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A New Approach for Image Segmentation Based on Graph Cuts

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Abstract

The paper proposed a novel image segmentation algorithm based on the improved affinity propagation algorithm and graph cuts. Firstly, the similarity matrix of the improved affinity propagation algorithm is constructed by using three fundamental features of the image, and each feature is assigned weight according to their distribution in the image. So the improved affinity propagation algorithm can be implemented to cluster the image into numbers of high quality regions. Secondly, these high quality regions are represented by suitable models and these models are selected as labels to construct the data term and smooth term of the energy function. According to the energy function, corresponding weights are assigned to the edges of the graph. Finally, the min-cut/max-flow algorithm is used to search for the minimum cut of the weighted graph and get the final segmentation results. The segmentation results of the proposed algorithm are evaluated through probabilistic rand index and global consistency error methods. It is shown that the presented segmentation method provides effective results in terms of both accuracy and computational efficiency.

***Keywords**: Image Segmentation, Graph Cuts, Affinity Propagation, Minimum Cut*

1. Introduction

Image segmentation divides an image into meaningful pieces or segments with perceptually same features and properties. As a fundamental problem in computer vision, its aim is to make it more meaningful and easy to analyze the image with the simplification of the image. It plays an important role in image analysis and pattern recognition [1-3]. In recent years, great efforts have been made in recent years to investigate segmentation of color images due to the needs and people put forward many segmentation methods based on specific theory [4-10]. In one of these methods, image segmentation based on graph cuts has been a significant research area. However, traditional graph cuts exist some disadvantages in the image segmentation precision and efficiency. In order to solve these problems, various methods have been developed. For instance, Gaussian mixture models have been used to construct a model of the color space of color images [11], which performed better in segmentation results; iterative graph cuts has been proposed for image segmentation [12]; the combination of the geodesic information and edge information under the optimized framework of graph cuts and using other methods to offer seeds to decrease the man-machine interaction [13]. Although segmentation of graph cuts have been promoted by these technologies, it still exists some drawbacks such as low efficiency and the manually seeds which can cause unsatisfactory results and so on.

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Traditional image segmentation based on graph cuts needs seeds to construct the energy function and the weighted graph. But all the seeds are offered manually, which affects the segmentation results negatively. So the paper proposes an approach to give the seeds automatically. According to the research, the clustering algorithm can divide the image into many regions and suitable regional models can be regarded as the seeds. So we use the affinity propagation algorithm (AP) [14] to give the image high-quality seeds for its stability and no need to give the number of clustering. However, the AP algorithm has some shortages such as low efficiency and high space complexity. In order to solve the problems, the paper develops an affinity propagation algorithm based on adaptive weight feature (AWF-AP). The similarity matrix of AWF-AP combines three fundamental features of the image and automatically assign the weight to the features. It obviously reduces the complexity of space and time. In the paper, we propose a novel approach for image segmentation based on AWF-AP and graph cuts. At first, the AWF-AP algorithm is used to cluster the image into numbers of regions. Then suitable models can be established to express the data of the regions and these models are regarded as labels to construct the energy function and the graph. Finally, we use the α-expansion of min-cut/max-flow algorithm to search the minimum cut and get the segmentation results of the image.

This paper is organized as follows. Section 2, introduces the AWF-AP algorithm and describes the construction of the similarity matrix in detail. In Section 3, it introduces the construction of energy function through the combination of the results of the Section 2, and graph cuts. Section 4, describes the experiments of our algorithm and we have a conclusion in Section 5.

