An efficient Stereo matching method to reduce disparity quantization error

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ABSTRACT
Efficiently utilizing the stereo Images to generate a desirable semi dense disparity map is a challenging problem. Disparity image is a projected geometric space contains more primitive information directly computed from stereo Images. Stereo matching is considered as difficult in image processing due to complexity and structure ambiguity. In this Paper, we propose a novel efficient disparity image processing to resolve the difficulties of the seed growing algorithms for small fraction of disparity space. The proposed model is computed using squared intensity and absolute intensity difference based disparity space for both low and high resolution images to achieve smoothness property. To reduce the disparity quantization error, we use multi fitting algorithm through sub pixel disparity estimation to obtain the effective and consistency in disparity mapping. The experimental results on Middlebury data's with ground truth disparities to demonstrate that proposed method with quantitative results in order to produces high quality disparity map with less computation time and high matching accuracy along complexity Q1reduction.

KEYWORDS: Disparity Image Space, Stereo Matching Algorithm, Sub pixel sampling

INTRODUCTION
There are lot of researches carried out in the stereo images to estimate the disparity image using dense stereo matching algorithm [1]. Area based dense stereoscopic matching algorithm performs exhaustive search on the entire disparity space. To optimize the performance of matching against smoothness constraints is attributed as improvement using matching metrics. Hence Pixel Sampled Intensity difference can be attributed for seed growing algorithms. Stereo matching algorithms implies seed growing algorithm based on the matching cost computation and disparity computation. To avoid visiting entire space, local algorithms are used for reliable seed correspondence. Cost aggregation methods are traditionally performed locally by summing/averaging matching cost over windows with constant disparity. The most efficient local cost aggregation method is normalized box filtering which runs in linear time. (Relative to the number of image pixels) using integral image [2]. Blurs in the in the edges demonstrated and filtered using edge-aware filters like bilateral filter [3] are very effective for preserving depth edges. However, full kernel implementation of the bilateral filter is slow. When a match of better image similarity is found at a given pixel, it overrides the previous match but it does not grow further, hence the correction is only local and there is no ability to follow a new disparity component of high image similarity. If the seeds in the queue are processed in a different order, (very) different results are obtained. Moreover, images in this algorithm do not have a symmetric role, which means the resulting matching violates uniqueness constraint. The disadvantage of the approaches is that the decision on a match is local in the sense that other matches do not influence the optimization of the density of area increases (no global optimization is involved). Efficient disparity image processing is proposed Method is used to resolve the difficulties of the seed growing algorithms for small fraction of disparity space. The proposed model is computed using squared intensity and absolute intensity difference based disparity space for...
both low and high resolution images to achieve smoothness property. To reduce the disparity quantization error, we use multi fitting algorithm to obtain the effective and consistency in disparity mapping. It is more accurate than the previous methods so that every pixel in the image can correctly contribute to all the other pixels during cost aggregation. In contrast, local cost aggregation methods require a user-specified or automatically detected window, and only pixels inside this window provide supports. The proposed method is thus a non-local solution for cost aggregation problem. It is theoretically better than traditional local solutions for low texture regions. This is straightforward as the window used by the local methods cannot guarantee to cover the whole low textured region. The rest of the paper is organized as follows; Section 2 describes the problem that has to be solved with related work to it. The details of the proposed system are presented in section 3. Section 4 explains the experimental results and discuss their performance against the existing approaches. We conclude the work in section 5.

2.1. Problem Statement:

The Combining process of the left image and right image by producing is disparity map is the problem of the work. At the coarse level disparity estimation, most methods suffer from disparity quantization errors, which cause wrong initialization for the next level, the boundary blurring is inherent to the multiresolution approaches, which is deteriorated by up sampling processes, which produce better final disparity from multi-scale processing, a fusion method that combines multiple intermediate estimates is required.

2.2. Related Work:

2.2.1. Cost Aggregation Using the Bilateral Filter:

Edge-aware filters like bilateral filter are known to be effective for edge-preserving smoothing and have been demonstrated to be very effective for local matching cost aggregation [4]. Let \( K_d(P) \) denote the matching cost for pixel (P) at disparity level d, \( K_s(p) \) denotes the aggregate cost, using reference image, the bilateral cost can be used to compute the aggregated cost.

