

A New Segment-based Stereo Matching using Graph Cuts

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Abstract—In the paper, we formulate a new energy function followed by the use of graph cuts to refine the disparity map which takes segment as node. Firstly, the robust disparity plane fitting is modeled and the method of Singular Value Decomposition (SVD) is used to solve least square. In order to ensure reliable pixel sets for the segment, we filter out outliers through three main rules, namely; cross-checking, judging reliable area and measuring the distance between previous disparity to the computed disparity plane. Secondly, we apply improve hierarchical clustering algorithm to merge neighbor. Finally, the final disparity map is obtained. Experimental results demonstrate that our approach is effective in improving the state of the art.

Keywords: *stereo matching; color segmentation; graph cuts; disparity plane fitting*

I. INTRODUCTION

Stereo matching is one of the most active research areas in computer vision. It serves as an important step in many applications, such as the fields of machine vision, robot navigation and 3D environment reconstruction [1].

Its main problem consists of finding a correspondence between left and right images. Although many researches study on the field of stereo matching and propose lots of algorithm for it [2, 3, 4, 5], especially for disparity map calculation, there are still many challenging works needed to be done caused by textureless, occlusion, etc. In general matching algorithm can be classified into local and global

methods. Local approaches are utilizing the color or intensity values within a finite window to determine the disparity for each pixel. Global approaches are incorporating explicit smoothness assumptions and are determining all disparities simultaneously by applying energy minimization techniques such as graph cuts[2, 9], belief propagation[3, 14], dynamic programming[18], and scanline optimization.

Recently, segment-based methods[11, 12, 13, 2, 16,14] have attracted attention due to their good performance. They are based on the assumption that the scene structure can be approximated by a set of non-overlapping planes in the disparity space and that each plane is coincident with at least one homogeneous color segment in the reference image. Our method also base on segment stereo matching. Generally speaking, performing of the segment-based stereo matching has four steps [8]. First, segment the reference image using robust segmentation method; second, get initial disparity map using local match method; third, a plane fitting technique is employed to obtain disparity planes; finally, an optimal disparity plane assignment is approximated using BP or graph cut optimization method. Although we also share these steps, there are three distinguishing features.

Our approach provides three advantages. Firstly the obtained disparity parameters are more accurate. This is done using SVD to solve disparity plane least equation and building three rules for filtering outliers in disparity plane fitting, namely; cross-checking, judging reliable area and comparing the distance between previous disparity to the computed disparity plane. Secondly, we use improved hierarchical clustering algorithm to merge the neighbouring

segments. The geometrical relationship of adjacent planes such as parallelism and intersection is employed for determination of whether two planes shall be merged. Finally, the new energy function is formulated, and graph cut is employed to get minimization the energy function, which takes segment as graph node.

This paper is organized as follows. In section 2, color segmentation is introduced. In section 3, the initial disparity is presented. In section 4, disparity plane estimation and merging segment are betrayed. In section 5, the method of graph cut is introduced to refine disparity map. In section 6, the experiment results are shown. Finally section 7, the conclusions are given. The overall algorithm is shown in Fig. 1.

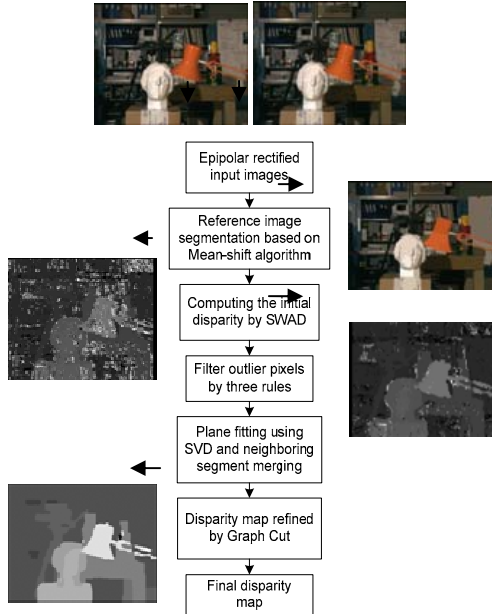


Figure 1. Flow chart of stereo matching algorithm

II. COLOR SEGMENTATION

Our approach is base on the segmentation region, so the first step in our algorithm is decompose the reference image into regions of homogeneous color or grayscale. The color segmentation algorithm has two assumptions: (1) disparity values vary smoothly in those regions; (2) and depth

discontinuities only occur on region boundaries. In this paper, we strictly enforce disparity continuity inside each color segment, therefore under-segmentation is not preferred, whereas over-segmentation is preferred, since it helps to meet this assumption in practice. We propose mean-shift color segmentation method which successfully applied to image segmentation by Comaniciu and Meer[15]. The main advantage of the man-shift approach is based on the fact that edge information is incorporated as well. The segmentation result is shown in the Fig.1.

