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Application of Improved Fuzzy C-means Algorithm to Texture Image Segmentation

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Abstract: This study presents an efficient method for texture image segmentation based on dual-tree complex wavelet transform (DT-CWT)and improved Fuzzy C-means (FCM) algorithm. The procedure toward complete segmentation consists of two steps: texture feature extraction and feature classification. Firstly, texture feature is extracted in dual-tree complex wavelet domain for its shift invariance and more direction selectivity, we choose mean and variance of six high-frequency magnitude sub-bands as the texture features. Secondly, the fuzzy c-means algorithm is applied to the feature classification, but due to the random selectivity of initial clustering center, the clustering seeds may be too close which makes the FCM algorithm easily fall into local minimum, aiming at the problem, a new method based on maximun distance is proposed. In addition, to improve the membership function, the fuzzy connectedness of samples in the same cluster is proposed. Compared with the FCM algorithm, the experimental results show that the presented algorithm is more effective in texture image segmentation. At the same time, the presented algorithm is well applied to the segmentation of aero-image corrupted by noise.

Key words: Image, texture segmentation, feature extraction, fuzzy c-means, connectedness

INTRODUCTION

The main objective of texture segmentation is to divide the texture image into several regions with the distinguished texture features. Texture segmentation is one of the most widely studied problems in texture analysis and computer vision and, it is a important step towards image understanding. It mainly consists of texture feature extraction and feature classification, where the selectivity of texture feature has significant influence on the segmentation effect (Arivazhagan and Ganesan, 2003). In recent years, the wavelet transform is commonly used for texture feature extraction for its multi-resolution analysis, especially the pyramid-structured algorithm proposed by Mallat (Mallat, 1989) for its simplicity and easy implementation. However, the algorithm has two limitations, one of which is the lack of shift invariance, another is the less selectivity of filter direction. Fortunately, the dual-tree complex wavelet transform can make up for these limitations for its approximate shift invariance and more direction selectivity (Kingsbury, 2001) which make it better describe the texture feature of an image. In order to obtain much more effective texture feature, it is extracted in the dual-tree complex wavelet domain. The original texture image is firstly decomposed using the dual-tree complex wavelet, with six high-frequency sub-bands obtained in each scale. We choose mean and variance of six high-frequency magnitude sub-bands in different scales as the texture measurement to form the texture features in this study.

In texture segmentation, feature classification is another crucial question which aims at partitioning the similar features into the same class so that image can be segmented into different regions with different texture characteristics. Under the same dual-tree complex wavelet domain to describe the texture feature, edge-based segmentation methods segment the image, on the basis of the information conveyed by the edges that exist in an image (Horng, 2011). Region-based segmentation methods perform segmentation by diving an image into zones of maximum homogeneity (Phadke, 2009; Kang *et al*., 2012), some criteria can be done to make region growing to form consistent object in the image. MRF model-based segmentation methods makes use of MRF model to model the label of category, to realize the Bayesian estimation, it belongs to supervised segmentation (Wang and Jiao, 2007). The segmentation method based on support vector machine must use quadratic programming to solve the support vector which makes the learning speed of the system very slow for its largely training samples (Xie *et al*., 2008) . K-means clustering algorithm is used for texture segmentation for its simplicity and easy implementation, but it does not consider the fuzziness existing the texture image (Celik and Tjahjadi, 2009). Compared with them, FCM algorithm can better segment the texture image for its fuzziness and its uncertainty, in addition, it does not need the training sample, but directly through machine learning, to achieve automatic classification. However, due to the random selectivity of initial clustering center, the clustering seeds may be too close which makes the FCM algorithm easily fall into local minimum, aiming at the problem, a new method based on maximun distance is proposed. In addition, the traditional membership function is designed only based on the distance between a sample and its cluster center which is irrational for the dataset with non-spherical-shape distribution, therefore, the fuzzy connectedness among samples is introduced to improve the traditional membership function in this study.

The rest of the study is organized as follows. Section 2 describes the dual-tree complex wavelet transform and choose mean and variance of six high-frequency magnitude sub-bands at different scales as the texture features. Section 3 introduces the FCM algoritnm, gives the selectivity of initial clustering center and the method to improve the traditional membership function. Section 4 gives the experiment results. At last, the conclusion is drawn in Section 5.

