recently, neural adaptive stereo matching [13] are done by trained neural networks based on window size and shape. One dimensional cellular automation filter [16] makes the algorithm more adaptive to each window. Almost real-time performance method is reported in [15] presented by Yoon. It uses SAD method and a left-right consistency check. This method is able to find out the errors in the problematic regions are reduced using different sized correlation windows. Accordingly, a median filter is used in order to interpolate the results. The algorithm can process 7 fps for 320x240 pixels images and 32 disparity levels. The result has been justified by using an Intel Pentium 4 at 2.66GHz Processor.

The uses of Cellular Automata (CA) are presented in [16]. This work presents architecture for real-time extraction of disparity maps. The proposed method can process 1Mpixels image pairs at more than 40 fps. The key idea behind the algorithm relies on matching pixels of each scan-line using a one-dimensional window and the SAD matching cost. According to the method a pre-processing mean filtering step and a post-processing CA based filtering ones are employed. CA's are models of physical systems, where space and time are discrete and interactions are local. They can easily handle complicated boundary and initial conditions. In CA analysis, physical processes and systems are described by a cell array and a local rule which defines the new state of a cell depending on the states of its neighbors.

A window-based method is presented in [18] that use different support-weights. The support-weights of the pixels in a given support window are adjusted based on geometric proximity and color similarity to reduce the image ambiguity [19]. The running time for the Tsukuba image pair with a 35x35 pixels support window is about 0.016 fps on an AMD 2700+ processor. The error ratio is 1.29%, 0.97%, 0.99%, and 1.13% for the Tsukuba, Sawtooth, Venus and Map image sets respectively. The experimental results can be further improved through a left-right consistency checking.

In a global algorithm, the disparity of every single pixel is calculated by taking into consideration the whole image. Global optimization methodologies involve segmentation of the input images according to their colors. The accuracy of the global methods is very high but the computational costs are also high due to repetitive comparison.

The research work presented in [18] based on unified framework that supports the fusion of any partial knowledge such as matching features and surfaces about disparities. Accordingly, it combines the results of edge, corner and dense stereo matching algorithm to act as a guide points to the standard dynamic programming method. The result is a fully automatic dense stereo system with up to four times faster running speed and greater accuracy compared to results obtained by the sole use of dynamic programming.

A method based on the Bayesian estimation theory with a prior Markov Random Fields model for the assigned disparities is described in [20]. According to this method, the continuity, coherence, occlusion constraints and the adjacency principal are taken into considerations. The optimal estimator is computed using a Gauss-Markov random field model for the corresponding posterior marginal, which results in a diffusion process in the probability space. The results are accurate but the algorithm is not suitable for real-time applications, since it needs a few minutes to process a 256x255 stereo pair with up to 32 disparity levels, on an Intel Pentium III running at 450 MHz.

Image color segmentation is reported in [21]. By this method disparity map is estimated using an adapting window based technique. The segments are combined in larger layers iteratively. A global cost function is used to optimize the segments to layers. The quality of the disparity map is measured by warping the reference image to the second view and comparing it with the real image and calculating the color dissimilarity. For the 384x288 pixel Tsukuba and the 434x383 pixel Venus test set, the algorithm produces results at 0.05 fps rate and needed 20 s to produce results. For the 450x375 pixel Teddy image pair, the running speed decreased to 0.01 fps due to the increased scene complexity. Running speeds refer to an Intel Pentium 4 2.0GHz processor. The root mean square error obtained is 0.73 for the Tsukuba, 0.31 for the Venus and 1.07 for the Teddy image pair.

It is aimed that this approximation method will be useful in such situations for speedy determination of dense disparity.

## 2. APPROXIMATION METHOD

In the proposed approximation method, experimental left and right images has been shrinked three times with a view to reduce the computational time and searching area of given standard images. The SSD method has been applied for all candidate pixels in the right image within the searching range. To reconstruct the original disparity image, extrapolation is applied on the experimentally estimated disparity image. Various methods can be used for shrinking the left and right images for extrapolation. Proposed method uses the pixel quantization technique for extrapolation. The Figure 1 shows the hierarchical schematic diagram of the approximation method for disparity estimation.

