Signal Processing and Renewable Energy
September 2023, (pp. 13-29)
ISSN: 2588-7327
eISSN: 2588-7335

Entropy-based Kernel Graph Cut with Weighted K-Means for Textural Image Region Segmentation

Mehrnaz Niazi[1], Kambiz Rahbar[1*], Mansour Sheikhan[2], Maryam Khademi[3]

[1] Department of Computer Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran.
[2] Department of Electrical Engineering, South Tehran Branch, Islamic Azad University, Tehran, Iran.
[3] Department of Applied Mathematics, South Tehran Branch, Islamic Azad University, Tehran, Iran.

Received: 01-Nov-2022, Revised: 04-Jan-2023, Accepted: 05-Apr-2023.

Abstract
Recently, image segmentation based on graph cut methods has shown impressive performance on a set of image data. Although the kernel graph cut method provides good performance, its performance is highly dependent on the data mapping to the transformation space and image features. Entropy-based kernel graph cut method is suitable for segmentation of textured images. However, the quality of its segmentation is affected by the quality of extracting kernel centers. This paper examines the segmentation of textured images using the entropy-based kernel graph cut method based on weighted k-means. Using the advantages of kernel space, the objective function consists of two data terms to transfer the data standard deviation of each area in the segmented image and the regularization term. The proposed method, while using the advantages of suitable computational load of graph cut methods, will be a suitable alternative for segmenting textured images. Laboratory results have been taken on a set of well-known datasets that include textured shapes in order to evaluate the efficiency of the algorithm compared to other states-of-the-art methods in the field of kernel graph cut.

Keywords: Image segmentation, kernel graph cut, radial basis function kernel, textured images, weighted clustering.

1. INTRODUCTION

The purpose of image segmentation is to simplify and change the display of an image in such a way that becomes more meaningful

*Corresponding Authors Email: k_rahbar@azad.ac.ir

and easier to analyze[1]. In other words, in image segmentation, a label is assigned to each pixel in the image, and the pixels with common characteristics are placed in a category. This can be important in a variety of applications such as medical images[2], video processing[3], and image restoration[4][5], because it allows you to isolate and analyze specific objects or regions of interest within an image. For example, in the field of medicine, due to the complex structure of the human body, it is very difficult to accurately diagnose many medical problems, including tumors and tissue lesions, and image segmentation can be an effective help[2]. In video processing, moving objects usually have very important information for video surveillance and traffic control, recording human movements, etc. In most cases, removing the background is necessary to distinguish different features in moving objects. This issue has led to the discussion of segmentation in this field [3], [6]. In agricultural sciences, automatic diagnosis of plant diseases is a very popular branch. Using image segmentation to detect diseased areas in plants is very common and many papers have been presented in this field [7], [8]. Also, image segmentation is very widely used in remote sensing to detect environmental changes. In this regard, image segmentation is used to divide the land cover [9]. In addition, Image segmentation is important in anomaly detection because it can distinguish anomalous objects or regions in an image, thereby improves the effectiveness of anomaly detection algorithms. For example, Zue et al. describe a novel anomaly detection method for hyperspectral remote sensing that includes image segmentation as part of the process. This method involves two main steps: an anomaly characterization step using a statistical model and matrix decomposition algorithm, and a local representation process using an improved image segmentation method to identify latent false alarms and suppress their response values. Image segmentation is described as playing a crucial role in this AD method by helping to accurately identify and distinguish anomalies in the data[10]. In recent years, various methods have been presented for image segmentation, which can be referred to as methods based on mean displacement [11]–[13] and methods based on graph cut. In this paper, an attempt is made to improve the initial segmentation in the kernel graph cut algorithm, to increase the segmentation quality in the image.

In general, research in the field of kernel graph cut is divided into 5 main approaches, which are: 1) determining the type of noise and removing noise to improve segmentation, 2) extracting suitable features for segmentation, 3) Choosing the proper kernel or combining different kernels for data mapping, 4) data mapping using the selected kernel and 5) improving the segmentation of the segmented image.

In the approach of determining the type of noise and removing noise, the type and intensity of the noise of the model are first considered, and finally, the corresponding noise is removed from the image. In this regard, Yang et al., identified three basic problems in the processing of combined aperture radar images, the ability to detect the correct number of clusters, the ability to remove speckle noise, and the better clustering quality in the segmentation of images. In order to remove noise in composite aperture radar images, first, an integrated filter, which consists of maximum similarity estimator and partial non-local mean filter, has been used[11]. Panigrahi et al also stated that ultrasound images are one of the most famous tools used for breast cancer screening. The segmentation is one of the most challenging phases in cancer diagnosis in computer systems based on ultrasound images due to the presence of the speckle effects and also the shadow effect. The aim of the paper is to present an automatic segmentation method with high accuracy in detecting cancer in ultrasound images even with the presence of noise and other artifacts. In this regard, first, the images are filtered using the inhomogeneous propagation method to reduce the speckle, and then other steps of segmentation are performed[12].

In the approach of extracting the appropriate features, first, if needed, the super pixels of the input image are determined and the appropriate features such as color, texture, location, and dimensions are determined. Then, if there is a need to combine features, a number of features are combined to improve segmentation quality. Finally, among the features collected in the previous step, the set of features that are more useful for segmentation is selected. Several papers have improved image segmentation by selecting more appropriate features, for example, in the paper written by Niazi et al., the feature vector with two layers (one gray level layer and one entropy) is suggested. This proposal has provided good results in the segmentation of heterogeneous and textured images. However, the above algorithm cannot separate the images with small size and complex texture well[14]. Rahbar's paper used Krawtchouck polynomial to model the probability distribution function of brightness values, and Krawtchouck polynomial components are considered as Eigen functions of different expressions. The paper deals with improving the estimation of brightness values and therefore improving image segmentation[15]. Chen et al.'s paper, presents an automatic method for brain tumor detection based on superpixels. In this regard, first, specific superpixels and histogram features and locations of superpixels are extracted and the features are combined to provide a simple yet efficient feature for kernels[16]. Zhang et al. presented a method to improve image segmentation in images, in which an initial segmentation was performed on the image using the fuzzy edge detection method, and the superpixels of the image were extracted. Then it uses the resulting superpixels to build a compact weighted graph[17]. Also, in Zeng et al. paper, different types of features are grouped. Then, a linear combination of all kernels with optimal weights is built to map features[18].