2. The Improved Algorithm of AP

Affinity propagation is an unsupervised clustering algorithm and it clusters according to the similarity between the data points under the premise without giving the number of clustering. It views all the data points as potential exemplar and transforms the responsibility information $r(i,k)$ and availability information $a(i,k)$ until convergence. The $r(i,k)$ is sent from the data point x_i to candidate exemplar x_k, which reflects the accumulated evidence for how well-suited point x_k is served as the exemplar for point x_i. The $a(i,k)$ is sent from the candidate exemplar point x_k to the data point x_i, which reflects the accumulated evidence for how appropriate it would be for point x_i to choose point x_k as its exemplar. The input of AP contains the similarity matrix $S=[s(i,k)]_{n\times n}$ and the preference p. $s(i,k)$ means the similarity between the data point x_i and x_k, which generally measured by Euclidean distance, $s(i,k)=-\|I_i-I_k\|_2$, I_i and I_k are the feature value of x_i and x_k. The preference p is defined as $s(k,k)$ which affects the number of clustering.

Both the similarity matrix and the preference are related to the effectiveness of information transformation of AP, so the measure of similarity directly decides the performance of the algorithm. Traditional similarity only uses color information and ignores other useful information like texture and shape, which restrict the robust of the algorithm. In addition, traditional algorithm constructs similarity matrix by all image pixels. If the image size is $n\times n$, the dimension of S will be $(n\times n)^2$, which not only causes the data redundancy but also affects the real-time performance of the algorithm.

2.1. Building the Similarity Matrix

The paper selects the color (F_1), texture (F_2) and shape (F_3) of the image to construct the feature space that measure the similarity, however, because different feature have different distribution in different images, so the paper automatically assigns corresponding weight on basis of the feature's distribution in the image.

Given an image and divided it into N blocks with the same size (each size is 10×10) $R_n(n=1,2,...,N)$, then the block's feature space is $F_{(n\cdot)}=\{F_{(n1)},F_{(n2)},F_{(n3)}\}$. $F_{(n1)}$ is the mean value of R,G,B channels' pixels in the n^{th} block, $F_{(n1)}=(\overline{r_n},\overline{g_n},\overline{b_n})$. $F_{(n2)}$ is the Rotation Invariant Uniform LBP texture feature of block R_n, which has low dimension. According to [15] and [16], the paper selects LBP_8^1 and $F_{(n2)}=(x_{n1},x_{n2},...,x_{n9})$, where $x_{n1}\sim x_{n9}$ are the statistical number of different sequences. F_{n3} is the Hu moment invariants of block R_n [17] and $F_{(n3)}=(y_{n1},y_{n2},...,y_{n7})$, where $y_{n1}\sim y_{n2}$ are the seven moment invariants.

The paper defines $F_{(\cdot m)}$ as the m^{th} feature of image $(m=1,2,3)$ and $F_{(\cdot m)}=\bigcup_{n=1}^{N}F_{(nm)}$ ($F_{(nm)}$ is the m^{th} feature of the n^{th} block), then the feature space of the image is $F=\bigcup_{m=1}^{3}F_{(\cdot m)}$. In order to measure the distribution of these features accurately in the same range, it is necessary to normalize F and get the normalized feature space F'. This paper chooses the variance of these normalized features to measure their distribution, if the variance of one feature is bigger, it suggests that the feature has a higher degree of distribution than others and the feature can measure the blocks' similarity more accurately. So the paper assigns the corresponding weight to these features according to their variance in the image, the distribution of the normalized m^{th} feature of the image $F_{(\cdot m)}'$ is defined as:

$$V_m=\tfrac{1}{N}\sum_{n=1}^{N}(F_{(nm)}'-\tfrac{1}{N}\sum_{n=1}^{N}F_{(nm)}')^2, n=1,2,3,...,N, m=1,2,3 \tag{1}$$

where $F_{(nm)}'$ is the normalized m^{th} feature of block R_n. The weight of $F_{(\cdot m)}'$ is calculated as:

$$W_m=V_m\big/\sum_{m=1}^{3}V_m, m=1,2,3 \tag{2}$$

then features of the normalized feature space $F_{(n\cdot)}'$ is weighted as:

$$F_{(nm)}''=W_m\cdot F_{(nm)}' \tag{3}$$

so the weighted feature space of block R_n can be written as:

$$F_{(n\cdot)}''=\{F_{(n1)}'',F_{(n2)}'',F_{(n3)}''\} \tag{4}$$

In consideration of the feature space to construct the similarity matrix, the paper also views the position information of the blocks. For the block R_n, its position information is defined as the upper left pixel coordinates of R_n:

$$P_n=(x_n,y_n) \tag{5}$$

where (x_n,y_n) is the upper left pixel coordinates of R_n.