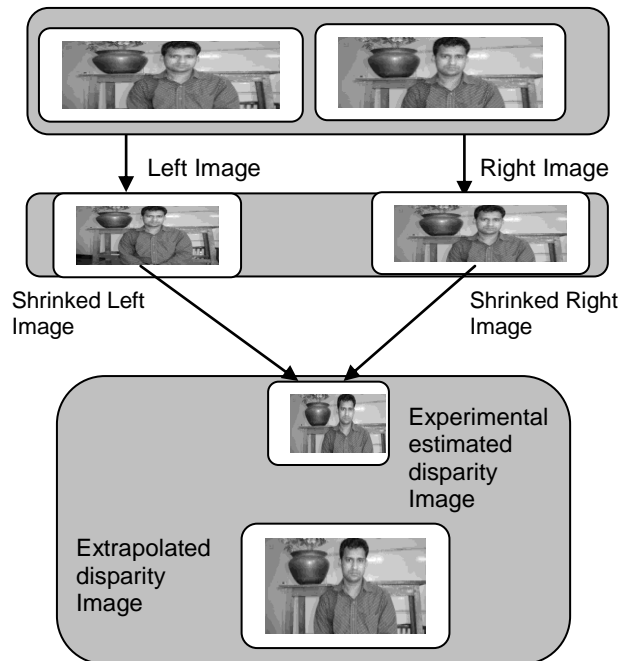


FIGURE 1: Hierarchical schematic diagram of approximation method.

### 3. SHRINKING PROCESS

Shrinking process can be viewed as the technique of quantization under a part of the approximation method. Window averaging method is used to shrink the left and right images in the proposed method. The key idea behind the technique is that nine pixels (consider the first window of right image) of original image are quantized to single pixel in shrunked image of Figure 2. This single pixel is marked by dark area in Figure 2 at last portion and it demonstrates all things on behalf of nine pixels of original image. Next nine pixels of original image are quantized to single pixel following the same manner but it will be allocated in the second coordinate of the shrunked image. The consecutive nine pixels of original image relocated in the third coordinate of the shrunked image and so on. The original image size was  $[m-1] \times [n-1]$ . After quantization the image size has been reduced to  $\{[m-1]/3 \times [n-1]/3\}$ . As the experimental images are shrunked two dimensionally i.e. nine times  $[3 \times 3]$ , so the computational costs are also reduced nine times compared to the traditional methods.

The total prefecture of our proposed method is represented by the flow chart of Figure-3. Actually, this method involved three looping steps which are quantization, disparity selection and extrapolation those are shown separately in the flow chart of Figure 3.