In the approach of selecting the appropriate kernel or combining different kernels, in order to improve the performance of segmentation, kernels that follow Mercer theory are used. It is also possible to obtain the appropriate kernel from the linear combination of the previous kernels. In this regard, in the paper by Qi et al., a new spatial distance and contour direction are used in the energy function. In other words, the structure of the energy graph has been changed by using the initial constraint. Finally, using the pseudoflow algorithm, the maximum flow in the energy graph is calculated. As a result, segmentation is improved in images with closed foreground and background features. However, it still has some challenges in separating images with weak borders [19]. Kang et al. stated that the construction of a neighborhood graph is the basis of graph-based clustering. Graph learning in kernel space has provided acceptable results in a set of databases, although its performance is completely dependent on the type of kernel. In this regard, several kernel learning algorithms have been used to determine the optimal kernel among the predefined kernels, and the above methods may be dependent on the kernel and limit the ability to display the collective kernel. Learning a kernel matrix with a lower rank that takes advantage of the nature of similarity in the kernel matrix and searching for the optimal kernel among the neighbors of the candidate kernels is discussed. By formulating the graph structure and kernel learning in an integrated framework, the collective graph and the kernel can reinforce each other by repetition [20]. In addition to the above, in Zeng's paper, after grouping the features, a combined kernel is created to map the feature groups to the space of each kernel and then linearly combine the whole kernel with optimal weights[18].

At the approach of kernel mapping in kernel graph cut, first a preliminary segmentation must be done by clustering algorithms. The first step in clustering is to determine the number of categories that can be fixed or determined through appropriate algorithms. After determining the number of categories and the type of clustering, the primary centers are extracted. Each energy function in kernel graph cut consists of two data and regularization terms, in which the amount of data deviation in each area after mapping is determined by the data term, and the regularization term deals with smoothing the boundaries. The segmentation energy function is obtained by using their sum. After determining the energy function, it is necessary to optimize the segmentation by minimizing its energy function, which can also be done through the graph cut algorithm. For this purpose, segmentation improvement is repeated until no change in areas and converges. It is worth mentioning that some papers have also presented innovations in the field of kernel graph cut with different magnifications and even combining their results. In this regard, Ben Saleh presented a multi-region kernel graph cut method in which kernel mapping was used as an unsupervised graph cut model for image segmentation. The centers are first determined using the k-means method, and then the distance of the data to the cluster center is given to the Gaussian kernel. Finally, kernel graph cut is used to segment the image. In fact, the image is implicitly mapped to data with higher dimensions through the kernel function and the data is displayed through the kernel function. In this regard, two main terms are defined in the energy function. One is the data term, which shows the amount of data deviation after the transfer, and the other is the regularization term, which is used to smooth and improve the boundaries [21]. In Yang's paper, the difficulty of determining the appropriate magnification factor in the kernel graph cut regularization term is stated. So, a set of kernel graph cuts with different magnification factors is used and the results are combined. In addition, due to the use of principal component analysis, kernel graph cut is applied in a space with lower dimensions to remove the noise. Finally, the output of all kernels is entered into the fuzzy c-means clustering algorithm to receive the output[17].

In the approach of segmentation improvement, the segmented image is re-segmented by a clustering algorithm to improve the segmentation of the segmented image. In this context, Harini stated that one model may not be suitable for all areas. For example, the gamma distribution in radar images, the Gaussian distribution in shadowed images under sunlight, and the Rayleigh distribution in reflective areas are appropriate. The nearest neighbor algorithm is a multivariate interactive algorithm. The role of this algorithm in medical images is to estimate the values of undetermined points using the determined points around them. In this regard, the nearest neighbor algorithm is applied to the segmented image areas, which will increase the efficiency of segmentation without concern about the type of distribution[22]. A summary of the related papers is reviewed in Table 1 along with their advantages and disadvantages.

In this paper, similar to Niazi et al.'s paper, the entropy-based kernel graph cut algorithm is used as an unsupervised model for image segmentation. The use of entropy makes the kernel graph cut algorithm independent of the intensity. This feature space makes the kernel graph cut algorithm more efficient for pixel segmentation. In this regard, the centers are first determined using the k-means method, and then the distance of the data to the center of the cluster is given to the radius-based kernel, and finally, based on that, the kernel graph cut is done. In fact, the image is implicitly mapped to data with higher dimensions through the kernel function and the data is displayed through the kernel function[21]. However, the k-means algorithm is sensitive to initial points, as cluster centers do. This algorithm does not guarantee proper clustering in textured images because it may not achieve proper centers by choosing random, initial centers and the possibility of choosing centers on the borders.

Determining the centers will have a significant impact on the segmentation quality using unsupervised kernel graph cut algorithm. In this paper, an attempt is made to increase the accuracy and stability of the results obtained from the unsupervised kernel graph cut algorithm by improving the clustering algorithm based on the weighted image. Next, in section 2, the entropy-based kernel graph cut method is reviewed, in section 3, the analysis of the entropy-based kernel graph cut algorithm based on weighted k-means is discussed, in section 4, the experimental results and finally, in section 5, the conclusion of the paper is presented.

