ICIC Express Letters
Part B: Applications
Volume **7**, Number **3**, March **2016**

ICIC International ©2016 ISSN 2185-2766
pp. **627–632**

COLOR IMAGE SEGMENTATION BASED ON AWF-AP AND GRAPH CUTS

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Received September 2015; accepted December 2015

Abstract. *In this paper, we propose a new image segmentation algorithm based on AWF-AP (affinity propagation algorithm based on adaptive weight feature) and graph cuts. Firstly, the image is clustered into numbers of regions by using AWF-AP and we choose proper models to express these regions. Then the proper models are regarded as labels to construct the energy function and the weighted graph. Finally, graph cuts is applied to achieving energy minimization and getting the segmentation results. According to the experimental results, it shows that the presented segmentation method performs effective results in terms of both accuracy and computation efficiency.*
Keywords: Image segmentation, Graph cuts, AWF-AP

1. **Introduction.** Image segmentation is one of the fundamental problems in computer vision and image processing [1]. In recent years, people put forward many segmentation technologies that are based on graph cuts [2-4]. Normalized cuts is a normalized cut algorithm based on graph theory [5] and it can reduce the isolated points of the segmentation results. However, it has an unsatisfactory performance on segmentation precision. Traditional image segmentation using graph cuts has many problems such as low segmentation precision and low efficiency. To solve these problems, Blake et al. used the Gaussian mixture model to model the foreground and background color space [6], which improved the segmentation results for color images; Rother et al. proposed grab cut using iterative graph cut for image segmentation [7]. Although these methods have promoted the application of graph cuts in image segmentation, there are still some shortages needed to be improved, such as large computation, unstable segmentation results which depend on the manual labels and so on.

According to these problems, the paper wants to give the image high-quality seeds automatically, which can be regarded as labels to construct the energy function. Because clustering algorithm can produce high quality regions, proper regional models can be selected as labels for the image, which are more stable and accurate than the manual labels. This paper chooses the affinity propagation (AP) algorithm [8] to cluster images for its stability and it does not need to specify the number of clustering. Because the AP algorithm has long computation time and high space complexity, the paper proposed the AWF-AP algorithm which apparently reduces the complexity of space and time. So the paper proposed a novel algorithm by combining the AWF-AP and graph cuts. Firstly, we use the improved AP algorithm to cluster the image, which not only improves the speed of clustering but also obtains numbers of high quality regions. Secondly, the data of these regions are described by constant models, which served as labels to construct the energy function and the graph. At last, energy minimization is achieved through the min-cut/max-flow algorithm and we can get the final segmentation results.

The remainder of this paper is organized as follows. The next section introduces the AWF-AP algorithm and the construction of energy function in detail. Section 3 describes the validation experiments and Section 4 contains a conclusion of the paper.

2. **Segmentation Based on AWF-AP and Graph Cuts.**

2.1. **The AWF-AP algorithm.** As an input of AP, the similarity matrix S is essential to the performance of AP. However, traditional AP only uses color information and it constructs similarity matrix by all pixels of the image, which not only causes the data redundancy but also affects the efficiency of the AP algorithm.

2.1.1. *The promotion of similarity matrix.* The paper selects the color, texture and shape of the image to construct the feature space that measures the similarity, and the paper automatically assigns corresponding weight on basis of the distribution of the feature in the image. Given an image and divide it into N blocks with the same size (each size is 10×10) R_n ($n = 1, 2, \ldots, N$), then the feature space of the block is defined as $F_{(n\cdot)} = [F_{(n1)}, F_{(n2)}, F_{(n3)}]$. $F_{(n1)}$ is the mean value of R, G, B channels' pixels in the n^{th} block, $F_{(n1)} = \left(\overline{r_n}, \overline{g_n}, \overline{b_n}\right)$. $F_{(n2)}$ is the Rotation Invariant Uniform LBP texture feature of block R_n, which has low dimension. The paper selects LBP_8^1 and $F_{(n2)} = (x_{n1}, x_{n2}, \ldots, x_{n9})$, where $x_{n1} \sim x_{n9}$ are the statistic number of different sequences. $F_{(n3)}$ is the Hu moment invariants of block R_n and $F_{(n3)} = (y_{n1}, y_{n2})$, where y_{n1}, y_{n2} are the first two moment invariants. The paper defines $F_{(\cdot m)}$ as the m^{th} feature of the image ($m = 1, 2, 3$) and $F_{(\cdot m)} = \bigcup_{n=1}^{N} F_{(nm)}$, where $F_{(nm)}$ is the m^{th} feature of the n^{th} block, and 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, and 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 similarity of the blocks more accurately. So the distribution of the normalized m^{th} feature of the image $F_{(\cdot m)}{}'$ is defined as:

$$V_m = \frac{1}{N}\sum_{n=1}^{N}\left(F_{(nm)}{}' - \frac{1}{N}\sum_{n=1}^{N}F_{(nm)}{}'\right)^2, \quad n = 1, 2, 3, \ldots, N, \quad m = 1, 2, 3 \tag{1}$$