Therefore, for any two blocks R_u and R_v, whose feature space are $F_{(u\cdot)}''$ and $F_{(v\cdot)}''$ and position information are P_u and P_v, their similarity can be calculated as:

$$s(u,v) = (-\| P_u - P_v \|_2) \cdot \exp\left(\| F_{(u\cdot)}{}'' - F_{(v\cdot)}{}'' \|_2 / 2\right) \tag{6}$$

where $\{u,v\} \in \{1,2,3,...,N\}$. $\| P_u - P_v \|_2$ is the Euclidean distance of P_u and P_v:

$$\| P_u - P_v \|_2 = \sqrt{(x_u - x_v)^2 + (y_u - y_v)^2} \tag{7}$$

2.2. Steps of Clustering

Step1: Get all the blocks' feature space and position information as the input of the algorithm.
Step2: Calculate the similarity matrix S from (6). The preference p is calculated as the mean value of the diagonal elements of S.
Step3: Initialize $r(u,v) = 0$, $a(u,v) = 0$. Then $r(u,v)$ and $a(u,v)$ are updated iteratively and the updated results are the weighted sum of the update value in the current iteration and the results of the previous iteration. Let t be the current number of iteration, the weighted formula is as follows:

$$r^{(t)}(u,v) = (1-\lambda) \times \left(s(u,v) - \max_{v'(v' \neq v)} \{ a^{(t-1)}(u,v') + s(u,v') \} \right) + \lambda \times r^{(t-1)}(u,v) \tag{8}$$

$$a^{(t)}(u,v) = (1-\lambda) \times \left(\min\{0, r^{(t-1)}(v,v) + \textstyle\sum_{u'(u' \notin \{u,v\})} \max\{0, r^{(t)}(u',v)\}\} \right) + \lambda \times a^{(t-1)}(u,v) \tag{9}$$

$$a^{(t)}(v,v) = (1-\lambda) \times \left(\textstyle\sum_{u'(u' \notin \{u,v\})} \max\{0, r^{(t)}(u',v)\} \right) + \lambda \times a^{(t-1)}(u,v) \tag{10}$$

where $\lambda = 0.9$.
Step4: Use Formula (8)-(10) to update $r(u,v)$ and $a(u,v)$ until convergence and get the final clustering result.

3. The Minimum Cut based on Graph Cuts

3.1. The Construction of the Energy Function

The core idea of image segmentation based on graph cuts is to construct an energy function that reflects the property of image. According to the energy function, the weighted graph is designed and the optimization of energy function can be converted into the optimal solution for the minimum cut of the graph to achieve the optimal segmentation of the image. In order to illustrate how to construct an energy function with the result of AWF-AP, the paper uses the example of a butterfly image, as depicted in Figure 1. Figure 1.(a), displays the original image, and Figure 1.(b) depicts the result image after applying the proposed algorithm in Section II. Figure 1.(c), shows the contours of Figure 1.(b) and the labeled regions. In Figure 1.(c), each region can be regarded as a type of data, and each type of data corresponds with the only label. Figure 1.(d), is the weighted graph derived from the labeled regions.