2. AN OVERVIEW OF ENTROPY-BASED KERNEL GRAPH CUT ALGORITHM

Assuming that I is the intensity matrix of the image. Image I is divided into N_{reg} homogeneous region $\{R_l\}_{l=1}^{N_{reg}}$. l is the label of each pixel that is selected from the set L. R_l is the area where the set of pixels labeled

l is located. In order to segment the image, the objective function must be determined and minimized. The objective function consists of two data terms in order to adapt the statistical model and a regularization term to smooth the borders. The objective function $\mathcal{F}$ is defined as equation 1.

$$\mathcal{F}(\lambda) = D(\lambda) + \alpha\Re(\lambda) \tag{1}$$

where D is the data term, R is the regularization term, λ is an indexing function to determine the area of each pixel, and α is

Table 1. ***A summary of the energy-based image segmentation algorithm.***

Author	Method	Scope	Advantages	Disadvantages
Yang et al.	Integrated filter consists of maximum similarity estimator and partial non-local mean filter	aperture radar images	Detect the correct number of clusters, remove speckle noise, improve clustering quality	Not identifying the true number of categories in high noise levels, computationally intensive
Panigrahi et al.	Inhomogeneous propagation method	Ultrasound images	High accuracy for detecting cancer in ultrasound images	sensitive to parameters, computationally intensive
Niazi et al.	Feature vector with gray level and entropy layers	Heterogeneous and textured images	Decrease intensity dependency	Cannot segment small size and complex texture images
Rahbar	Krawtchouck polynomial to a model probability distribution function	Synthetic and natural images	accurate segmentation in the presence of noise	Cannot segment heterogeneous images, computationally intensive
Chen et al.	Superpixels and histogram features	tumor detection	more informative and robust representation of an image	difficult to tune the various hyper parameters
Zhang et al.	Fuzzy edge detection method and superpixel extraction	Global scope	Good performance on low-contrast and high-noise images	Hyper parameter tuning
Zeng et al.	Linear combination of kernels with optimal weights	Global scope	Greater flexibility and adaptability	define proper kernel weight, computationally intensive
Qi et al.	Spatial distance and contour direction for graph cuts	Natural images	ability to modify the energy graph with initial constraints	Challenges in separating images with weak borders.
Kang et al.	Multiple kernel learning and graph cuts	Remote sensing images	learn a kernel with a lower rank	Dependency to the initial kernel, computationally intensive
Salah et al.	multi-region kernel graph cut	Global scope	Map data Implicitly	Cannot segment low contrast images
Yang	Combine kernel graph cuts with different magnification factors	Global scope	robust to noise and ability to non-linearly separable data	determine the appropriate magnification factor, computationally intensive
Harini	The nearest neighbor algorithm is applied to the segmented image areas	Global scope	Improve segmentation with the estimation of the undetermined points	computationally intensive

a positive coefficient. The data term is defined as equation 2:

$$D(\lambda) = \sum_{p \in \Omega} D_p\big(\lambda(p)\big) = \sum_{l \in \mathcal{L}} \sum_{p \in R_l} \left(F_p - \mu_l\right)^2 \tag{2}$$

where p pixel is from the set of Ω pixels, μ_l is the average of l area, F_p is the feature vector of two layers (one gray level layer and one entropy layer) of pixel p. The regularization term is also defined as equation 3.

$$\Re(\lambda) = \sum_{\{p,q\} \in N} r\big(\lambda(p), \lambda(q)\big) \tag{3}$$

where N is the set of neighbors of pixel p, $\{p, q\}$ pairs of neighboring pixels and $r\big(\lambda(p), \lambda(q)\big)$ is the regularization function based on the squared difference of the average area of neighboring pixels. The regularization function is bounded using the constant T according to equation 4.

$$r\big(\lambda(p), \lambda(q)\big) = min\left(T, \left|\mu_{\lambda(p)} - \mu_{\lambda(q)}\right|^2\right), T > 0 \tag{4}$$

In order to optimize the energy function in the kernel graph cut algorithm, in the first step, region labels are determined as fixed parameters. The objective function is minimized according to the average statistical parameters of each area. In the second step, the optimal image labels are determined according to the parameters extracted in the first step using the graph cut algorithm. The above steps are repeated until the local minimum is reached.

In the kernel graph cut algorithm based on entropy, the centers are determined using the k-means algorithm[23]. In the k-means algorithm, clustering is done in such a way that the function of the sum of squares within the clusters becomes the smallest possible value. Equation 5 shows the objective function S in the k-means algorithm.

$$S = min \sum_{l=1}^{N_{reg}} \sum_{p=1}^{n_l} z_{pl} \left|F_p - \mu_l\right|^2 \tag{5}$$

where N_{reg} is the number of clusters, n_l is the number of data in each cluster, μ_l is the average of the lst cluster and z_{pl} is the data membership term F_p in the lst cluster, which is specified by zero or one. In order to minimize the objective function, the square of the distance between points in different clusters should be maximized. In this regard, the distance criterion can be calculated based on the Euclidean distance in the form of equation 6.

$$d = \sqrt{\sum_{i=1}^{f} (x_i - y_i)^2} \tag{6}$$

where f is the number of features and x_i and y_i are the ith features of two data samples x and y. In the k-means algorithm, in order to improve the quality of clustering, the internal evaluation index (Silhouette Coefficient) is used to evaluate the clustering by calculating the similarity within the cluster or the dissimilarity or the size between the clusters, which is calculated according to equation 7.

$$\begin{cases} \dfrac{b(i) - a(i)}{max\{a(i)|b(i)\}} & if\ n_l > 1 \\ 0 & if\ \ n_l = 0 \end{cases} \tag{7}$$

where $a(i)$ is the average distance of a sample from the lst cluster with other samples of the same cluster and is calculated according to equation 8.

$$a(i) = \frac{1}{n_l - 1} \sum_{j \in R_l, i \neq j} d_{ij} \qquad (8)$$

n_l indicates the number of members of the l_{st} cluster, R_l indicates the l_{st} cluster and d_{ij} is the value of the distance between the i_{st} and j_{st} data. b(i) also measures the minimum average distance of the i_{st} sample with all points in other clusters and is calculated based on equation 9.

$$b(i) = min \frac{1}{n_l} \sum_{j \in R_l, i \notin R_l} d_{ij} \qquad (9)$$

where n_l is the number of members of the l_{st} cluster. The k-means algorithm cannot determine the centers well in images with complex textures due to the possibility of random selection of the initial centers on the borders and a variety of textures. Therefore, more accurate determination of centers can be very effective in improving segmentation performance.

3. KERNEL GRAPH CUT BASED ON ENTROPY WITH WEIGHTED K-MEANS

The main parameter in the segmentation of the entropy-based kernel graph cut algorithm is the image centers. Because the data mapping to the new space is based on the RBF kernel setting on the above centers. In the kernel graph cut algorithm based on weighted entropy, the centers of the background and foreground areas are determined based on the weighted k-means algorithm, and the RBF kernel is set in the above centers to implicitly map the data to a higher space. This can help to separate the data linearly in higher space.