TEXTURE FEATURES EXTRACTION BASED ON DT-CWT

The one-dimensional decomposition of the dual-tree complex wavelet consists of two parallel wavelet tree which are Tree-a and Tree-b. A filter corresponding to each tree is bi-orthogonal, one of which is odd high-pass with even symmetry of the sampling sequence midpoint, another of which is even high-pass with odd symmetry of the sampling sequence midpoint. Because the output of their alternate filtering is corresponding to the real part and the imaginary part of complex wavelet transform, so it not only retains all the advantages of the traditional wavelet transform, but also has good performance in direction.

Similar to the one-dimensional signal, the two-dimensional signal is decomposed along the column firstly and then along the line using the separable filter. It is a kind of limited redundant transform with 4:1 redundancy, via which the shift invariance is gained and each scale can be decomposed into six complex high-frequent sub-band with ±15°, ±45°, ±75°. So it has good performance in directional selectivity.

In order to obtain the stable texture feature, we do not directly use the wavelet coefficient of each scale for its quite sparse, but use the mean and variance of six high-frequency magnitude sub-bands at different scales as the energy measure to get features in this study and the formula for calculating texture features is as follows:

$$m_{x,y}^{k} = \frac{1}{w \times w}\sum_{i,j=1}^{w}\left|\mathrm{coef}\,(i,j)\right| \qquad (1)$$

$$v_{x,y}^{k} = \frac{1}{w \times w}\sum_{i,j=1}^{w}\left(\left|\mathrm{coef}(i,j)\right| - m_{x,y}^{k}\right)^2 \qquad (2)$$

where, $m_{x,y}^{k}$ and $v_{x,y}^{k}$ denote the mean and variance respectively, let coef(i, j) be the complex wavelet coefficient of the window with the size of w×w and centered at pixel (i, j) of the k^{th} high-frequency sub-band. In this study, the original image is decomposed in one level using the dual-tree complex wavelet transform algorithm. Construct a 12-dimension feature vector denoting $g_{x,y}$ for each pixel of the texture image, $g_{x,y}$ is as follows:

$$g_{x,y} = \{m_{x,y}^{k}, v_{x,y}^{k}\},\ k = 1, 2, \cdots 6 \qquad (3)$$

TEXTURE SEGMENTATION BASED ON IMPROVED FCM ALGORITHM

FCM algorithm: In order to achieve the appropriate texture segmentation, the next process is feature classification after texture features are obtained. The FCM algorithm is the common approach in feature classification for its fuzziness and its uncertainty. FCM algorithm optimizes the objective function based on the weighted similar measure between the image pixel and the cluster centers, to determine the optimal clustering. The FCM algorithm is described as the follows:

$$\mu_{ij} = \left(\sum_{l=1}^{c}\left[\left(\frac{d_{ij}}{d_{il}}\right)^{\frac{2}{m-1}}\right]\right)^{-1},\ i = 1, 2, \cdots, n,\quad j = 1, 2, \cdots, c \qquad (4)$$

$$v_j = \frac{\sum_{i=1}^{n}(\mu_{ij})^m x_i}{\sum_{i=1}^{n}(\mu_{ij})^m} \qquad (5)$$

$$\mathrm{Min}J_m = \sum_{i=1}^{n}\sum_{j=1}^{c}\mu_{ij}^m (d_{ij})^2 \qquad (6)$$

and satisfy the constraint conditions:

$$\sum_{j=1}^{c}\mu_{ij} = 1 \qquad (7)$$

where, m denotes the fuzzy exponential, c is the clustering number, n is the data number of the clustering space, μ_{ij} is the membership function of the i^{th} sample to the samples in the j^{th} cluster, $d_{ij}^2 = (x_i - v_j)^t (x_i - v_j)$ denotes the Euclidean distance of the sample x_i to custering center v_j,

$x_i \in R^3$, $v_j \in R^3$, s is the dimension of the clustering space, $U = \{\mu_{ij}\}$ and $V = \{v_1, v_2, \ldots, v_c\}$ denote the matrix with the size $c \times n$ and $s \times c$ respectively, $J_m(U, V)$ is the objective function. FCM algorithm minimizes the objective function described in Eq. 6 by iterating the Eq. 4 and the Eq. 5, to obtain the optimal texture classification.

