

Improvement of Target Extraction and Dense Matching

Zetao Jiang

Nanchang Hangkong University/ School of Information Engineering, Nanchang, China
Email: zetaojiang@126.com

Qiang Wang and Yanru Cui

Nanchang Hangkong University/ School of Information Engineering, Nanchang, China
Email: wangqiang000ws@126.com, cuiyanrumwyauavk@163.com

Abstract—In order to obtain dense 3D point clouds of the target based on image sequence, it is necessary to ensure the accuracy of the target extraction and the dense of the disparity which based on the dense matching of image sequence target. A new method that was used to improve the target extraction and dense matching was proposed in this paper. In the image target extraction, many interactive iteration segmentations method was adopted to amend the inaccurate region that was segmented by traditional GrabCut; and in the dense matching, the image texture features information was introduced to divide the image into the texture-rich region and sparse texture region, and different dense matching methods were applied to the different regions. This method solved the problem that image target cannot be accurately extracted from a complex scene; On the other hand, the localized reconstruction due to the fact that image texture sparse region cannot be achieved quasi-dense matching was also solved. The results displayed that, after the using of this method, good results have been showed, and the accuracy of three-dimensional reconstruction was improved.

Index Terms—image segmentation, texture analysis, dense matching

I. INTRODUCTION

The image object extraction is the use of image segmentation method to extract useful target in the image. The traditional image segmentation methods can be divided into three categories: segmentation method based on threshold, segmentation method based on edge and segmentation method based on region. The premise of the threshold segmentation method is the assumption that the gray level range of the target and the background are strictly separated, which have some requirements for the histogram model, there are many images do not meet these requirements. Images edge detection method is the use of the edge information of discrete points to segment, this method is susceptible to images noise. The segmentation method based on region uses the regional

consistency as a criterion. It is so widely used for certain noise immunity. Nowadays, interactive technologies take advantage of the awareness of people for the object to find the boundary and obtain high performance segment through appropriate interactive. Classical methods include Snakes [1], Intelligent Scissors [2], GrapCut [3, 4, 5] and so on. The article is the use of many interactive iteration segmentations method to amend the inaccurate region that has been segmented by the traditional GrabCut. And ultimately the accurate target extraction of complex scenes images.

In the field of computer vision, the results of image matching will directly impact the subsequent 3D reconstruction. In order to achieve the 3D reconstruction of image sequences, it is necessary to ensure the accuracy and efficiency of the Image dense matching. The earlier proposed dense stereo matching method is a window matching algorithm [6] which relied on the window constraints, the main idea of their method use the gray of adjacent pixel in a window to compare, and use its similarity to determine whether match with the center of the window. The quality of the method depends on the size of the window. Selecting the optimal window size which is determined by the image texture and local variation of parallax, what is more it is often difficult to determine the best window in the experiment. In modern times, many domestic and foreign scholars have been carried out a lot of research on the dense stereo matching algorithm. Otha [7] presented image correction, and then used the dynamic programming algorithm to compute dense stereo matching based on image scan lines. This method uses all the pixels unit of the scan line to match. So the method is cumbersome and large amount of computation. Then the dynamic programming algorithm is proposed, which changes the problem of stereo matching into a maximum flow problem. By calculating the shortest path of the maximum flow can disposable obtain parallax surface of the whole image. The disparity map is obtained by the algorithm that is more accurate than Otha. Dense matching based on image divided dissemination method can be applied without correction and large disparity map; at the same time obtained more mistake matching by this method. Collaborative iterative

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algorithm [8] takes global constraints and iterative algorithm to get a better disparity map. But the algorithm uses a variety of algorithms, so it is the computational complexity and taking up storage space. Dense matching method based on triangulation [9] uses the specific characteristics of a triangle to limit the geometric structure of objects. This algorithm can narrow the scope of the matching, thereby improving the speed and accuracy of the matching.

The above dense matching methods have the good performance, but some algorithms only have good effect in the texture-rich region, the dense matching is not effective in the sparse texture region. To solve this problem, this paper presented an improved dense stereo matching method: different dense matching methods were applied to the different regions. The method can solve the problem of the stereo matching in sparse texture region and improve the accuracy of the disparity map.

II. IMPROVED IMAGE TARGET EXTRACTION BASED ON GRAB CUT

This following describes the GrabCut segmentation algorithm: iterative estimation and incomplete labeling.