III. INITIAL DISPARITY

In our paper, initial disparity is obtained by the local matching approach, which is the method of Sum of the Weighted Absolute intensity Differences (SWAD). Each pixel is assigned a weight $w(i,j,d)$, the value of which results from the 2D Gaussian function of the pixel's Euclidean distance from the central pixel. The Gaussian weight function remains for fixed width of the support window. Thus, it can be considered as a fixed mask that can be computed once, and the applied to all the windows.

$$w(i,j,d) = \exp\left(-\frac{d_g}{r_g}\right) \quad (1)$$

Where d_g is the pixel's Euclidean distance from the central pixel, r_g is the constant parameter.

The SWAD local cost function can be written as follows:

$$c_{data}(i,j,d) = \sum_{(i,j) \in N(i,j)} w(i,j,d) |I_l(i,j) - I_r(i+d,j)| \quad (2)$$

Where the $N(i,j)$ is 5×5 surrounding window at the center of the window (i,j) . We obtain the accurate initial disparity which minimizes the matching cost is selected as the initial disparity of pixel (i,j) using WTA (Winner-Takes-All) method. The result of SWAD to image is shown in the Fig.1.

IV. DISPARITY PLANE ESTIMATION

Our disparity plane is created base on reliable pixels in segment. The detail expresses as following:

A. Plane fitting

Tao et al. [16] gives a detailed description of plane fitting from the initial disparities in a segment. Each segment is modeled as

$$d(x, y) = ax + by + c \quad (3)$$

Where a, b, c are the plane parameters and d is the corresponding disparity of the image pixel (x, y) . (a, b, c) is the least square solution of a linear system

$$A[a, b, c]^T = B \quad (4)$$

Where the i -th row of A is $[x_i, y_i, 1]$, the i -th element in B is $d(x_i, y_i)$. Here we use Singular Value Decomposition (SVD) for least square solution.

$$[a, b, c]^T = A^+ B \quad (5)$$

Where A^+ is the pseudoinverse of A , the A^+ can be computed by SVD. Using psedoinverse A^+ , which compute through SVD, irrespective of A being singular or not.

However, as is generally known least square solutions are very sensitive to outliers. The estimated plane may be disturbed due to remaining outliers. So we first formulate rules to filter outliers. The detail rules as follow:

Set U is the set of all pixels inside the segment, U''' is the reliable pixels set.

1) *Cross-checking*. The cross checking is adopted to get the reliable pixel and filter out occluded pixels and area of the low texture where disparity estimates tend to be unreliable. Let the D_L is the disparity set from left image to right image and the D_R is the disparity set from right image to left image.

Cross checking condition is

$$|D_L(x_L) - D_R(x_L - D_L(x_L))| < 1 \quad (6)$$

If the pixel's disparity satisfies the Eq. (6), we consider the pixel is reliable pixel and vice versa. So we take these pixels as occlusion pixels.

2) *Judging reliable region*. We build a rule to judge the reliable region or unreliable region, the regularity as follow:

$$\rho_1 = \frac{N_{unreliable}}{N_{segment}} > \gamma_{segment} \quad (7)$$

Where ρ_1 is the ratio between the number of the unreliable pixel in the same segment and the number of the segment's pixel, $\gamma_{segment}$ is constant threshold. $N_{unreliable}$ and $N_{segment}$ are respectively the unreliable pixel number of the segment, and the number of pixel in the segment.

If a segment satisfies the Eq. (7), then the all pixels in the segment are labeled by unreliable, which represents that lack sufficient data to provide reliable plane estimations, and vice versa. So we can skip these very small segments.