In this algorithm, the value of pixels is determined based on the edges of the image. It is considered that the suitable centers are the centers that are located in homogeneous areas with low frequency, or in other words, are far away from the main edges of the image. Therefore, after removing the weak edges in the image using the Gaussian blur filter, the strong edges in the image are extracted based on a high-pass filter. Finally, the weighted image $\boldsymbol{F'}$ is calculated based on the Euclidean distance transformation based on the pixel distance to the nearest non-edge pixel. Figure 1 shows the weighted image based on Euclidean distance transformation.

In the weighted image, pixels inside the border and outside the border have more weight, and pixels on the border have less weight. After extracting the weight of the pixels in the image, this image is used to extract the centers based on the importance of the pixels in the weighted k-means algorithm. In this way, after determining the centers, the data is assigned to the closest cluster center according to their membership degree. Equation 10 shows the membership degree of the F_p data in the l_{st} cluster.

$$m(\mu_l | F_p) = \frac{\left\| F_p - \mu_l \right\|^2}{\sum_{l=1:N_{reg}} \left\| F_p - \mu_l \right\|^2} \qquad (10)$$

Then, for each cluster center, the cluster centers are recalculated based on the membership degree and the weight of the pixels. Equation 11 shows how to calculate

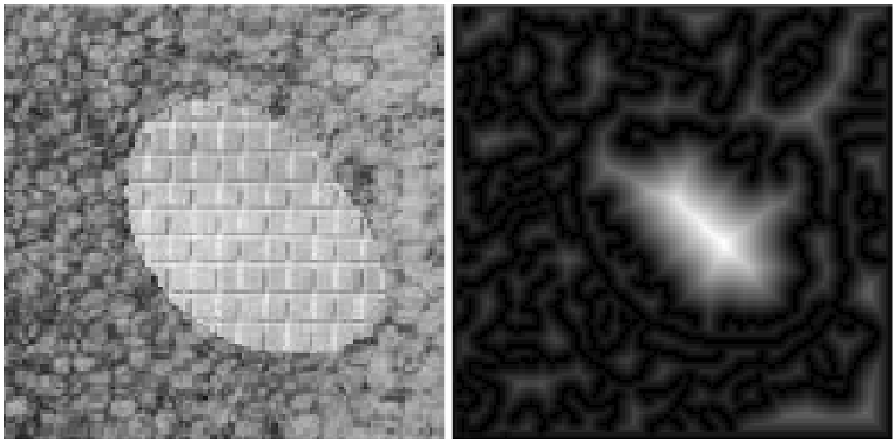

Fig. 1. Weighted image based on the output of the high-pass filter.

centers in the weighted k-means algorithm.

$$\mu_l = \frac{\sum_{p=1:n_l} m(\mu_l|F_p) F'_p F_p}{\sum_{p=1:n_l} m(\mu_l|F_p) F'_p} \tag{11}$$

where F'_p is the weight given to each pixel and n_l is the number of samples in each cluster. In other words, in this algorithm, the data affects the centers in proportion to their importance. Choosing more optimal centers improves the output of the kernel because the closer the feature vector is to the center of the kernel; the more coefficient is assigned to it. After receiving the kernel output, the data term based on the kernel, and the regularization term based on the obtained averages are calculated. The energy function is determined based on two data and regularization terms, and the image graph is made based on that. Finally, using the minimum cut algorithm, the graph is divided into background and foreground. In order to optimize the energy function in the kernel graph cut algorithm, region labels are determined as fixed parameters in each step. The objective function is minimized according to the average statistical parameters of each area. Then, the optimal labels of the image are determined according to the parameters extracted in the first step using the graph cut algorithm. The above steps are repeated until the local minimum is reached. Figure 2 shows the flowchart of the weighted entropy graph cut algorithm.

4. EXPERIMENTAL RESULTS

In order to have a comprehensive performance evaluation of the proposed algorithm, the results of the proposed method are compared with eight representative graph cut methods: RBF kernel [21], Entropy-based kernel graph cut [14], Krawtchouk [15], L2S [24], maximum continuous flow (C-MaxflowCut) [25], LoGRSF [26], LocalPrefitting [27] and AMOE [۱۹] and evaluation has been done using the following two datasets: 1) Brodatz dataset images, 2) DTD dataset images. It should be mentioned that the above datasets consist of 120 images in total. In order to evaluate the performance of segmentation methods, six criteria have been adopted. Dice similarity criterion [28],