Selectivity of initial clustering center: The principle of selecting the initial clustering center in this study, is trying to make the distance among all the initial culstering centers greater than the advanced threshold which can obtain the initial clustering center in much more feasible domain, so it can make the FCM algorithm avoid converging to the local minimum.

Let $X = \{x_1, x_2, \ldots x_n\}$ be the classified sample set, α is the minimum distance threshold amone the clustering centers, the step of the selectivity of initial clustering center as the follows:

- Calculate the distance between any two samples and generate the distance matrix D, make the nearest two samples as the same cluster and take the mid-point of the two samples as the first clustering center
- Select the distance threshold α, the distance matrix D is used to obtain all the samples with any distance between them and the two ones in the first cluster is greater than α, make the nearest two samples as the same cluster and take the mid-point of the two samples as the second clustering center
- In the same way, among the rest samples, find all the ones with any distance between them and the found ones is greater than α, make the nearest two samples as the same cluster and take the mid-point of the two samples as the second clustering center
- Repeat step 3, until find all the culstering center with the number C

After taking the nearest two samples as the same cluster, we adopt the method of searching the distance matrix D to determine the distance between the sample and the identified one is whether greater than the threshold α, not using the distance between the clustering center and all the samples to determine which avoids a lot of time of calculating the Euclidean distance. Though there exists a certain error, but considering the role of this part in the whole method is purposeful to select initial clustering center, the accurate clustering can be completed by the following steps, so the error is allowed. It is noteworthy that if there is no a pair of samples between which distance within the threshold α, need to reduce the α.

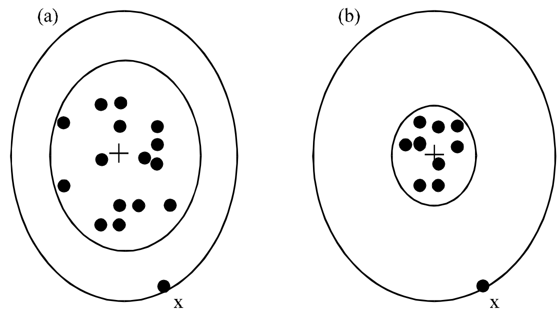

Fig. 1(a-b): Difference of the compactness between two clusters (a) cluster 1 and (b) cluster 2

Improved of the membership function: From Eq. 4, it can be seen that the traditional membership function in FCM algorithm is designed based on the distance between the sample and the clustering center, each sample in the cluster is considered in the same way, so that the effective samples and the noisy ones can not be well distinguished, therefore, it does not effectively reflect the uncertainty of the sample which is irrational for the dataset with non-spherical-shape distribution, aiming at the problem, the fuzzy connectedness among samples in the same cluster is introduced to improve the traditional membership function.

Figure 1 shows the difference of the compactness between two clusters, from Fig. 2a and b, we can see that the distance between the sample x and the respective clustering center is equal. If the membership degrees are determined only based on the distance, they will be the same belong to their respective cluster. However, for Fig. 2b, the distance between the sample x and other samples does not be considered, for Fig. 2a, the sample x can be effective sample, for Fig. 2b, the possibility of the sample x belong to noisy sample is very large. In fact, the membership of the sample x belong to the cluster in Fig. 2a should be greater than the one of the sample x belong to the cluster in Fig. 2b.

Aiming at the problem, the fuzzy connectedness among samples is introduced to improve the traditional membership function in this study. The method is not only considering the distance between the sample and the clustering center, but also considering the realation between the sample and the other ones in the same cluster, then, the realation can be reflected by the connectedness among samples. Based on the analysis mentioned above, the membership based on the connectedness is consisted of two parts, the equation is as the follows:

$$\mu(x_i) = f(\mu_d(x_i), \mu_t(x_i, \bar{x})) \tag{8}$$

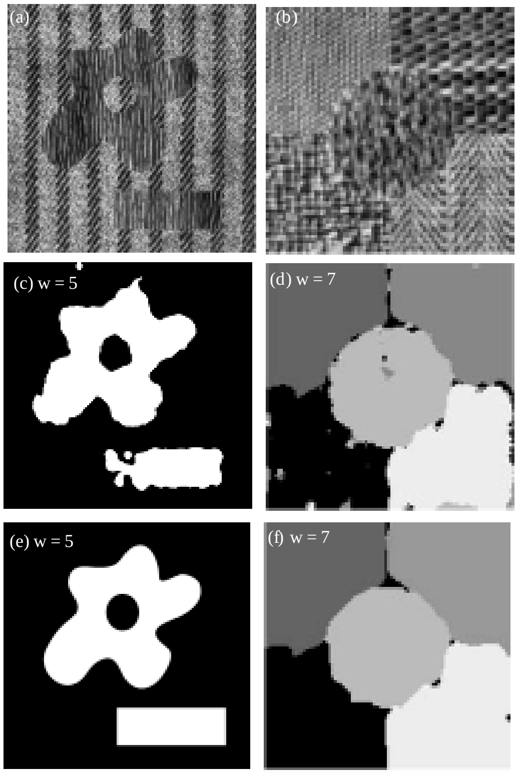

Fig. 2(a-f): Segmentation results. (a-b) the original images, (c-d) using FCM Algorithm and (e-f) using Improved FCM algorithm

Where:

① $\mu(x_i)$ denotes the membership of the sample belong to its cluster

② $\mu_d(x_i)$ which is determined by Eq. 4, reflects the distance realation between the sample x_i and its clustering center

③ $\mu_t(x_i,\bar{x})$ is the fuzzy connectedness (Udupa and Samarasekera, 1996) between the sample x_i and its clustering center which reflects the compactness realation between the sample x_i and other sample in the same cluster and is described as follows:

$$\mu_t(x_i,\bar{x}) = \max_{\rho(x_i,\bar{x})\in P(x_i,\bar{x})}\left[\min\begin{pmatrix}\mu_t(c_1,c_2),\\ \mu_t(c_2,c_3),\\ \cdots\mu_t(c_{m-1},c_m)\end{pmatrix}\right] \tag{9}$$

where, $\rho(x_i,\bar{x})$ denotes the path from x_i to $\bar{x}$, each point in the path is described using $x_1, c_2, \ldots, c_m$, $m\geq 2$, where $c_1 = x_i$ and $c_m = \bar{x}$, $P(x_i,\bar{x})$ denotes the set which is formed of all the path from x_i to $\bar{x}$.

④ F(.,.) denotes a function realation, we take the product as the funciton realation in this study, so Eq. 8 becomes as follows:

$$\mu(x_i) = \mu_d(x_i)\times\mu_t(x_i,\bar{x}) \tag{10}$$

Texture segmentation algorithm:

- **Step 1:** Texture feature extraction; first, the original image with the size N×N is decomposed by the DT-CWT in one level, second, Eq. 3 is used to obtain a 12-dimension feature vector for each pixel positioned with (x, y), then, the feature space denoted G is formed by all the feature vector
- **Step 2:** feature classification

① Select clustering center with the number C to form the set $C^{(0)}$, using the maximun distance method proposed above and let k = 1

② Equation 10 is used to calculate the memebership $U^{(k)}$, the description is as follows:

$$\mu_{ij}^{(k)} = \left(\sum_{l=1}^{c}\left[\left(\frac{d_{ij}^{(k)}}{d_{il}^{(k)}}\right)^{\frac{2}{m-1}}\right]\right)^{-1}\times\mu_t(i,j) \tag{11}$$

$$, i = 1,2,\cdots,N\times N,\quad j = 1,2,\cdots,c$$

where, $\mu_t(i, j)$ denotes the fuzzy connectedness between the sample x_i and the j clustering center.

③ Equation 10 is used to calculate $V^{(k)}$, the description is as follows:

$$v_j^{(k)} = \frac{\sum_{i=1}^{n}(\mu_{ij}^{(k-1)})^m x_i}{\sum_{i=1}^{n}(\mu_{ij}^{(k-1)})^m},\ j = 1,2,\cdots,c \tag{12}$$

If $d_{ij}^{(k)} = 0$, $\mu_{ij}^{(k)} = 1$ and $\forall j\neq 1$, $\mu_{il}^{(k)} = 0$.