3) *Measuring the distance between previous disparity to the computed disparity plane*. After the above steps filter outliers, we measure the distance between previous disparity to the computed disparity plane, the rule as follow:

$$|d_i - (ax_i + by_i + c)| \leq t_{outlier} \quad (8)$$

So the reliable set is updated to U''' . A new plane is then fitted to the pixels in U''' using Eq. (4).

For the above 1), 2) and 3) steps filter outliers, the process of estimation disparity parameters algorithm is then iterated until

$$e^{-(|a-a'|+|b-b'|+|c-c'|)} > \varepsilon \quad (9)$$

With a', b', c' are the parameters of the new plane, a, b, c are the parameters of the plane that was obtained in the previous iteration and ε is threshold the convergence value of the iterative Eq.(9) and will be set a very small value (typically 0.99). The Fig. 2 shows the detail step of the estimation disparity parameters.

B. Neighboring Segment Merging.

After using the color segmentation, the image contains lots of segmentation region. One single surface that contains texture is usually divided into several segments by applying mean-shift algorithm. However, for segments of

the same surface the planar models should be very similar, as long as the surface can be well approximated as a plane. So we should merge those segments.

Hierarchical clustering algorithm[17], which is based on cohesion, is applied to merge the neighboring segmented regions[14]. In addition, we make a new similarity measures on the clustering algorithm in terms of this research.

Given two segment regions A and B randomly, the plane equations are given by:

$$d_A = a_A x + b_A y + c_A \quad (10)$$

$$d_B = a_B x + b_B y + c_B \quad (11)$$

Then, we can decide whether the two planes are the same or not from two conditions.

(1) The angle θ

$$\theta = \arccos \left(\frac{\sqrt{(a_A \times a_B + b_A \times b_B + c_A \times c_B)}}{\sqrt{(a_A^2 + b_A^2 + c_A^2) \times (a_B^2 + b_B^2 + c_B^2)}} \right) \quad (12)$$

(2) The distance between the two planes

$$d_{distance} = \frac{|d_A - \frac{d_B}{\tau}|}{\sqrt{(a_A^2 + b_A^2 + c_A^2)}} \quad (13)$$

Where τ is the scale factor which transforms Eq. (11) to Eq. (10) with the same disparity parameters.

Here, we use Gaussian function in two conditions, so the similarity measures as follow function:

$$\pi = \begin{cases} e^{-\theta} & , \text{ if } A \nparallel B \\ e^{-d_{distance}} & , \text{ if } A \parallel B \end{cases} \quad (14)$$

If $\pi > \lambda$, where λ is constant threshold, then we consider two regions are the same and we merge two segments.

V. REFINED DISPARITY MAPS BY GRAPH CUTS

We use graph cuts for refined disparity, so we firstly formulate the new energy function. The energy function minimization problem for the labeling f that is assigned to each segment $s \in R$ a corresponding plane $f(s) \in D$, where

D is the disparity plane set. The energy for a labeling f is given by:

$$E(f) = E_{data}(f) + E_{occ}(f) + E_{sm}(f) \quad (15)$$

Where $E(f)$ is the energy function. $E_{data}(f)$ is the data cost function. $E_{occ}(f)$ is the occlusion pixel penalty function. $E_{sm}(f)$ is the smoothness penalty function.

For the term of the data cost function, the matching cost is calculated for each segment-to-plane assignment. It is computed by summing up the matching cost for each pixel inside the segment s , the function as following:

$$C(f) = \sum_{(x,y) \in N_r} c_{data}(x, y, d) \quad (16)$$

Where the $c_{data}(x, y, d)$ is defined as the section 3.2. N_r is a set of reliable pixel in s segment.

$$E_{data}(f) = \sum_{s \in R} C(s, f(s)) \quad (17)$$

The term of the occlusion energy function is

$$E_{occ}(f) = \sum_{s \in R} \omega_{occ} \cdot N_{occ} \quad (18)$$

Where ω_{occ} is the penalty coefficient for occlusion, N_{occ} is the pixel number of detected occlusions which include unreliable pixels in the s segment.

The term of the smooth energy function is

$$E_{ism}(f) = \sum_{((s_i, s_j) \in S_N | f(s_i) \neq f(s_j))} \xi_{disc}(s_i, s_j) \quad (19)$$

Where S_N represents a set of all adjacent segments and s_i, s_j are neighboring segments, $\xi_{disc}(s_i, s_j)$ is a discontinuity penalty that incorporates the common border lengths and the mean color similarity as proposed in [6].