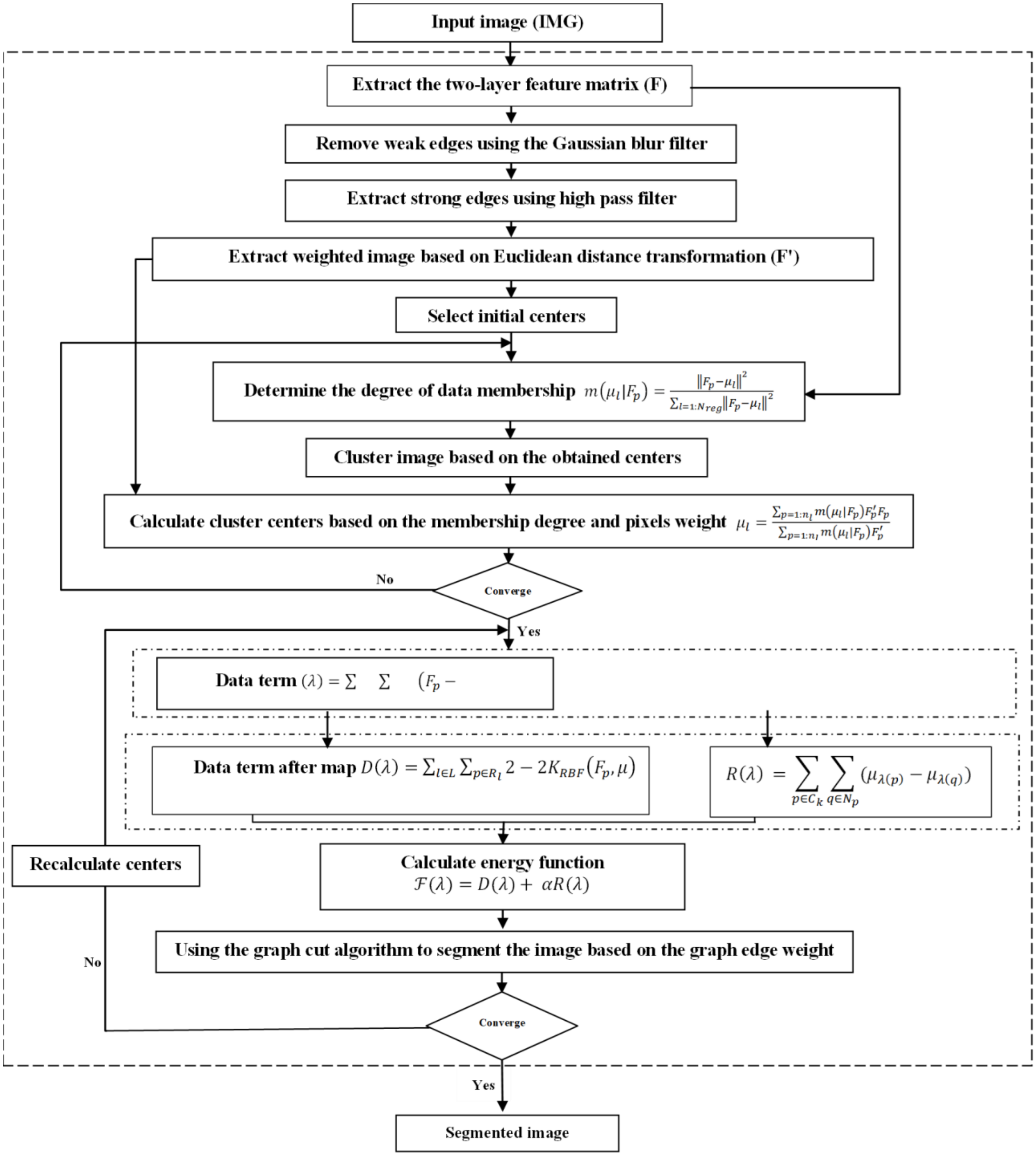

Fig. 2. Flowchart of weighted entropy kernel graph cut algorithm.

Jaccard similarity criterion [29], Accuracy [30], Peak signal-to-noise Ratio (PSNR)[31], Mean Sum of Square Distance (MSSD) [32], and Elapsed Time criterion. The test environment of the above study is Intel® Core™i7 CPU @ 2.20 GHz, memory 8.00 GB, and it is programmed with MATLAB 2020 Alpha.

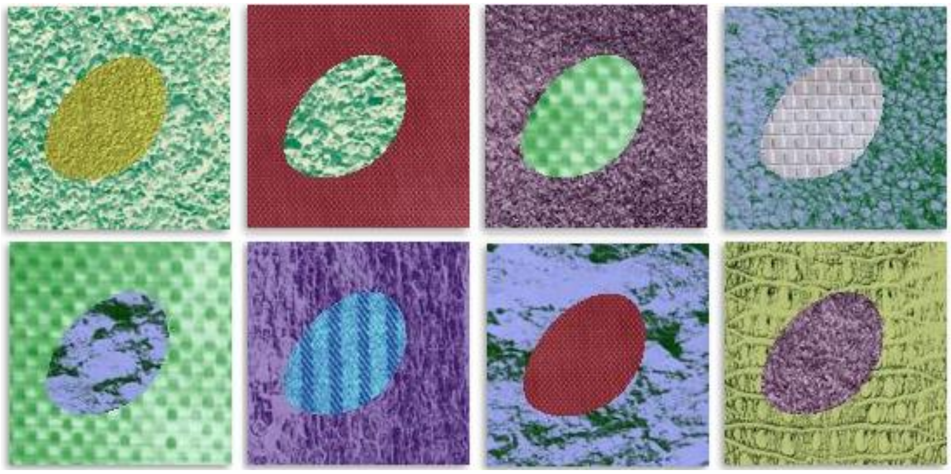

Fig. 3. Sample images of the Brodatz dataset.

Table 2. ***Comparison of energy-based methods with different evaluation criteria on Brodatz images.***

Method	Evaluation Metrics					
	Dice	Jaccard	Accuracy	PSNR	MSSD	E-time
Proposed	98.62	97.27	93.29	64.97	0.02	0.04
Entropy	98.40	96.87	92.45	64.79	0.02	1.72
Kernel RBF	75.36	62.77	53.92	54.25	0.29	2.30
Krawtchouk	45.06	29.41	29.39	56.18	0.16	2.30
L2S	72.40	58.17	58.34	58.69	0.09	1.95
C-Maxflow	88.07	78.83	31.22	55.44	0.20	1.82
LoGRSF	61.53	44.78	7.60	51.23	0.49	2.78
LocalPrefitting	64.43	47.93	9.19	51.49	0.47	4.84
AMOE	95.91	92.28	70.09	62.06	0.07	10.35

4.1. Statistical Results on The Brodatz Dataset

In order to evaluate the proposed algorithm, a laboratory study has been carried out on an artificial geometric shape modeled with the Brodatz color dataset. The Brodatz texture dataset is widely used and consists of 105 texture images. This dataset was chosen because of its texture diversity. A set of sample images is shown in Figure 3.

Table 2 shows the results of the Brodatz dataset compared to other algorithms in this field. Compared to other methods, the proposed method is superior with a difference of 0.22 in Dice similarity, 0.4 in Jaccard similarity, 0.84 in accuracy, 0.18 in peak signal-to-noise ratio, and it has the lowest average sum of squared distance. Also, due to the fact that the algorithm selects the optimal center, it converges in fewer iterations, and therefore the time spent in the algorithm is much lower than other algorithms.

Qualitative studies also prove the superiority of the proposed method over other methods. Figure 4 also shows the segmentation results of Brodatz dataset samples. As can be seen, the proposed algorithm has been able to segment the geometric shape and the background well in all the images with different background and foreground textures. While in the Entropy and RBF algorithm, the geometrical shape of the foreground is well segmented, the background pixels that are selected as the foreground have caused a drop in the quality of the algorithm. Contrasted with it in the Krawtchouk, L2S, c-Maxflow and AMOE algorithms, although the background is segmented well, in most cases, it failed to segment the foreground well. The two algorithms LocalPrefitting and LoGRSF have not been able to separate the background and the foreground from each other and have provided weak results.