Let I be the original image, and P is a set containing all pixels of I. The number of labeled regions is N_{seg} (N_{seg} =50 in Figure 1). Let x be an indexing function:

$$x :\rightarrow x(p) \in L, p \in P \tag{11}$$

where L is the finite set of regional indices whose cardinality is less or equal to N_{seg}. $L=\{l_1,l_2,...,l_i,...,l_{\dot{N}seg}\}$ and l_i is the label of the i^{th} region. Therefore, a region A_{l_i} is defined as the set of pixels whose label is l_i:

$$A_{l_i}=\{p\in P\,|\,x(p)=l_i, l_i\in L\} \tag{12}$$

Depending on these labels, the weighted graph is designed like Figure 1.(d). In the graph, $w_{\{p,l_i\}}$ equals the cost for assigning label l_i to pixel p, which reflects how well the model of region A_{l_i} fits pixel p. To reduce the calculation and improving the speed of the algorithm, this paper chooses the average value of region's pixels in R,G,B channels as the regional models. For the region A_{l_i}, its model is u_{l_i} and $u_{l_i}=(\overline{u_{l_i(r)}},\overline{u_{l_i(g)}},\overline{u_{l_i(b)}})$. So $w_{\{p,l_i\}}$ can be calculated as:

$$w_{\{p,l_i\}}=\|I_p-u_{l_i}\|^2 \tag{13}$$

where I_p is the color value of p in R,G,B channels.

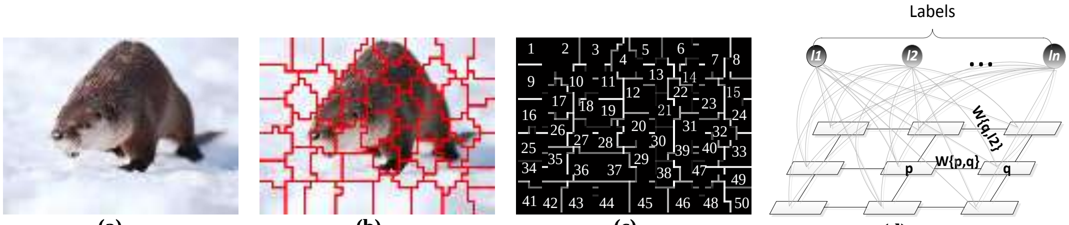

Figure 1. Example: (a) Original Image (b) The Results of AWF-AP (c) The Labeled Regions (d) The Weighted Graph

The data term of the energy function measures the correspondence between the image's data and regional models and it is formulated as:

$$E_{data}(L)=\sum_{l_i\in L}\sum_{p\in P}w_{\{p,l_i\}}=\sum_{l_i\in L}\sum_{p\in P}\|I_p-u_{l_i}\|^2 \tag{14}$$

when $w_{\{p,l_i\}}$ is getting smaller, it indicates that the fitness between pixel p and the model u_{l_i} is getting larger and it is more likely to assign label l_i to pixel p. On the contrary, if $w_{\{p,l_i\}}$ becomes higher, it means the cost for assigning label l_i to pixel p is getting bigger and so is the data tem of energy function.

In the weighted graph, there is another type of data $w_{\{p,q\}}$, which means the penalty of discontinuity between two adjacent pixels p and q. It is calculated as:

$$w_{\{p,q\}}=\exp(-\|I_p-I_q\|^2/2) \tag{15}$$

Therefore, the smooth term of the energy function is expressed as:

$$E_{smooth}(L)=\sum_{\{p,q\}\in N}w_{\{p,q\}}\cdot\theta(x(p),x(q))=\sum_{\{p,q\}\in N}\exp(-\|I_p-I_q\|^2/2)\cdot\theta(x(p),x(q)) \tag{16}$$

$$\theta(x(p),x(q))=\begin{cases}1, x(p)\neq x(q)\\ 0, x(p)=x(q)\end{cases} \tag{17}$$

where N is a set containing all pairs of neighboring pixels. Under the condition of $x(p) \neq x(q)$, the smaller the $w_{\{p,q\}}$, the greater the difference between p and q, and it is more likely to segment p and q to keep the discontinuity of the edge; however, when $w_{\{p,q\}}$ is getting bigger, it indicates the possibility that segmenting p and q becomes lower, which reduces the over-segmentation.