We apply graph cuts to approximate the global minimum of our energy function. Notice that in our work, the graph nodes represent segments instead of pixels, and the label set is composed of all the estimated disparity planes instead of all possible discrete values in the disparity range. We present the detail graph cuts [2] steps as the following:

step1. Start with an initial labeling f .

step2. Set success := 0.

step3. Select in a random (or fixed) order a disparity plane $P \in D$.

step3.1. Find $f_{min} = \arg \min E(f')$ among f' within one α -expansion of f .

step3.2. if $E(f_{min}) = E(f)$, set $f := f_{min}$ and success:=1

step4. If success == 1 goto 2.

step5. Return f .

The solution converges usually with 2-5 iterations. In addition, it is extremely insensitive to the initial labeling.

VI. EXPERIMENTAL RESULTS

In this section, we test our approach and give out results. We employ four standard image pairs which are downloaded from: <http://vision.middlebury.edu/stereo>. The test images consist of a variety of cases, including textureless regions, disparity discontinuous boundaries and occluded portions. The Fig. 2 shows our approach test results. The first column is the reference images, the middle is the true disparity maps, the third is our experiment results and the last is bad pixel match. occluded portions. The table 1 shows our result in Middlebury stereo evaluation on different algorithms, it shows the performance comparison of error rate in whole image with other methods and it also demonstrates that our approach is effective in improving the state of the art.

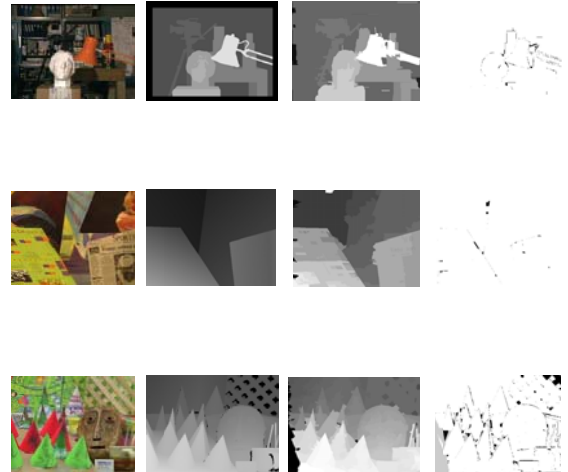
The running time of the algorithm is related to the number of iterations. By using a computer with CPU of 2.83 GHz, the total time for processing the stereo pair is about 12s except image segment. The parameters used in the experiments are below: $\omega_{occ} = 5$, $\xi_{disc} = 5$, $\gamma_{segment} = 0.9$.

VII. CONCLUSION

This paper presents a new segment-based stereo matching algorithm using graph cuts. The algorithm permits us to obtain the high quality dense disparity map of a scene from its initial disparity estimation. Our good points in this paper have three contributions, namely; robust disparity plane fitting, improving Hierarchical clustering algorithm to merge segment and using graph cuts optimization to the new energy function. But in the current, we use plane to fit the region with consistent disparities. It can be further improved by introducing B-spline fitting technique or similar ones. In addition, the Mean-shift method is a time-consuming image segmentation algorithm. How to find a more rapid as well as more robust real time image segmentation algorithm is another challenging work.

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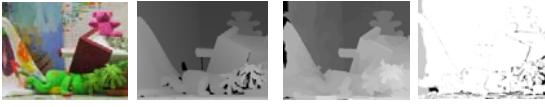


Figure 2. the disparity maps of the standard stereo image pairs on Middlebury website obtain by our algorithm: the 1st row- Tsukuba, the 2nd row- Venus, the 3rd row- Cones, and 4th row- Teddy. The 1st column- reference image, the 2nd column – ground truth, the 3rd column – our algorithm, the 4th column – ‘bad pixel’ match

TABLE I. PERFORMANCE COMPARISON OF ERROR RATE IN WHOLE IMAGE WITH OTHER METHODS

Algorithm	Tsukuba	Venus	Teddy	Cones
GenModel[19]	4.74	3.08	15.0	14.9
TreeDP[20]	2.84	2.10	23.9	18.3
GC[5]	4.12	3.44	25.0	18.2
CSBP[21]	4.17	3.11	20.2	16.5
Our method	3.59	2.12	16.7	13.6

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