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

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

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

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

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

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

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 coordinates of the upper left pixel of R_n:

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

where (x_n, y_n) is the coordinates of the upper left pixel 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 $\{u, v\} \in \{1, 2, 3, \ldots, N\}$. $||P_u - P_v||_2$ is the Euclidean distance of P_u and P_v:

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

2.1.2. *Steps of clustering.*

Step 1: According to the (1)-(5), to get the feature space and position information of all the blocks.

Step 2: Calculate the similarity matrix S from (6). The preference p is calculated as the mean value of the diagonal elements of S.

Step 3: Initialize the responsibility information $r(u, v) = 0$ and the availability information $a(u, v) = 0$. Then update $r(u, v)$ and $a(u, v)$ according to [8] until convergence and get the final clustering result.

2.2. **Constructing the energy function and the weighted graph.** In order to illustrate how to construct the energy function and the weighted graph with the result of AWF-AP, the paper shows an example in Figure 1. Figure 1(a) shows the original image and Figure 1(b) depicts the result of the AWF-AP algorithm. Figure 1(c) shows the contours of Figure 1(b) and the labeled regions. 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.

Let I be the original image, and P is a set containing all pixels of I. The number of labeled regions is N_{seg} ($N_{seg} = 39$ in Figure 1). Let χ be an indexing function:

$$\chi :\longrightarrow \chi(p) \in L, \quad p \in P \tag{8}$$

where L is the finite set of regional indices whose cardinality is less or equal to N_{seg}. $L = \{l_1, l_2, \ldots, l_i, \ldots, l_{N_{seg}}\}$ 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:

$$A_{l_i} = \{p \in P | \chi(p) = l_i, l_i \in L\} \tag{9}$$

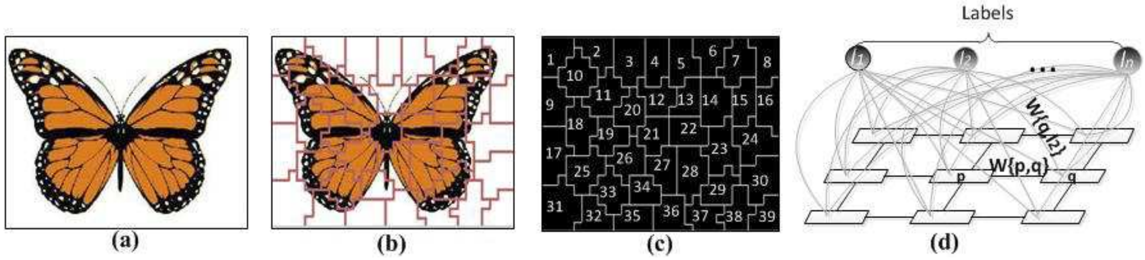

Figure 1. (a) Original image, (b) result after using AWF-AP, (c) contours and labeled regions, (d) the weighted graph

According to 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. The model of region A_{l_i} is defined as u_{l_i} and $u_{l_i} = \left[\overline{u_{l_i(r)}}, \overline{u_{l_i(g)}}, \overline{u_{l_i(b)}}\right]$, where $\overline{u_{l_i(r)}}, \overline{u_{l_i(g)}}, \overline{u_{l_i(b)}}$ mean the average value of the pixels of region in R, G, B channels. So $w_{(p,l_i)}$ can be calculated as:

$$w_{\{p,l_i\}} = ||I_p - u_{l_i}||^2 \tag{10}$$

where I_p is the value of pixel p in R, G, B channels. The data term of the energy function measures the correspondence between the data of the image and regional models and it is formulated as:

$$E_{data}(L) = \sum_{l_i \in L} \sum_{p \in P} w_{\{p,l_i\}} = \sum_{l_i \in L} \sum_{p \in P} ||I_p - u_{l_i}||^2 \tag{11}$$

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:

$$w_{\{p,q\}} = \exp\left(-||I_p - I_q||^2/2\right) \tag{12}$$

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

$$E_{smooth}(L) = \sum_{\{p,q\} \in N} w_{\{p,q\}} = \sum_{\{p,q\} \in N} \exp(-||I_p - I_q||^2/2) \tag{13}$$

where N is a set containing all pairs of neighboring pixels and $\chi(p) \neq \chi(q)$.