Based on Formula (14) and (16), the energy function can be written as:

$$E(L) = E_{data}(L) + E_{smooth}(L) = \sum_{l_i \in L} \sum_{p \in P} \| I_p - u_{l_i} \|^2 + \sum_{\{p,q\} \in N} \exp(-\| I_p - I_q \|^2 /2) \cdot \theta(x(p), x(q)) \quad (18)$$

3.2. The Minimum Cut of the Weighted Graph

For any image, let $G =< V, E >$ be a weighted graph, where V is the set of vertices and E is the set of edges. V contains all the image's pixels and labels and E contains two types of edges, whose weight are assigned according to the energy Function (18). When the edge is $\{p, l_i\}$ and $p \in P, l_i \in L$, its weight is confined as $w_{\{p,l_i\}}$. If the edge is $\{p,q\}$ and $\{p,q\} \in N$, the weight of the edge is $w_{\{p,q\}}$. Then the paper uses α*-expansion* of min-cut/max-flow algorithm to search for the minimum cut of the graph iteratively and get the final results of segmentation.

Algorithm 1: Proposed algorithm for image segmentation

1. Given an image and divide it into *N* blocks.
2. Extract the color, texture and shape feature of every block to construct the feature space:
3. Normalize the feature space and assign corresponding weight to each feature.
4. Construct the similarity matrix of the AWF-AP as follows:
   a. Get the position information P_n of each block from (5).
   b. Calculate the similarity $s(u,v)$ of the blocks from (6).
   c. Construct the similarity matrix ***S***.
5. Initialize $r(u,v) = 0$, $a(u,v) = 0$ and use Formula (8)-(10) to update $r(u,v)$ and $a(u,v)$ until convergence and get the final clustering result.
6. Construct the energy function formulation as follows:
   a. Calculate the data term of the image from (13), (14).
   b. Calculate the smooth term of the image from (15), (16).
   c. Construct the energy function from (18).
7. Build the weighted graph $G =< V, E >$ according to the energy function.
8. Use the α*-expansion* of min-cut/max-flow algorithm to search for the minimum cut.
9. Get the final segmentation results.

4. Results and Analysis

In order to evaluate the effectiveness and feasibility of the proposed algorithm, the paper performed two experiments for images from Columbia University Image Library. The results show that our algorithm achieves robustness and an improvement on the segmentation accuracy and real-time performance.

4.1. Experiment I

The noise of the image has a large impact on the results of image segmentation. In the paper, Gaussian noises of different intensities are added to the image to test the robustness of our algorithm. Part of the results is showed in Figure 2.

The paper use Global Consistency Error (GCE) [18] to measure the results of noisy images with the results of the original image, which is depicted in Table 1. When the value of GCE is getting smaller, it shows that our algorithm performs well in robustness. From Figure 2, and Table 1, we can truly find that the result of our algorithm still performing well with the increase of the intensity of the noise.

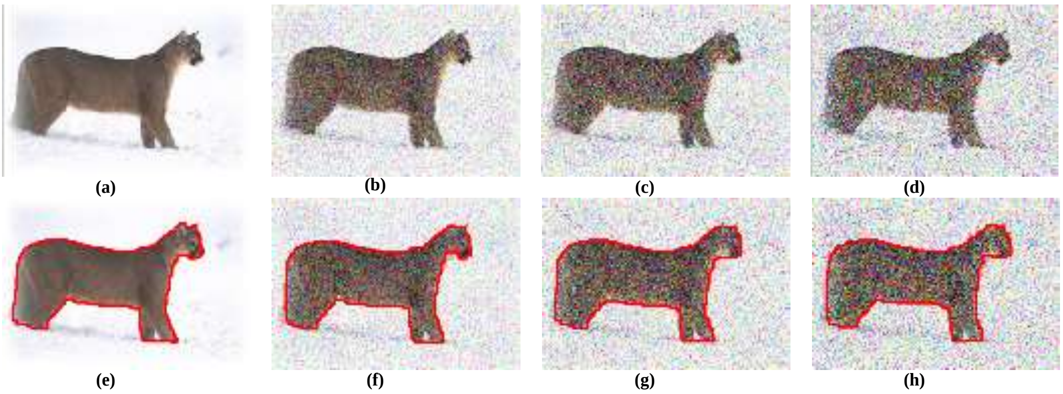

Figure 2. Part of the Segmentation Results of the Noisy Images (a) Original Image. (b)-(d) Image with Noise Intensity σ^2=0.035, 0.065, 0.1. (e)-(f) The Segmentation Results of the Noisy Images (a)-(d)