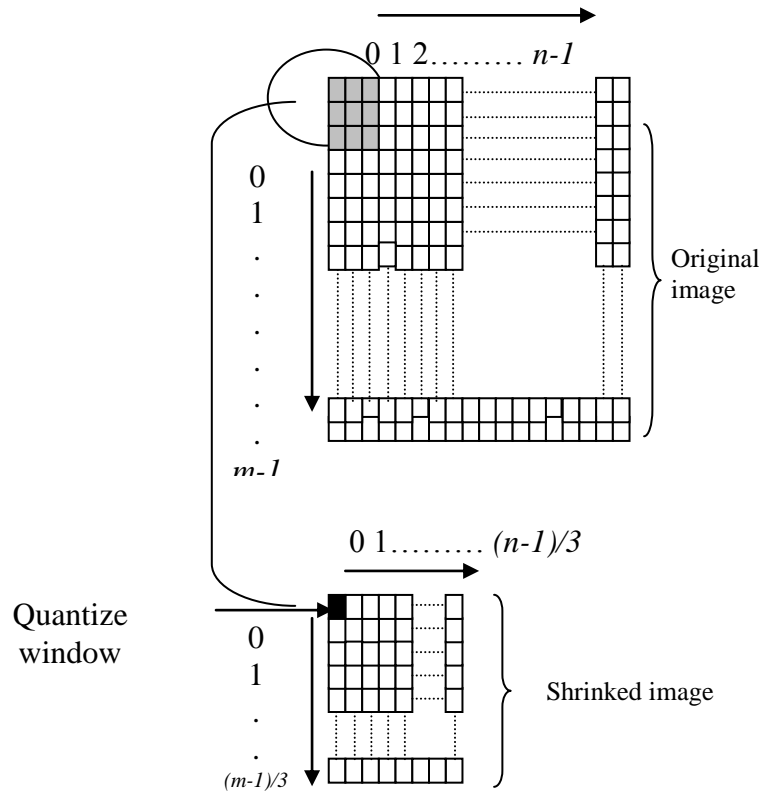


FIGURE 2: Shrinking Process.

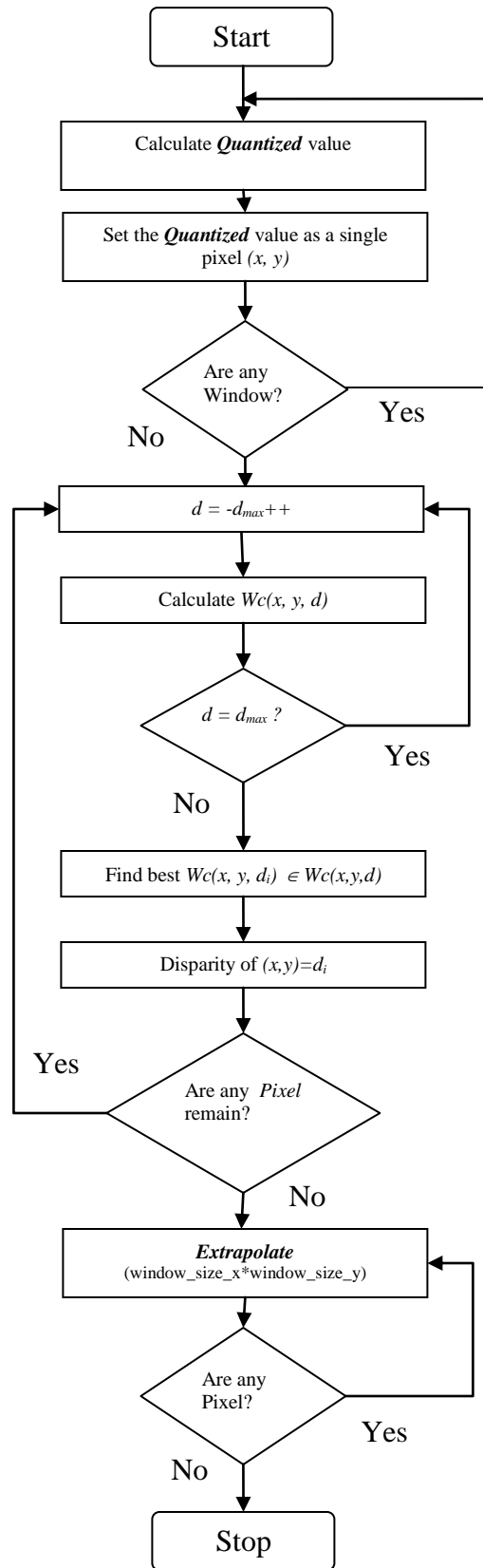


FIGURE 3: Flow chart of proposed approximation method.