④ Let k = k+1 and turn to ② until the new clustering centroids do not vary, that is to say:

$$\left\|J_m(U^{(k)},V^{(k)}) - J_m(U^{(k-1)},V^{(k-1)})\right\|\leq\varepsilon$$

or the iteration number is out of the threshold determined in advance.

COMPUTATIONAL RESULTS AND COMPARISONS

Simulation experiments are done to test the performance of the algorithm mentioned above. In the

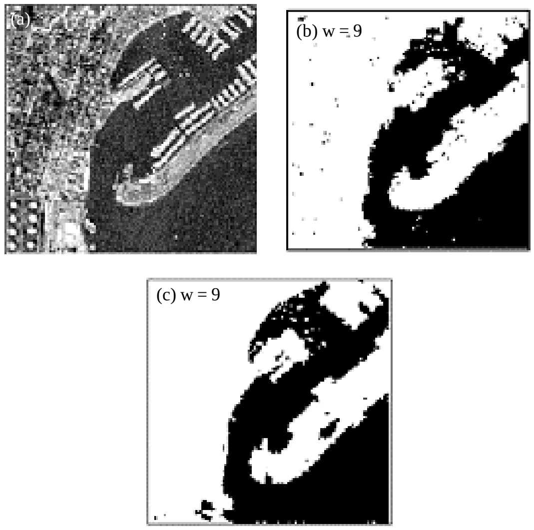

Fig.3 (a-c): Segmentation results, (a) the original aero-image, (b) using FCM Algorithm and (c) using Improved FCM algorithm

experiment, m = 2 and $\epsilon = 0.0001$ and images with 256 gray levels and the size of $N\times N = 256\times 256$ are taken from Brodata album.

Segmentation error rate, boundary precision, region harmony are used to evaluate the texture segmentation performance of the algorithm. The segmentation error rate ER% is defined as:

$$ER\% = \frac{n_1}{N\times N}\% \tag{13}$$

where, n_1 is the error segmented pixels. The boundary precision describes the degree of the boundary that coincides with the true one after segmentation and region harmony is used to demonstrate whether all pixels of the region with same texture in the original image exist in the same region of the segmented image.

The texture segmentation results on FCM algorithm and improved FCM algorithm are illustrated in Fg. 2. For the result in the Fig. 2c, e, w = 5 is a sufficient neighborhood size to capture the texture feature. For the result in the Fig. 2d, f, w = 7 is a suf?cient neighborhood size to capture the texture feature. It can be seen from Fig. 2 that boundary precision and region harmony are improved largely using the improved FCM algorithm, compared with the FCM algorithm.

Figure 3 is the real aero-image joined the pulse noise with the density of 0.1, Fig. 3a is the segmentation result with FCM algorithm, Fig. 3b is the segmentation result with the improved FCM algorithm. it can also be seen from

Table 1: Comparition of the segmentation error rate and the iterations number

	Image No.	FCM	Improved FCM
ER%	2	12.56	7.92
	3	6.31	1.03
	5	10.31	2.46
Iteration No.			
	2	16	11
	3	24	16
	5	48	26

Fig. 3 that the border between sea and land is much more clear, at the same time, it can restrain the noise very well.

Table 1 shows the segmentation error rates derived from the algorithms with FCM and improved FCM and the number of iterations respectively.

From Table 1, it also can be seen that the segmentation error rate with improved FCM algorithm decreases obviously and we can see from Table 1 that the segmentation error of the algorithm based on the improved FCM decreased by 5.28% for the segmentation of the image with 3 textures and 7.85% for the image with 5textures and 4.64% for the real aero-image.

CONCLUSION

In this study, a new method based on maximun distance is proposed to select the initial clustering center, at the same time, to improve the membership function of the FCM algorithm, the fuzzy connectedness of samples in the same cluster is proposed. Compared with the FCM algorithm, the experimental results show that the presented algorithm is more effective in texture image segmentation. In addition, the presented algorithm is well applied to the segmentation of aero-image corrupted by noise.

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