A. Colour Data Modelling

The colour image is composed of pixels in the RGB colour space. As it is unrealistic to construct adequate colour space histograms, it takes measures to use GMM model to construct data model of colour image. Each GMM (one for the background and one for the foreground) is taken to be a full-covariance Gaussian mixture with K components (typically K=5). In order to deal with the GMM conveniently, an additional vector $k=\{k_1, \dots, k_n, \dots, k_N\}$ is introduced as a unique GMM component to each pixel for optimization process. The opacity of the corresponding pixels either from the background or the foreground model, according as $\alpha_n = 0$ or 1.

The Gibbs energy is rewritten as following:

$$E(\alpha, k, \theta, z) = U(\alpha, k, \theta, z) + V(\alpha, z), \quad (1)$$

where α is opacity, $\alpha \in [0, 1]$. 0 is the background, 1 is the foreground, θ is grayscale histogram of the background or the foreground, z is gray value array. The formula (1) is affected by k . The data term U is now defined, taking account of the colour GMM models, as

$$U(\alpha, k, \theta, z) = \sum_n D(\alpha_n, k_n, \theta, z_n), \quad (2)$$

where $D(\alpha_n, k_n, \theta, z) = -\log p(z_n | \alpha_n, k_n, \theta) - \log \pi(\alpha_n - k_n)$, and $p(\cdot)$ is a Gaussian probability distribution, and $\pi(\cdot)$ are mixture weighting coefficients (up to a constant), then:

$$D(\alpha_n, k_n, \theta, z_n) = -\log \pi(\alpha_n, k_n) + \frac{1}{2} \log \det \Sigma(\alpha_n, k_n) + \frac{1}{2} [z_n - \mu(\alpha_n, k_n)]^T \Sigma(\alpha_n, k_n)^{-1} [z_n - \mu(\alpha_n, k_n)] \quad (3)$$

Therefore, the parameters of the model are identified as;

$$\theta = \{\pi(\alpha, k), \mu(\alpha, k), \Sigma(\alpha, k), \alpha = 0, 1, k = 1 \dots K\} \quad (4)$$

The smooth entry of colour image is:

$$v(\alpha, z) = \gamma \sum_{(m,n) \in C} [\alpha_n \neq \alpha_m] \exp - \beta \|z_m - z_n\|^2 \quad (5)$$

B. Segmentation by Iterative Energy Minimization

The energy minimization in GrabCut works iteratively, in place of Graph cuts algorithm that is the one-time completion. This has the advantage of allowing automatic refinement of the opacity α , as redetermine the pixels from the T_U region of the initial trimap are used to re-correct the colour GMM parameters θ .

The process of GrabCut algorithm is described as follows:

1) Initialisation

(a) User initialises trimap T by setting only T_B .

The foreground is set to $T_F = \varnothing$; T_U is complement of the background that is set to $T_U = \bar{T}_B$.

(b) Initialise $\alpha_n = 0$ for $n \in T_B$ and $\alpha_n = 1$ for $n \in T_U$.

(c) Background and foreground GMM initialised from sets $\alpha_n = 0$ and $\alpha_n = 1$ respectively.

2) Iterative minimization

(a) Assign GMM components to pixels: for each n in T_U ,

$$k_n := \arg \min_{k_n} D_n(\alpha_n, k_n, \theta, z_n) \quad (6)$$

(b) Learn GMM parameters from data z :

$$\theta := \arg \min_{\theta} U(\alpha, k, \theta, z) \quad (7)$$

(c) Estimate segmentation: use min cut to solve:

$$\min_{\{\alpha_n, n \in T_U\}} \min E(\alpha, k, \theta, z) \quad (8)$$

(d) Repeat from step (a), until convergence.

(e) Apply border matting

3) User editing

(a) Edit: fix some pixels either to $\alpha_n = 0$ (the background) or $\alpha_n = 1$ (the foreground); update trimap T

acc-

ordingly. Perform step (c) above.

(b) Optimization: perform entire iterative minimisation algorithm.

C. User Interaction and Incomplete trimaps

Incomplete labelling becomes feasible, which in place of the full trimap, the user needs only specify the background region T_B , leaving the foreground $T_F = 0$. Iterative minimisation deals with this incompleteness by allowing provisional labels on some pixels (in the foreground) which can subsequently be retracted, but the

labels are fixed (in the background). The initial TB is determined by the user marked rectangle.