2.2.2. Edge identification in High Texture area using Canny Edge Detection:

Canny edge detector produces complicated edge structures in the ground area where high-textures exist while the proposed edge function yields consistently low values [4]. Consequently, low edge strength in high-textured area will be able to reduce ambiguities by restricting the disparity search range.

3. Proposed System:

The proposed System is decomposed into two phases to perform the matching of the growth of disparity components in the left and right images (between two Images),

3.1. Identification of Seed and its constraint growth of the disparity component:

The stereo image is represented in the 3D discrete disparity space as each element denotes the correspondence. Distortion of the image from its neighbours is calculated based on associated parameters of the image seeds selection. The Parameters can be updated during the growth process to accommodate the region in the 3D surface,

![Fig. 1: Left stereo Image and right stereo Image used to generate the disparity information and identify distortions in 3D representation.](image)

In figure 1 stereo image are considered for the disparity identification using seed growing algorithm. Given two input images, we wish to find a disparity map such that the two images match as closely as possible.

We define the 3D difference image (SDI) as the intensity (or color) difference between the shifted left and right images,

\[
DI(x, y, d) = I_l(x, y) - I_r(x - d, y)
\]  

(1)
The 3D Reconstructed Image is presented as
\[ R(x, y) = \sum_{i=0}^{n} I(x, y)g(x, y) \]  

(2)

Where \( g(x, y) \) is reconstruction filter.

### 3.2. Square Difference based on Image Matching:

The proposed principle is to simply compute one additional squared difference between pixels, and to then fit a piecewise quadratic model. We then compute the squared differences between all of the interpolated and shifted samples, as opposed to just between the original left (reference) images pixels and the interpolated and shifted right (matching) image samples. This difference signal is then reduced back to the original horizontal image sampling rate (i.e., to a single value per original pixel) using a symmetric box (moving average) filter of width \( s \) and then downsampling. A higher-order filter could potentially be used, but we wish to keep discontinuities in depth sharp in the disparity Space Image (DSI).

When the DSI has been adequately sampled, however, this is a useful alternative for estimating the analytic minimum from the (fractionally) sampled DSI. Note that we use the parabola fit here not to obtain subpixel disparities, but rather to reconstruct the minimum DSI value, i.e., the actual smallest matching cost in the vicinity of the sampled value. In order to reduce the noise in the DSI before fitting, we apply spatial aggregation (averaging with neighbors) first.

We use a fixed uniformly weighted square window (i.e., box filter), which performs well in textured areas, as long as the window does not straddle a depth boundary. While the use of shift able windows (windows offset from the center pixel) [6] can improve the performance of matching near depth discontinuities, it makes the analysis of matching costs more difficult.

### 3.1.1. Sub Pixel Disparity:

Sub-pixel disparity estimation is performed at each level, which is used for the next level initialization and refinement. The more reliable the initial estimate is, the more accurate the disparity result at the next level will be. Integer approaches may increase disparity deviation from ground truth at the next level compared to sub-pixel ones. We consider a sub-pixel algorithm to increase disparity precision on object surface by reducing quantization errors, which can be simply integrated with the existing disparity methods. One of most popular algorithms is quadratic polynomial interpolation, known as parabolic fitting. It computes the fractional minimum point by fitting a parabolic function to three discrete matching costs, which consist of an initial minimum cost (center point) and two adjacent costs. Thus, the performance of the parabolic fitting directly depends on the cost function. In addition, such a fitting method is simply applicable to various local disparity methods as well as reduces the disparity discontinuity caused by the quantization [7, 8].

### 3.2. Multi fitting Algorithm:

Multiple fitting is not only efficient to implement but also improves the disparity accuracy while alleviating the drawback of the conventional method. We investigate the spatial-multi-resolution total variation (TV) to enforce spatial and multi-resolution (scaling) consistency. The adaptive disparity search range and spatial-multiresolution total variation play a role in fusing multi-scale disparity results by combining their complementary information [5].