The energy function contains data term and smooth term, so it can be written as:

$$\begin{aligned} E_{(L)} &= E_{data}(L) + E_{smooth}(L) = \sum_{l_i \in L} \sum_{p \in P} ||I_p - u_{l_i}||^2 \\ &+ \sum_{\{p,q\} \in N} \exp\left(-||I_p - I_q||^2/2\right) \end{aligned} \tag{14}$$

2.3. **The minimum cut of the graph.** For any image, let $G =< V, E >$ be the weighted graph, where V is the set of vertices and E is the set of edges. V contains all the pixels and labels of the image and E contains two types of edges, whose weight are assigned according to the energy function. It is showed in Table 1. The paper uses $\alpha - expansion$ of min-cut/max-flow algorithm to search for the minimum cut of the graph iteratively and get the final results of segmentation.

TABLE 1. The weight of the two types of edges

edge	*weight*	*limitation*
$\{p, l_i\}$	$w_{\{p,l_i\}}$	$p \in P, l_i \in L$
$\{p, q\}$	$w_{\{p,q\}}$	$\{p, q\} \in N$

3. **Results and Discussion.** To estimate the robustness of the proposed algorithm, Gaussian noises of different intensities are added to the image, and part of the results is showed in Figure 2. In Figure 2, it is obvious to see that with the increase of the noise strength, our algorithm is still performing a good segmentation result. The paper uses global consistency error (GCE) [9] to compare the results of noisy images with the results of the original image, which is depicted in Table 2. When the value of GCE is getting smaller, it indicates that robustness of the algorithm is getting stronger.

We also compared the segmentation results from the proposed method with traditional graph cuts based method and general normalized cuts method [5]. Figure 3 shows part of the experimental results. The paper uses the probabilistic rand index (PRI) [10] and GCE to measure the precision of segmentation, at the same time, it also records the running time of three algorithms to estimate the speed of our algorithm. The results are depicted in Table 3. Figures 3(a)-3(d) are part of the test images.

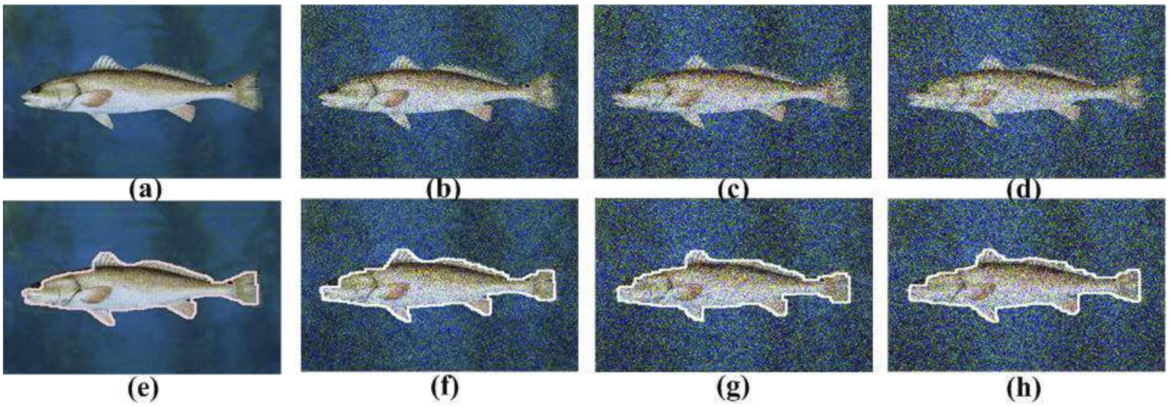

FIGURE 2. Part of the segmentation results of the images with different noise intensities: (a) original image, (b)-(d) image with noises of different intensities ($\sigma^2 = 0.04, 0.08, 0.1$), (e)-(h) the corresponding segmentation results of (a)-(d)

TABLE 2. The influence of noise on the proposed algorithm

(σ^2)	GCE	σ^2	GCE
0.01	0.0044	0.06	0.0127
0.02	0.0067	0.07	0.0129
0.03	0.0099	0.08	0.0157
0.04	0.0099	0.09	0.0158
0.05	0.0128	0.1	0.0156