If the given initialization information is not sufficient to be satisfied with the segmentation results, then further user editing is needed to provide more information. In addition, the optimization of the optional improved operation can update the colour models information based on user edits. Note that for efficiency the optimal flow, computed by Graph Cut, can be re-used during user edits.

This paper used GrabCut segmentation method to achieve object extraction. The experimental result is as follows:

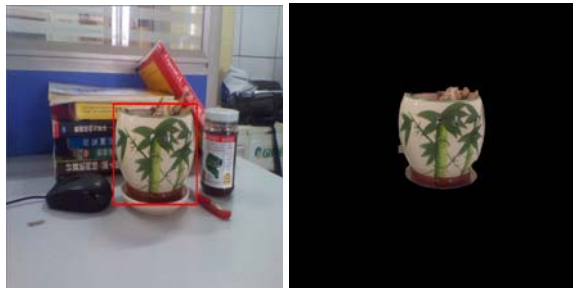


Figure 1. The GrabCut algorithm

The traditional GrabCut algorithm is sensitive to the changes of image brightness, so it will be inaccurate target object for GrabCut to extract target in span brightness variations of the image [10, 11].

In order to solve the disadvantage of the traditional GrabCut algorithm, this paper presented an improved method based on GrabCut, which was the use of multiple mouse interactions and iteration segmentations method to amend the inaccurate region that had been segmented by the traditional GrabCut. The improved method is as follows:

(1) First of all, the initial target was segmented by GrabCut and calculated the contour area of the initial target; Followed by, the initial region was interacted again by the mouse, the interaction region together with the contour of the previous target object calculated the region which did not meet user requirements. Last, the interaction region and the previous contour line together formed the correction area, which was used to amend the inaccurate region based on GrabCut;

(2) According to the above of the foreground and background model remaped the correction area to s-t network, then amended image by minimum cost cutting iterative method;

(3) Output corrected results until iterative minimize.

This paper used the traditional GrabCut segmentation method and improvement of GrabCut to achieve object extraction. The experimental results are as follows:

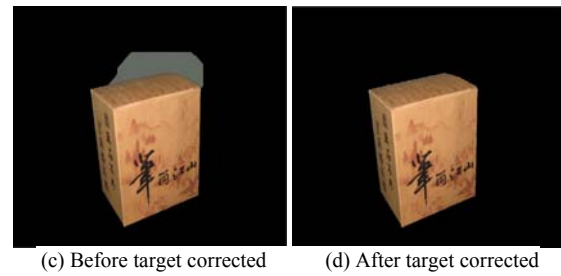
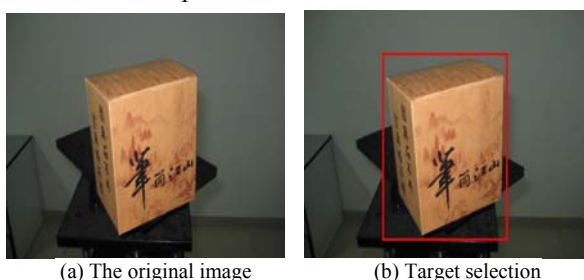