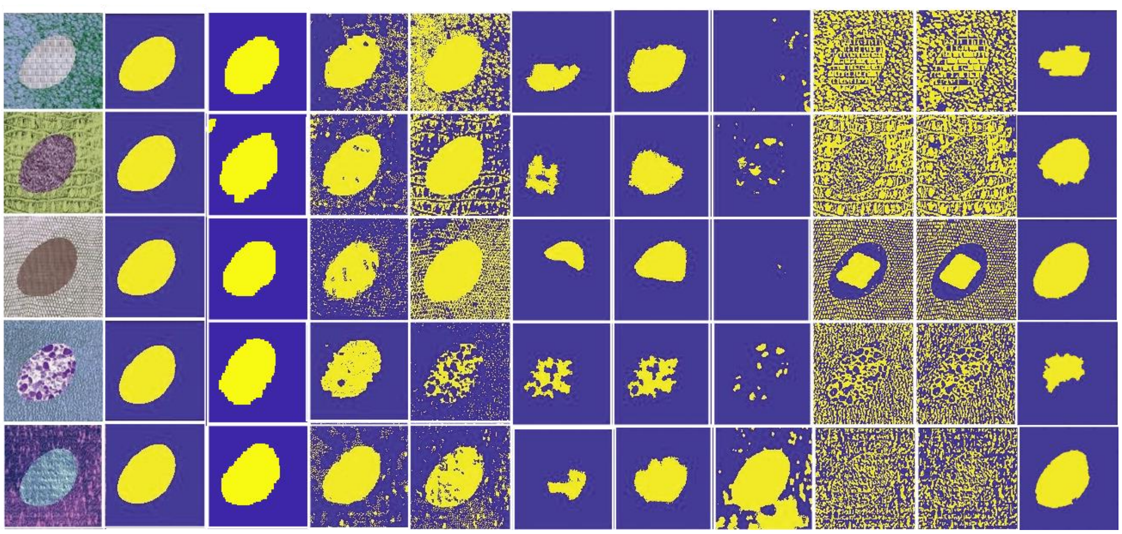

***Fig. 4. Includes different evaluations of Brodatz images, and each row includes the original image, Groundtruth image, proposed method, Entropy*[33]*, RBF Kernel[۳۴], Krawtchouk*[35]*, Mukherjee and Acton*[24]*, Continuous MaxflowCut*[36]*, LoGRSF*[37] *and LocalPrefitting[۳۸] and AMOE*[19]**.**

Fig. 5. Sample of DTD data images.

Table 3. ***Comparison of energy-based methods with different evaluation criteria on DTD images***

Methods	Evaluation Metrics					
	Dice	Jaccard	Accuracy	PSNR	MSSD	E-time
Proposed	92.62	86.84	86.09	59.71	0.10	0.08
Entropy	83.34	72.89	63.38	56.24	0.22	2.09
Kernel RBF	76.44	63.70	51.26	54.69	0.30	2.26
Krawtchouk	33.25	21.12	20.63	55.63	0.18	2.28
L2S	51.22	37.60	37.56	56.85	0.14	2.00
C-Maxflow	60.52	46.14	34.56	51.95	0.45	1.62
LoGRSF	68.36	52.40	18.01	51.95	0.42	2.63
LocalPrefitting	70.91	55.60	17.32	52.23	0.40	4.70
AMOE	91.77	85.29	35.09	60.00	0.15	10.48

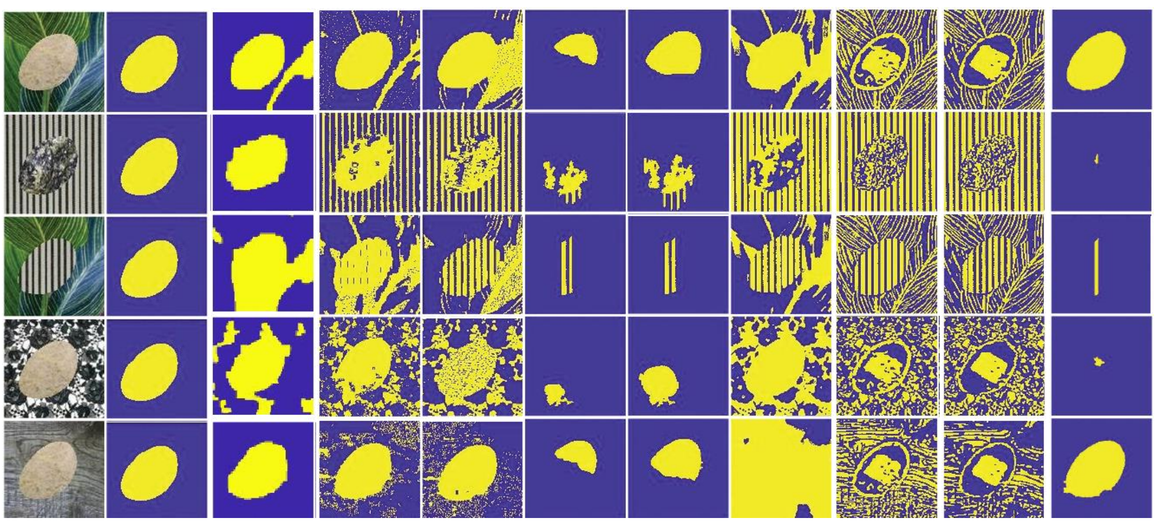

Fig. 6. Includes different evaluations of DTD images, and each row includes the original image, reference image, proposed method, Entropy[33]***, RBF Kernel[۳۴], Krawtchouk***[35]***, Mukherjee and Acton***[24]***, Continuous MaxflowCut***[36]***, LoGRSF***[37]***, LocalPrefitting[۳۸], and AMOE***[19]**.**

4.2. Statistical Results on DTD Dataset

In order to evaluate the proposed algorithm, a laboratory study has been conducted on DTD dataset digital images. This dataset contains a collection of images with complex descriptive textures, where natural and artificial patterns exist simultaneously in textures. A set of sample images is shown in Figure 5.