#### 4. APPROXIMATION ALGORITHM EMPLOYED FOR DISPARITY ESTIMATION

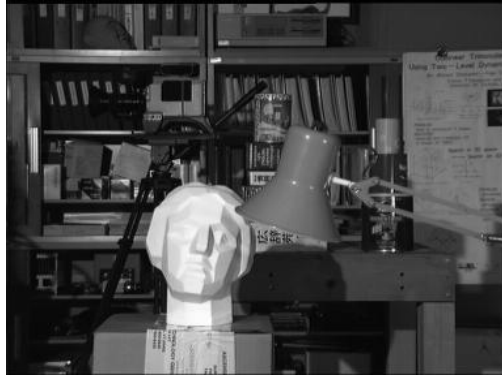
1. **for** each window
  - i) Calculate the quantization value
  - ii) Set quantized value as a single pixel  $(x,y)$**end** [ end of the quantization process]
2. **for** each pixel  $(x,y)$ 
  - for**  $d = -d_{max}$  to  $+d_{max}$  do
  - Calculate  $W_c(x,y,d)$
  - end** [ end of the searching range]
  - find best  $W_c(x,y,d_i) \in W_c(x,y,d)$
  - disparity of  $(x,y) = d_i$
3. **for** each pixel  $(x,y)$ 
  - Extrapolate** ( $window\_size\_x * window\_size\_y$ ) times
  - end** [ end of the extrapolation process]

#### 5. EXPERIMENTAL RESULTS

The accuracy and speed of this algorithm has been justified over some standard stereo images (Tsukuba Head). The images are provided by the computer Vision and Image Media Laboratory, University of Tsukuba, Japan. Experiments are performed on a corei5 3.2 GHz processor PC with 4 GB RAM. The algorithm has been implemented using Visual C++ programming language. Table 1 illustrates the summary of comparison between window based traditional method and proposed approximation method. The computational time using a corei5 3.2 GHz processor without any threshold for window sizes  $3 \times 3$  pixels is shown here. From this table, it reveals that for a window of size  $3 \times 3$  is applied for the disparity calculation of both methods, proposed approximation method reduced **76.34 %** of computational time. The following Figure 4 and Figure 5 shows the Tskuba Head of left and right images view. The Figure 6 and Figure 7 shows the shrunk images of left and right images respectively after applying quantization technique. Figure 8 shows the disparity image that is experimentally estimated from left and right image applying approximation method. The Figure 9 shows the extrapolated image of experimental disparity image. Experimental disparity images of Figure 8 and Figure 9 are histogram equalized for visualization purpose.



FIGURE 4: Left image 384 X 288.



**FIGURE 5:** Right image 384 X 288.



**FIGURE 6:** Shrunken left image 128 X 96.



**FIGURE 7:** Shrunken Right image 128 X 96.



**FIGURE 8:** Experimentally estimated disparity image 116 X 84.



**FIGURE 9:** Extrapolated image 348 X 252.

The size of the left and right image is (width × height) = (384 × 288) pixels, the shrunken image

size is (width × height) = (128 × 96) pixels, disparity image size is (width × height) = (116 × 84) pixels and extrapolated image size is (width × height) = (348 × 252) pixels.

Applying Methods	Window size	Computational time (in second)	Computational time reduction (%)
Window based traditional method	3 × 3	0.93	76.34
Approximation method	3 × 3	0.22	

**TABLE 1:** Computational time reduction (%) compare to Window based method.

From the above experimental results although the computational time reduction has been improved but some accuracy of ground truth image has been degraded (**FIGURE 8 and FIGURE 9**). This happened in shrinking process because 9 pixels are quantized at a single pixel. So eight (8) pixels might lose their some intensity attributes. Beside this some accuracy has been lost during the extrapolation process.

## 6. CONCLUSIONS

Experimental results confirm that we can easily reduce the computation time of about **76.34 %** with no appreciable degradation of accuracy. We believe that this approximation method will be useful for many applications where a very fast estimation of dense disparities is essential.

## 7. FURTHER IMPROVEMENT

For further improvement one can improve the accuracy of the disparity image. Different method can be used for shrinking the given left and right image. The accuracy might be retrieved by proper mapping of each pixel during the reconstruction of dense disparity.

## 8. ACKNOWLEDGEMENT

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