Figure 2. The first experiment: the target correction

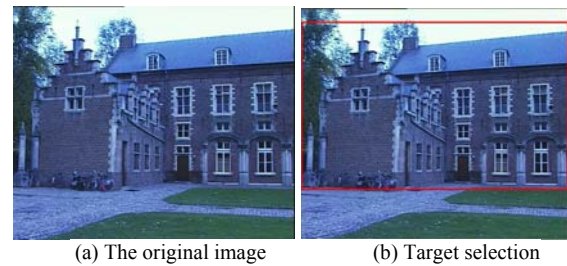


Figure 3. The second experiment: the target correction

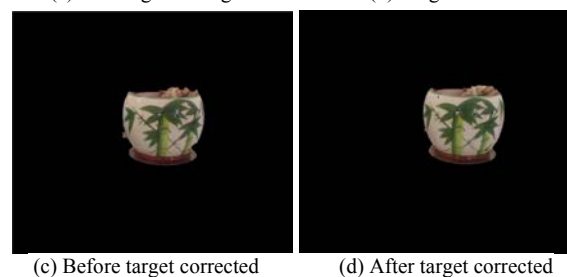


Figure 4. The third experiment: the target correction

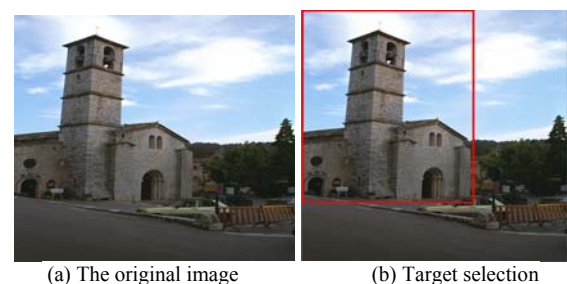




Figure 5. The fourth experiment: the target correction

Figure 2 (c), 3 (c), 4 (c), 5 (c) is the result that is before target corrected. Figure 2 (d), 3 (d), 4 (d), 5 (d) is the result that is target corrected. Compared the four groups of target extraction, the results confirm that the correction method is simple. This method is adopted to amend the inaccurate region that is obtained by the traditional GrabCut.

III. THE IMPROVED DENSE MATCHING ALGORITHM BASED ON REGIONAL GROWTH

Following the target extraction based on the improved GrabCut, The sparse matching was performed by feature matching based on SURF [12], and it is the situation that a lot of matching points appeared in the sparse region, a little matching point appeared in the texture-rich region. The image is made up with texture-rich region and the texture sparse region, and the existed sparse matching methods are difficult to solve the problem of matching in the sparse texture region, so it uses the traditional dense matching based on regional growth for the dense matching of the image target, which will make matching relations stop in the sparse texture region [13], and ultimately affect the accuracy of reconstruction. To solve this problem, an improved dense matching was proposed. The method uses a two-step strategy: matching in the texture-rich region and sparse region [14]. Many fine matching points were obtained by feature matching based on SURF in the texture-rich region, so dense matching would be carried out by using dense matching based on regional growth. After the calculation of the feature points information in texture sparse region, the points have obvious characteristics, which were chosen as key points, then the key points were seed points, Quasi-dense matching was conducted based on regional growth [15].

The overall process of the improved dense matching algorithm is shown in above Figure 6, and the key step of which is the mark of sparse texture and rich texture region.

A. Sparse Texture and Texture-rich Area Segmentation Based on Texture Features from Image

GLCM (gray level co-occurrence matrix) [16] is a commonly used method to describe the texture through the study of gray space-related features, which has high value in the research and analysis of texture images. Therefore, the GLCM was used to describe the image texture features in this paper.

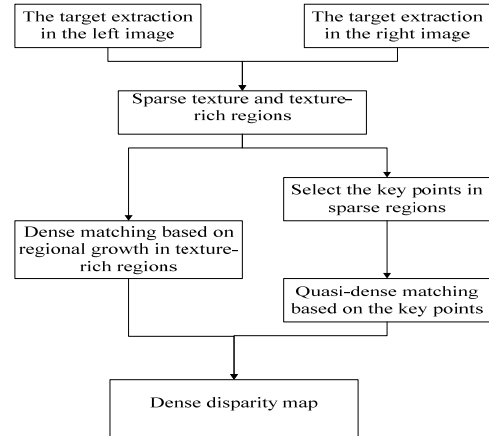


Figure 6. The process of the improved dense matching algorithm

GLCM is expressed by the joint probability density through two different pixels, which not only reflects the light distribution characteristics, but also reflects the characteristics of the location distribution among pixels of the same intensity or similar intensity. GLCM is the basis to constitute texture features, which has the second-order statistical properties of the image brightness changes since GLCM has the characteristics of computational complexity. Normalized probability density $P_{\delta}(i, j)$ of the co-occurrence matrices can be defined as follows.

$$P_{\delta}(i, j) = \frac{\#\{(x, y), (x+d, y+d) \in S \mid f(x, y) = i, f(x+d, y+d) = j\}}{\#S} \quad (9)$$

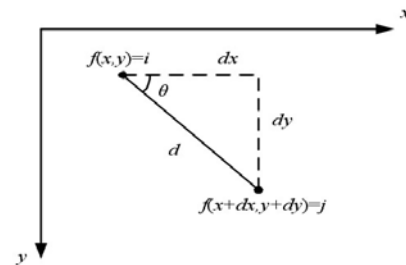


Figure 7. Grey level co-occurrence matrix

2	1	2	0	1
0	2	1	1	2
0	1	2	2	0
1	2	2	0	1
2	0	1	0	1

$i \quad | \quad j$

0	5	1
1	1	4
4	2	2

Figure 8. The demonstration of calculating the grey level co-occurrence matrix

$x, y=0, 1, \dots, N-1$ are co-ordinates of the pixel
 $i, j=0, 1, \dots, L-1$ are the gray levels

S is set of pixel pairs which have certain relationship in the image.