Table 3 shows the results of the DTD dataset compared to other algorithms. The proposed method has an increase of 0.85 in the Dice criterion, 1.55 in the Jaccard criterion, 22.71 in accuracy, a decrease of

0.29 in the peak signal-to-noise ratio, and 0.05 in the average value of the sum of squared distances. The high difference in the accuracy criterion compared to the Dice and Jacquard criteria is because the Dice and Jacquard criteria only give importance to the foreground, while the accuracy criterion evaluates the background and the foreground at the same time. Therefore, according to the fact that none of the algorithms is able to segment the background well, the accuracy criterion shows a great improvement. Also, due to the fact that the algorithm selects the optimal center, it converges in fewer iterations, and therefore the Elapsed time is much lower than other algorithms.

Qualitative studies in Figure 6, which show the segmentation results of DTD dataset samples, prove the superiority of the proposed method over other methods. The proposed algorithm has been able to segment the geometric shape better than other methods in all the images despite the diversity and complexity of the background and foreground texture. While in the Entropy algorithm, RBF, c-Maxflow, LoGRSF, and Local Prefitting could not segment the foreground well and many pixels of the background were segmented as foreground. In other algorithms, despite the fact that the background is segmented well, in most cases, it could not segment the geometric shape well.

5. CONCLUTION

In the segmentation process of RBF kernel graph cut based on entropy with k-means weighted, blurring filter and then high pass filter is used to extract strong edges and the weighted image is calculated based on Euclidean distance transformation. Then, the weighted image along with the membership degree component is used to extract more accurate centers. Using the weighted k-means algorithm to extract regions makes the proposed algorithm perform well in different images. Because the data affects the centers according to their importance. The closer the feature vector is to the center of the kernel, the higher the coefficient assigns to it, and choosing the optimal centers improves the output of the kernel. After receiving the output of the kernel, the energy function is determined based on two terms of the data and regularization. Finally, by using the minimum graph cut algorithm, the image is divided into two parts, background and foreground. Until the convergence of the algorithm, the optimization of the energy function in the kernel graph cut algorithm continues according to the average parameters determined in each step. In this study, two datasets of Brodatz and DTD images were analyzed in order to evaluate the performance of the proposed algorithm. According to the qualitative and quantitative results obtained from two datasets, the kernel graph cut algorithm has been able to provide higher and more flexible performance in image segmentation while providing more accurate centers. In future works, it will be possible to improve the entropy-based kernel graph cut algorithm for segmentation of images with narrow borders, because the above algorithm does not work well on images with narrow borders due to the blurring property of the RBF kernel.

REFERENCES

[1] D. Kaur and Y. Kaur, “Various Image

Segmentation Techniques: A Review," *Int. J. Comput. Sci. Mob. Comput.*, vol. 3, no. 5, pp. 809–814, 2014.

[2] P. Moeskops, M. A. Viergever, A. M. Mendrik, L. S. de Vries, M. J. N. L. Benders, and I. Isgum, "Automatic Segmentation of MR Brain Images With a Convolutional Neural Network," *IEEE Trans. Med. Imaging*, vol. 35, no. 5, pp. 1252–1261, May 2016.

[3] A. S. Mohan Resmi R, "Video Image Processing for Moving Object Detection and Segmentation using Background Subtraction," in *International Conference on Computational Systems and Communications (ICCSC)* |, 2014, pp. 288–292.

[4] I. Gonzalez-Diaz, C. E. Baz-Hormigos, and F. Diaz-de-Maria, "A Generative Model for Concurrent Image Retrieval and ROI Segmentation," *IEEE Trans. Multimed.*, vol. 16, no. 1, pp. 169–183, Jan. 2014.

[5] J. Da Rugna, G. Chareyron, and H. Konik, "About Segmentation Step in Content-based Image Retrieval Systems," *Proc. World Congr. Eng. Comput. Sci.*, vol. 1, 2011.

[6] Q. Xie, O. Remil, Y. Guo, M. Wang, M. Wei, and J. Wang, "Object Detection and Tracking Under Occlusion for Object-Level RGB-D Video Segmentation," *IEEE Trans. Multimed.*, vol. 20, no. 3, pp. 580–592, Mar. 2018.

[7] M. L. L, "Segmentation of Disease Affected Plant Leaves Using Fuzzy based Approach," *Int. Conf. Sci. Technol. Eng. Manag.*, pp. 889–894, 2017.

[8] M. Dhakate and Ingole A. B., "Diagnosis of pomegranate plant diseases using neural network," in *2015 Fifth National Conference on Computer Vision, Pattern Recognition, Image Processing and Graphics (NCVPRIPG)*, 2015, pp. 1–4.

[9] S. K. Mylonas, D. G. Stavrakoudis, J. B. Theocharis, G. C. Zalidis, and I. Z. Gitas, "A Local Search-Based GeneSIS algorithm for the Segmentation and Classification of Remote-Sensing Images," *IEEE J. Sel. Top. Appl. EARTH Obs. Remote Sens.*, 2016.

[10] S. Q. and X. Z. Zhu, G. Wen, "A Hybrid Statistics and Representation-Based Anomaly Detector for Hyperspectral Images," *IEEE J. Sel. Top. Appl. Earth Obs. Remote Sens.*, vol. 12, no. 9, pp. 3650–3664, 2019.

[11] D. Yang, R. Fei, J. Yao, and M. Gong, "Two-stage SAR image segmentation framework with an efficient union filter and multi-objective kernel clustering," *Appl. Soft Comput. J.*, vol. 44, pp. 30–44, 2016.

[12] L. Panigrahi, K. Verma, and B. Kumar, "Ultrasound image segmentation using a novel multi-scale Gaussian kernel fuzzy clustering and multi-scale vector field convolution," *Expert Syst. Appl.*, vol. 115, pp. 486–498, 2019.

[13] J. H. Park, G. S. Lee, and S. Y. Park, "Color image segmentation using adaptive mean shift and statistical model-based methods," *Comput. Math. with Appl.*, vol. 57, no. 6, pp. 970–980, Mar. 2009.