Table 1. The Robustness of Our Algorithm in Terms of GCE

σ^2	Global Consistency Error	σ^2	Global Consistency Error
0.015	0.0133	0.065	0.0155
0.025	0.0136	0.075	0.0123
0.035	0.0183	0.085	0.0121
0.045	0.0162	0.095	0.0192
0.055	0.0167	0.10	0.0158

4.2. Experiment II

In this experiment, image segmentation results from the proposed method are compared with traditional graph cuts based method and general normalized cuts method [19]. Part of the results of the experimental results is showed in Figure 3. The paper uses the Probabilistic Rand Index (PRI) [20] and GCE to show the precision of segmentation. The running time of different algorithms are showed in Table 3, to estimate the real-time character of our algorithm. Figure 3.(a)-(d), show the test images that used to experiment on the proposed algorithm.

From the results of Figure 3.(e)-(h), it is easy to see that segmentation results of traditional graph cuts have some over-segmentation. In Figure 3.(i)-(l), the results through the normalized cuts have an unsatisfactory performance in terms of the edge. The results of the proposed algorithm are showed in Figure 3.(m)-(p). According to the results and the data of Table 2, our approach has a better performance of segmentation than the other two algorithms in terms of precision and efficiency.

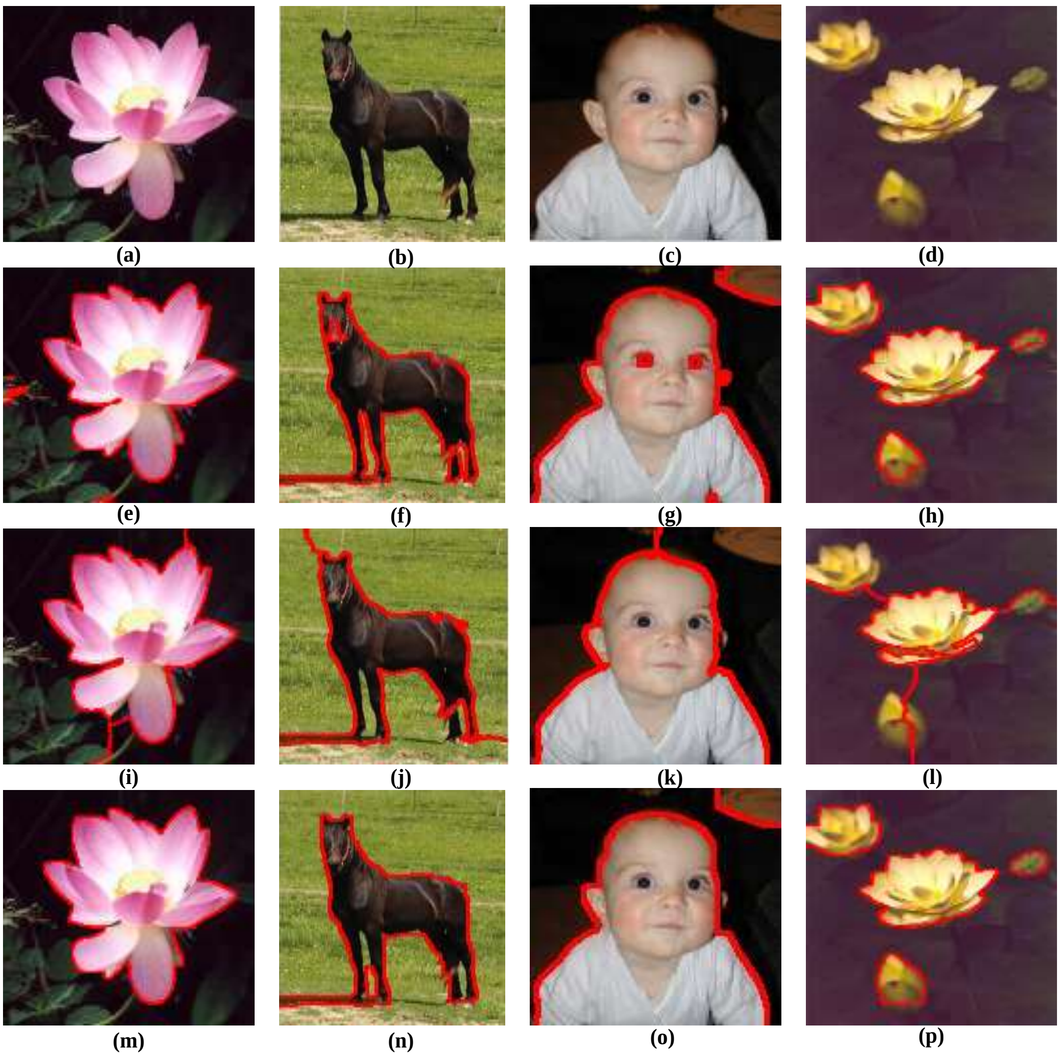

Figure 3. Results of the Three Algorithms: (a)-(d) Original Image. (e)-(h) Results of the Traditional Graph Cuts. (i)-(l) Results of the Normalized Cuts. (m)-(p) Results of the Proposed Algorithm