$P_{\delta}(i, j)$ is the probability density that the first pixel has intensity value i and the second j , which separated by distance $\delta = (dx, dy)$.

In order to reduce the complexity of the algorithm of extracting image texture features. It can take use of the symmetry characteristics of GLCM, and select four directions (0° , 45° , 90° , 135°) for operating. This makes the calculation of the entire algorithm greatly reduced[14]. The GLCM calculation formula is:

$$P(i, j) = \sum_{\substack{\theta=0^{\circ}, 45^{\circ}, 90^{\circ}, \\ 135^{\circ}, d=1}} P(i, j, d, \theta) \quad (10)$$

Access to a lot of literatures, the following four statistics were most commonly used to extract image texture features, which have the best results:

(1) Angular second moment

$$f_{ASM} = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} [P(i, j)]^2 \quad (11)$$

Angular second moment is the square of the various elements of GLCM, which is also known as energy. It is the uniform measure of the image texture gray, reflecting the uniformity degree of gray level distribution and texture coarseness.

(2) Contrast

$$f_{CON} = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (i-j)^2 P(i, j) \quad (12)$$

Contrast is the inertia moment of the GLCM near the main diagonal, which measures how the value of the matrix distributed, and the local change of the image, reflecting the image clarity and grooves depth of texture.

(3) Relevant

$$f_{CORRLN} = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} ijP(i, j) - \mu_i \mu_j / \sigma_i^2 \sigma_j^2 \quad (13)$$

It measures the similarity of the elements in the spatial gray level co-occurrence matrix on the row or column direction; therefore, the relevant values reflect the correlation of local gray-scale in the image.

(4) Entropy

$$f_{ENT} = \sum_{i=0}^{L-1} \sum_{j=0}^{L-1} (-\ln P(i, j)) P(i, j) \quad (14)$$

Entropy measures the randomness of the texture. It is maximum when all values of the space GLCM are equal; conversely, if the values of GLCM are very uneven, its value is small.

μ_i , μ_j , σ_i^2 , σ_j^2 are defined as:

$$\mu_i = \sum_{i=0}^{L-1} i \sum_{j=0}^{L-1} P(i, j) \quad (15)$$

$$\mu_j = \sum_{j=0}^{L-1} j \sum_{i=0}^{L-1} P(i, j) \quad (16)$$

$$\sigma_i^2 = \sum_{i=0}^{L-1} (i - \mu_i)^2 \sum_{j=0}^{L-1} P(i, j) \quad (17)$$

$$\sigma_j^2 = \sum_{j=0}^{L-1} (j - \mu_j)^2 \sum_{i=0}^{L-1} P(i, j) \quad (18)$$

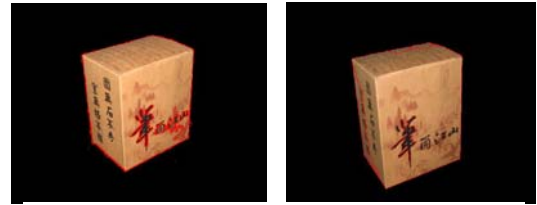
It can be seen from the above (10) - (13), when the value of fCON, fCORRLN and fENT is smaller, the gray scale of pixels is identical or similar in this region, namely, the region is the sparse texture region.

In order to achieve the texture divided, This paper set the threshold for fCON, fCORRLN and fENT, and ensured that the image was divided into rich texture and sparse texture regions. Here, the threshold of fCON, fCORRLN and fENT was set as t1, t2 and t3 respectively (the values of the introduction threshold t1, t2 and t3 depend on the texture feature of the specific image). Then, when they satisfied the following condition: fCON < t1, fCORRLN < t2, fENT < t3, the image region was a sparse texture region, otherwise, it was a texture-rich region.

Then, this paper used the above method to mark texture-rich region and sparse region. The results were shown in the following figure 9, figure 10 and figure 11.