Algorithm – Multi fitting algorithm:

- Define the cost function \( C1, C2, C3 \) using disparity values
- Find three minima for sub pixel precision \( d1, d2, d3 \) where
  - If Slope \( c1 > \) Slope \( c2 \)
    - Subpixel precision is \( d1 \)
  - If slope \( c2 > c3 \)
    - Subpixel precision is \( d2 \)
  - If slope \( c2 > c1 \)
    - Subpixel precision is \( d2 \)
    - Else
      - Subpixel precision is \( d1 \)
Endif
4. Experimental Results:

In this Section, we design and implement the disparity map using squared intensity and absolute intensity. Since there are so many alternatives possible for computing the DSI, it is better to sample the DSI at fractional disparities and to interpolate the resulting surface when looking for local minima. However, real images have noise and other artifacts such as aliasing and depth discontinuities. We therefore evaluate our new techniques using the Cones and Tsukuba, and Venus stereo test sequences with ground truth from [6], which are available at http://www.middlebury.edu/stereo. Two of these sequences are shown in Fig.2. We should note that the Cones data set have high-quality sub pixel accurate ground-truth estimates, while the Tsukuba ground truth has only integer disparities.

For Middlebury datasets, it is undesirable because their image size is too small to apply 3-level or more. For the Tsukuba image in the 3-level pyramid, the coarsest image size becomes 96*72 while the support window size for stereo matching is fixed to along scale levels. Moreover, the disparity range becomes indistinguishable. Sub-pixel algorithm should show robustness to various surface types.

The effect of different matching costs in textureless areas is harder to evaluate since the results depend strongly on the aggregation or Local optimization algorithm. We therefore restrict our analysis to textured areas and use a simple window-based correspondence algorithm. Untextured areas can be handled filled using aggregation with successively larger windows.

For our analysis, we select textured pixels by computing the squared horizontal gradient at each pixel (averaging the left and right values to remain symmetrical). These values are then averaged in a 3*3 neighbourhoods and threshold, using a threshold of 6 gray levels squared which is described in figure 2.

![Fig. 2a: Left Image, Fig. 2b: Right Image, Fig. 2c: Disparity Image, Fig. 2d: Reconstructed Image](image)

**Fig. 2:** Test Images and Results, 2a.Left stereo Image, 2b right stereo Image and 2c. Disparity Map with disparity information 2d. Distortions in 3D reconstructed representation.

<table>
<thead>
<tr>
<th>Image</th>
<th>Channel</th>
<th>Window Size</th>
<th>Max. Disparity</th>
<th>Matching Time</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cones</td>
<td>Red</td>
<td>21</td>
<td>39</td>
<td>1008ms</td>
</tr>
<tr>
<td>Tsukuba</td>
<td>Red</td>
<td>11</td>
<td>15</td>
<td>190ms</td>
</tr>
</tbody>
</table>

Table 1 shows the numerical results of some of our experiments. There is no single setting that consistently outperforms the Others but our new cost variants optimization generally do better than the original Costs in terms of squared difference and matching cost. Interval differences outperform squared differences on the Tsukuba and Venus data sets. Significant reduction of errors in high-frequency image regions can be carried out using window size, as predicted by our theoretical analysis. This is most apparent for the Venus images, which contain many such regions. Errors are also reduced in other areas affected by aliasing, such as strong intensity discontinuities or near-horizontal edges. Other errors, however, are not a direct result of the matching cost and can obscure the numerical results. The Tsukuba images in particular contain fewer high-frequency regions, but several areas with repetitive patterns and fine disparity variations that are challenging for a window-based method and, thus, result in spurious errors that are not directly a function of the matching cost used. Using linear interpolation, reconstruction of images can be given clearly for stereo images. Use of multiple fitting produces a smooth disparity surface along less computation cost.

**Conclusion:**

In this paper, we designed and implemented a novel efficient disparity image processing to resolve the difficulties of the seed growing algorithms for small fraction of disparity space. The proposed model computed the squared intensity difference based disparity space for both low and high resolution images to achieve
smoothness property. Disparity quantization error is reduced using multi fitting algorithm to obtain the effective and consistency in disparity mapping. The experimental results on Real dataset demonstrate that proposed method produces high quality disparity map with less computation time and high matching accuracy along complexity Q1reduction

REFERENCES