Table 2. Performances of the Algorithms in Terms of PRI, GCE and the Running Time

Image number	Traditional Graph Cuts			Normalized Cut			The proposed algorithm		
	PRI	GCE	Time/s	PRI	GCE	Time/s	PRI	GCE	Time/s
(a)	0.9743	0.0156	12.594	0.4366	0.2158	11.216	0.9915	0.0060	5.794
(b)	0.9014	0.0457	7.116	0.6356	0.0541	6.876	0.9926	0.0073	2.558
(c)	0.9058	0.0904	3.366	0.8762	0.0776	2.687	0.9442	0.0274	1.383
(d)	0.9336	0.0216	11.746	0.6880	0.1610	9.532	0.9825	0.0075	4.373

5. Conclusion

In this work, a new approach for image segmentation of color images based on AWF-AP and graph cuts is proposed. The AWF-AP algorithm firstly divides the image into many blocks to improve the speed and the similarity matrix ***S*** of AWF-AP is constructed using color, texture and shape features which are assigned weights according to their distribution of the image to produce high quality regions. These regions can be regarded as labels for the graph cuts. With the construction of the energy function and the weighted graph by these regions, rather than directly to the image pixels, the efficiency and precision of our approach are further promoted. The proposed algorithm is evaluated through probabilistic rand index and global consistency error. According to the experimental results, the proposed method provides good segmentation results and the computation time is effectively reduced. However, when the background of the image becomes more complicated, our algorithm has an unsatisfactory performance. In the future, we will consider about these problems in the future.