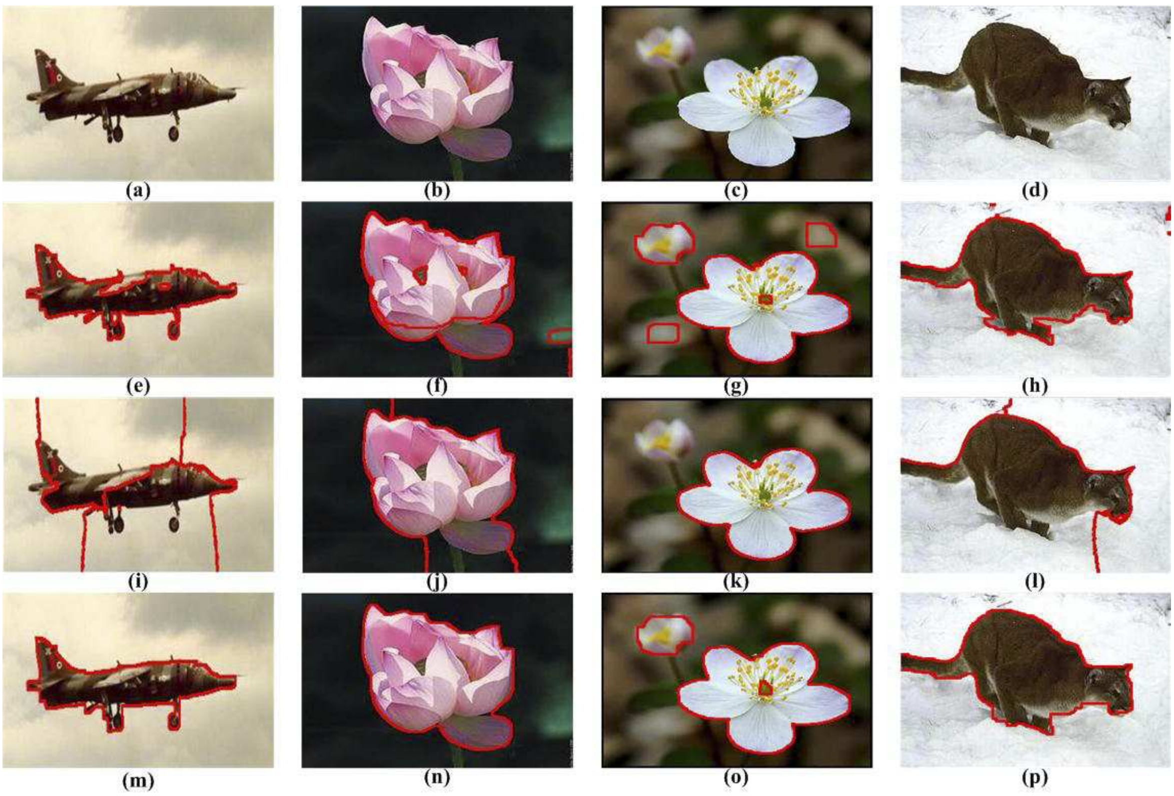

FIGURE 3. Comparisons of the segmentation results of these algorithms: (a)-(d) original image, (e)-(h) segmentation results using traditional graph cuts, (i)-(l) segmentation results using the normalized cuts, (m)-(p) segmentation results using the proposed method

Table 3. Comparison of the segmentation results between the three algorithms

	Traditional graph cuts			Normalized cuts			Our algorithm		
Test image	PRI	GCE	Time/s	PRI	GCE	Time/s	PRI	GCE	Time/s
(a)	0.643	0.033	10.762	0.437	0.216	9.415	0.978	0.002	4.536
(b)	0.946	0.058	12.186	0.688	0.161	8.194	0.968	0.008	4.922
(c)	0.937	0.063	14.058	0.932	0.061	9.675	0.979	0.007	6.536
(d)	0.953	0.037	12.625	0.504	0.291	9.730	0.986	0.005	5.945

In Figure 3, segmentation results through traditional graph cuts are shown in Figures 3(e)-3(h). It is obvious to observe that the results are not impressive as there is some over-segmentation. Figures 3(i)-3(l) depict the results by using normalized cuts, which performs unsatisfactorily on the edge of segmentation. From the data of Table 3, it indicates that compared with the other two algorithms, the proposed method of the paper has an obvious improvement on both the precision and the speed of segmentation.

4. **Conclusions.** In this correspondence, the paper has developed a new algorithm for the segmentation of color images. The proposed algorithm takes the advantages of the AWF-AP algorithm and graph cuts, whereas their drawbacks are avoided. The use of AWF-AP method not only reduces the computation time but also provides regions, which can be regarded as labels for graph cuts. On the other hand, the application of the weighted graph and graph cuts to the resulting segments, rather than directly to the image pixels, further improves the speed of our algorithm and the precision of segmentation. According to our experiments' results, the proposed method performs better results and lower computational complexity. However, the algorithm is influenced by more complicated backgrounds to some extent, and we will be committed to solving this problem in the future.

Acknowledgment. This project was supported by Xinjiang and Uygur Autonomous Regions University Science and Research Key Project (XJEDU2012I08), and the National Natural Science Foundation of China (61362030, 61201429).

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