[14] M. Niazi, K. Rahbar, M. Sheikhan, and M. Khademi, “Entropy-based kernel graph cut for textural image region segmentation,” *Multimed. Tools Appl. 2022*, pp. 1–21, Feb. 2022.

[15] K. Rahbar, “Image segmentation through modeling the illumination probability distribution function using the Krawtchouk polynomial,” *Signal Processing*, vol. 164, pp. 1–9, 2019.

[16] X. Chen, S. Member, and B. P. Nguyen, “Automated Brain Tumor Segmentation using Kernel Dictionary Learning and Superpixel-level Features,” in *2016 IEEE International Conference on Systems, Man, and Cybernetics • SMC 2016*, 2016, pp. 2547–2552.

[17] Q. Zhang, M. G. Xue, and P. C. Zhou, “Turbopixel with fuzzy edge detection and multiregional kernel graph cuts for image segmentation,” in *Proceedings - 2017 10th International Congress on Image and Signal Processing, BioMedical Engineering and Informatics, CISP-BMEI 2017*, 2017, pp. 1–6.

[18] S. Zeng, Z. Wang, R. Huang, L. Chen, and D. Feng, “A study on multi-kernel intuitionistic fuzzy C-means clustering with multiple attributes,” *Neurocomputing*, 2019.

[19] S. Qu, H. Tan, Q. Li, and Z. Peng, “Interactive image segmentation based on the appearance model and orientation energy,” *Comput. Vis. Image Underst.*, vol. 217, p. 103371, Mar. 2022.

[20] Z. Kang, L. Wen, W. Chen, and Z. Xu, “Knowledge-Based Systems Low-rank kernel learning for graph-based clustering,” *Knowledge-Based Syst.*, vol. 163, pp. 510–517, 2019.

[21] M. Ben Salah, A. Mitiche, and I. Ben Ayed, “Multiregion image segmentation by parametric kernel graph cuts,” *IEEE Trans. Image Process.*, vol. 20, no. 2, pp. 545–557, 2011.

[22] R. Harini and C. Chandrasekar, “Image segmentation using nearest neighbor classifiers based on kernel formation for medical images,” in *International Conference on Pattern Recognition, Informatics and Medical Engineering, PRIME 2012*, 2012, pp. 261–265.

[23] K. Ejaz, M. S. M. Rahim, U. I. Bajwa, H. Chaudhry, A. Rehman, and F. Ejaz, “Hybrid segmentation method with confidence region detection for tumor identification,” *IEEE Access*, vol. 9, pp. 35256–35278, 2021.

[24] S. Mukherjee and S. T. Acton, “Region based segmentation in presence of intensity inhomogeneity using legendre polynomials,” *IEEE Signal Process. Lett.*, vol. 22, no. 3, pp. 298–302, Mar. 2015.

[25] D. Kaba *et al.*, “Retina layer segmentation using kernel graph cuts and continuous max-flow,” *Opt. Express*, vol. 23, no. 6, p. 7366, Mar. 2015.

[26] K. Ding, L. Xiao, and G. Weng, “Active contours driven by region-scalable fitting and optimized Laplacian of Gaussian energy for image segmentation,” *Signal Processing*, vol. 134, pp. 224–233, May 2017.

[27] K. Ding, L. Xiao, and G. Weng,

"Active contours driven by local pre-fitting energy for fast image segmentation," *Pattern Recognit. Lett.*, vol. 104, pp. 29–36, Mar. 2018.

[28] K. Hajdowska, S. Student, and D. Borys, "Graph based method for cell segmentation and detection in live-cell fluorescence microscope imaging," *Biomed. Signal Process. Control*, vol. 71, no. PA, p. 103071, 2022.

[29] E. N. and S. W. Suphakit Niwattanakul*, Jatsada Singthongchai, "Using of Jaccard Coefficient for Keywords Similarity," in *Proceedings of the International MultiConference of Engineers and Computer Scientists*, 2013, vol. I.

[30] E. Fernandez-Moral, R. Martins, D. Wolf, and P. Rives, "A New Metric for Evaluating Semantic Segmentation: Leveraging Global and Contour Accuracy," in *2018 IEEE Intelligent Vehicles Symposium (IV)*, 2018, pp. 1051–1056.

[31] F. A. Fardo, V. H. Conforto, F. C. de Oliveira, and P. S. Rodrigues, "A Formal Evaluation of PSNR as Quality Measurement Parameter for Image Segmentation Algorithms," no. 0, pp. 1–11, 2016.

[32] X. Liao, Z. Yuan, Q. Zheng, Q. Yin, D. Zhang, and J. Zhao, "Multi-Scale and Shape Constrained Localized Region-Based Active Contour Segmentation of Uterine Fibroid Ultrasound Images in HIFU Therapy," *PLoS One*, vol. 9, no. 7, p. e103334, Jul. 2014.

[33] M. Niazi, K. Rahbar, M. Sheikhan, and M. Khademi, "Entropy-based kernel graph cut for textural image region segmentation," *Multimed. Tools Appl.*, pp. 1–21, Feb. 2022.

[34] M. Ben Salah, A. Mitiche, and I. Ben Ayed, "Multiregion image segmentation by parametric kernel graph cuts," *IEEE Trans. Image Process.*, vol. 20, no. 2, pp. 545–557, Feb. 2011.

[35] K. Rahbar, "Image segmentation through modeling the illumination probability distribution function using the Krawtchouk polynomial," *Signal Processing*, vol. 164, pp. 1–9, Nov. 2019.

[36] B. I. Dodo, Y. Li, D. Kaba, and X. Liu, "Retinal Layer Segmentation in Optical Coherence Tomography Images," *IEEE Access*, vol. 7, pp. 152388–152398, 2019.

[37] K. Ding, L. Xiao, and G. Weng, "Active contours driven by region-scalable fitting and optimized Laplacian of Gaussian energy for image segmentation," *Signal Processing*, vol. 134, pp. 224–233, May 2017.

[38] K. Ding, L. Xiao, and G. Weng, "Active contours driven by local pre-fitting energy for fast image segmentation," *Pattern Recognit. Lett.*, vol. 104, pp. 29–36, Mar. 2018.