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References

[1] D. Krstinic, A. K. Skelin and I. Slapnicar, "Fast Two-step Histogram-based Image Segmentation", Let Image Processing, vol 5, no. 1, **(2011)**, pp. 63-72.
[2] S. Petroudi and M. Brady, "Segmentation of Colorectal Pathology Images Using Level Sets", Proceedings of the 9th International Conference of Information Technology and Applications in Biomedicine, Larnaka, Cyprus, **(2009)** November 4-7.
[3] Z. Wang and M. Yang, "A Fast Clustering Algorithm in Image Segmentation", Proceedings of the 2th International Conference of Computer Engineering and Technology, Chengdu, China, **(2010)** April 16-18.
[4] P. Li, S. Wang and J. Jing, "The Segmentation in Textile Printing Image Based on Mean Shift", Proceedings of the IEEE 10th International Conference of Computer-Aided Industrial Design and Conceptual Design, Wenzhou, China, **(2009)** November 26-29.
[5] A. M. Martinez, P. Mittrapiyanuruk and A. C. Kak, "On Combining Graph–partitioning with Non-parametric Clustering for Image Segmentation", Computer Vision and Image Understanding, vol. 95, no. 1, **(2004)**, pp. 72-85.
[6] S. Vicente, V. Kolmogorov and C. Rother, "Graph Cut Based Image Segmentation with Connectivity Priors", Proceedings of IEEE Conference on Computer Vision and Pattern Recognition, Anchorage, AK, **(2008)** June 23-28.
[7] Y. Boykov and M. P. Jolly, "Interactive Graph Cuts for Optimal Boundary & Region Segmentation of Objects in N-D Images", Proceedings of the 8th IEEE International Conference on Computer Vision, Vancouver, Canada, **(2001)** July 07-14.
[8] Y. Boykov, O. Veksler and R. Zabih, "Fast Approximate Energy Minimization via Graph Cuts", IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 1, no. 11, **(2001)**, pp. 1222-1239.
[9] S. Wang and J. M. Siskind, "Image Segmentation with Ratio Cut", Pattern Analysis and Machine Intelligence IEEE Transactions on, vol. 25, no. 6, **(2003)**, pp. 675-690.
[10] T. H. Le, S. W. Jung, K. S. Choi and S. J. Ko, "Image Segmentation Based on Modified Graph-cut Algorithm", Electronics Letters, vol. 46, no, 16, **(2010)**, pp. 1121-1123.
[11] A. Blake, C. Rother, M. Brown, P. Perez and P. Torr, "Computer Vision – ECCV 2004", Edited T. Pajdla and J. Matas, Springer Berlin Heidelberg Publishers, Berlin, vol. 3021, **(2004)**, pp. 428-441.
[12] C. Rother, V. Kologorov and A. Blake, "Grab Cut: interactive foreground extraction using iterated graph cuts", Proceedings of the ACM SIGGRAPH Conference, Los Angeles, USA, **(2004)** August 11-14.
[13] B. L. Price, B. Morse and S. Cohen, "Geodesic Graph Cut for Interactive Image Segmentation", Proceedings of the 2010 IEEE Conference on Computer Vision and Pattern Recognition, San Francisco, USA, **(2010)** June 13-18.
[14] B. J. Frey and D. Dueck, "Clustering by Passing Messages between Data Points", Science, vol. 315, no. 5814, **(2007)**, pp. 972-976.
[15] T. Maenpaa and M. Pietikainen, "Texture Analysis with Local Binary Patterns", Handbook of Pattern Recognition & Computer Vision, **(2005)**.
[16] T. Ojala, M. Pietikainen and T. Maenpaa, "Multiresolution Gray Scale and Rotation Invariant Texture Classification with Local Binary Patterns", IEEE Transactions on Pattern Analysis & Machine Intelligence, vol. 24, no. 7, **(2002)**, pp. 971-987.
[17] M. K. Hu, "Visual Pattern Recognition by Moment Invariant", Information Theory lre Transactions on, vol. 8, no. 2, **(1962)**, pp.179-187.

[18] D. R. Martin, “An Empirical Approach to Grouping and Segmentation”, International Symposium on Physical Design, vol. 2, no. 64, **(2003)**, pp.8-12.
[19] J. Shi and J. Malik, “Normalized Cuts and Image Segmentation”, IEEE Transactions on Pattern Analysis and Machine Intelligence, vol. 22, no. 7, **(2000)**, pp.888-905.
[20] F. C. Monteiro and A. C. Campilho, “Image Analysis an Recognition”, Edited A. Campilho and M. S. Kamel, Springer Berlin Heidelberg Publishers, Berlin, vol. 4141, **(2006)**, pp.248-259.

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