(a) The targets extraction



(b) The texture-rich and sparse texture regions are marked

Figure 9. The first experiment: the texture-rich and sparse texture regions are marked

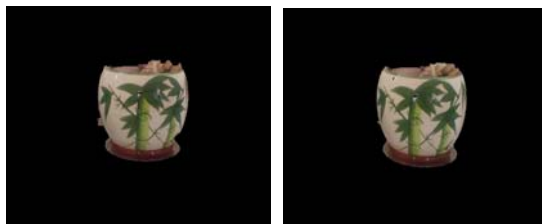


(a) The targets extraction



(b) The texture-rich and sparse texture regions are marked

Figure 10. The second experiment: the texture-rich and sparse texture regions are marked



(a) The targets extraction



(b) The texture-rich and sparse texture regions are marked

Figure 11. The third experiment: the texture-rich and sparse texture regions are marked

The red curve in the above experimental results divides the object of the image into many rich-texture regions and sparse-texture regions. The results show that the images are marked as rich-texture region and sparse-texture region by using in this method.

B. Matching of the Texture-rich Region and Sparse Texture Region

By the above method, image target was divided into rich texture region and sparse texture region. This paper used the dense matching based on regional growth for the texture-rich region. In the sparse texture region, firstly, points build stereo matching relations which were defined as the seed points; secondly, used the seed points as original point to achieve quasi-dense matching based on the regional growth method. By this way, the feature points matching from few or no to quasi-dense matching in the sparse texture region.

In the sparse texture region, this paper described feature points based on the synthesis of color features information and texture feature information. The feature points can be described as $V_p = (fCON, fCORRLN, fENT, R, G, B) = (T, C)$, in this formula, $fCON$, $fCORRLN$, $fENT$ are texture eigenvalue, R , G , B , the three characters express three channel color. $T = (fCON, fCORRLN, fENT)$ is texture feature vector, $C = (R, G, B)$ is color vector. We define the most remarkable feature of the point as the key point in sparse texture regions. The paper defined the most obvious feature of the comprehensive

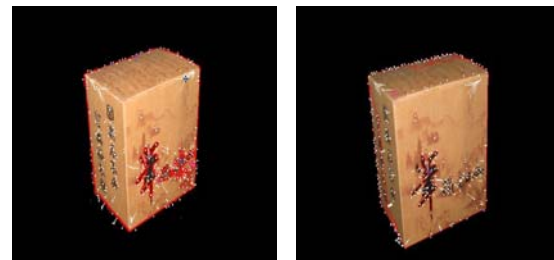
texture feature and color feature as the key point of the sparse texture region. Namely:

$$d = \sqrt{|T|^2 + |C|^2} \quad (11)$$

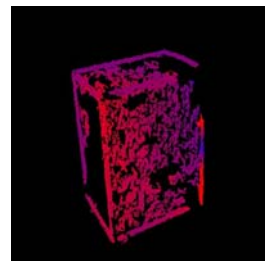
When d is the maximum, that point can be used as the key point [17]. The key points in sparse texture region are shown in map 12 (a)、13 (a)、14 (a), and then used the NCC method to establish the matching relation between key points in image sequence [18]. And then we used the key points as seed points to achieve dense matching based on regional growth. This paper achieved the sparse texture feature points region from few or no to quasi-dense matching.

The above method uses a two-step strategy to achieve image matching: Dense matching in the texture-rich region and sparse region. The dense disparity map can be obtained by this method, which provides a good foundation for the subsequent three-dimensional reconstruction.

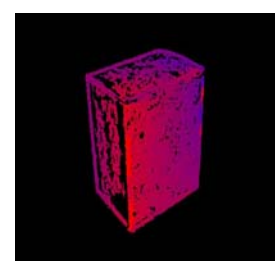
The experimental results are as follows:



(a) The set key points



(b) The disparity map of dense matching based on regional growth



(c) The disparity map of this algorithm

Figure 12. The disparity maps of this algorithm and dense matching based on regional growth



(a) The set key points

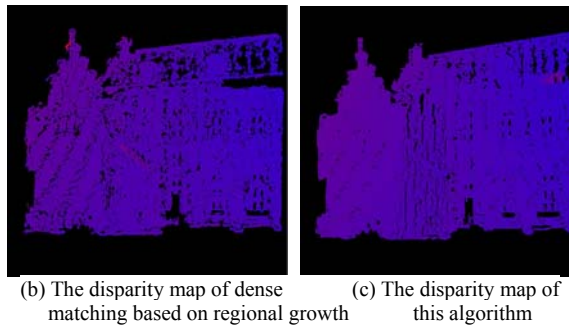


Figure 13. The disparity maps of this algorithm and dense matching based on regional growth

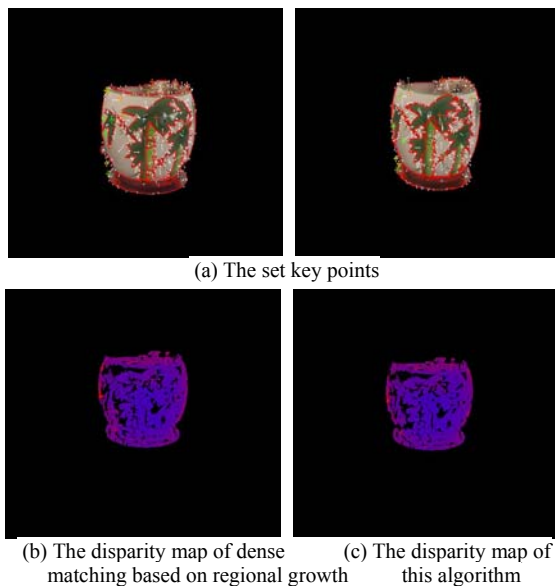


Figure 14. The disparity maps of this algorithm and dense matching based on regional growth

The color points like clover are the seed point of the texture-rich region and the key point of the sparse texture region, which are shown in Figure 11 (a), 12 (a), 13 (a). The disparity map of the traditional dense matching based on regional growth are shown in Figure 11 (b), 12 (b), 13 (b), the final disparity map of this algorithm are shown in Figure 11 (c), 12 (c), 13 (c) [19].

Comparison of experimental results by the above three groups confirm that the more dense disparity map can be obtained by this method. The proposed method improved the dense matching based on regional growth which cannot achieve image matching in the sparse texture region. So it provides a good basis for the follow-up dense three-dimensional surface information.

IV. CONCLUSIONS

In order to achieve the accurate target extraction, this paper presented an improved GrabCut algorithm for image object extraction, many interactive iteration segmentations method was adopted to amend the inaccurate region that was segmented by traditional GrabCut. Experimental results show that this method can amend region that was segmented by GrabCut, so that the revised target was more accurate.

In order to solve the problem of stereo matching of the sparse texture region, this paper presented an improved dense matching method, which uses a two-step strategy: in the texture-rich region, use the existing dense matching based on regional growth for dense matching of the texture-rich region; in sparse texture region, and use regional growth method based on the key point for dense matching. The localized reconstruction due to the fact that image texture sparse region cannot be achieved quasi-dense matching was also solved. Finally, this paper did multiple sets of experiments, and the results of experiments confirm the feasibility and accuracy of this method, which has practical value in the field of computer vision.

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Zetao Jiang Male, Born in 1961 in Jiangxi Province, professor, doctor. He is adjunct professor of Nanjing University of Aeronautics and Astronautics, PhD supervisor, academic leader in Jiangxi province. He received the B.S. degree in Beijing Normal University, Beijing, China, in 1986. He received the M.S. degree in Tongji University, Shanghai, China, in 1995 and received the Doctor of Philosophy in Northwestern Polytechnical University, Xi'an, China, in 2006. Main activities were research in the field of image processing and computer vision.

He works at School of Information Engineering at Nanchang Hangkong University in Jiangxi. He presided key technology research project "Control system based on multi-level security agent", which was awarded the second class prize in the 2009 annual science and technology progress of Jiangxi province. He presided the research of network and information security defense technology based on digital watermarking, which was awarded the first class prize in science and technology achievements of Jiangxi province. He presided and finished Nature Science Foundation of China (60673055), two subject Foundations of province, an open foundation of measurement and control center of province and more than 10 other subjects. Currently, he is presiding Nature Science Foundation of China (60673055) and Nature Science Foundation of Province, which is in the field of 3d reconstruction.

Dr. Jiang, Prof. Zetao is director of Chinese Society for Stereology.

Qiang Wang Male, Born in 1983 in Hubei Province, and received the B.S. degree in Huazhong University of Science and Technology Wuchang Branch, Wuhan, China, in 2009. Currently, he is pursuing the M.S. degree in Nanchang Hangkong University, and the main research area is image processing and computer vision.

Yanru Cui Female, Born in 1987 in Shanxi Province, and received the B.S. degree in Changzhi College, Changzhi, China, in 2009. Currently, she is pursuing the M.S. degree in Nanchang Hangkong University, and the main research area is image processing and computer vision.