Texture Image Segmentation Using Gabor Filter and Anisotropic Diffusion Filter

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ABSTRACT

Image segmentation is very important task in many image analysis or computer vision applications. In this paper a texture image segmentation method using Gabor filter, anisotropic filter, and k-mean clustering algorithm was proposed. The Gabor filter was used as a multi-channels filter to analyze the texture in the image. The extraction and enhancement of the texture features obtained using anisotropic diffusion filter. Then the k-mean algorithm used to cluster pixels into number of clusters representing the texture regions. The quality of segmentation using this method was evaluated using Ultimate Measurement Accuracy (UMA) metric. The experiments show that the performance of this method is effective, accurate and gives better results as compared with the Seo method from the view of quality of segmentation, the number of run times, the execution time and the capability of separating a large number of textures, and of segmented real images, random mosaics texture images, area of roofs and ground images, and to distinguish objects from background.

Keywords: **texture image segmentation, Gabor filter, anisotropic filter, k-mean clustering.**

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1-Introduction

Texture is a key factor for human perception and thus widely used in fields such as product design. Texture segregation received much attention in the scientific community during the last decades.

Textures are used extensively by the human visual system to perform tasks such as the segmentation of scenes into distinct objects and the analysis of surface geometries [1]. Texture analysis is a significant challenge however due to the complexity of the textural patterns and the infinity of different lighting conditions that must be taken into account. A texture can be informally defined as an irradiance pattern that is perceptually homogeneous. A formal definition of a texture is difficult to obtain and is not necessary for the purpose of texture segmentation. It is possible to do texture segmentation using only the knowledge of dominant features that distinguish the various textures present in an image. Each texture can be thought of as containing a narrow range of frequency and orientation components. By filtering the image with multiple band-pass filters tuned to the dominant frequency and orientation component of the textures, it is possible to locate each texture. The image thus passes through a set of channels, each of which applies a properly tuned filter. The output of the filters can be studied to determine the regions occupied by the textures.

The Gabor filters can be used as the channel filters. The Gabor filters are band-pass filters with tuneable center frequency, orientation and bandwidth. Many researches were using the Gabor filter for texture segmentation such as [2, 3]. Also Seo [4] chose the Gabor filter to implement a filtering method based image segmentation system.

An anisotropic diffusion filter [5] has been developed and applied to different areas of image processing including edge enhancement, noise reduction and segmentation. Anisotropic diffusion filtering provides smoothing of intra-region areas preferentially over inter-region areas, thereby providing a good prospective tool for removing unwanted noise and preserving the edges of desired objects.

In this paper a texture image segmentation method using Gabor filter and anisotropic diffusion filter was proposed. The Gabor filter was used to characterize the multi-channels of information. Then the feature was extracted using anisotropic diffusion filter. Finally these features were used along k-mean clustering for unsupervised texture segmentation.

The rest of this paper is organized as follows. Section 2, explained the background of the proposed method. Section 3 explained the evaluation technique to evaluate the performance of the proposed method. Section 4 shows the experimental results. Finally the conclusion was in section 5.

2. Background

Image segmentation is a difficult yet very important task in many image analysis or computer vision applications. Differences in the mean gray level or in color in small neighborhoods alone are not always sufficient for image segmentation. Rather, one has to rely on differences in the spatial arrangement of gray values of neighboring pixels - that is, on differences in texture. The problem of segmenting an image based on textural cues is referred to as *texture segmentation problem*. The multi-channel filtering approach to texture analysis is intuitively appealing because the dominant spatial-frequency components of different textures are different. An important advantage of the multi-channel filtering approach to texture analysis is that one can use simple statistics of gray values in the filtered images as texture features. This simplicity is the direct result of decomposing the original image into several filtered images with limited spectral information [2]. The original image either gray or color converted to gray image. Gabor filter bank was used to characterize the channels.

The process of texture segmentation using Gabor filters involves proper design of a filter bank tuned to different spatial-frequencies and orientations to cover the spatial-frequency space; decomposing the image into a number of filtered images; extraction of features from the filtered images; and the clustering of pixels in the feature space to produce the segmented image such as in [2,3,4]. Seo [4] presents in his work the texture segmentation system which is involves three steps 1) Decomposition of the input

image using a Gabor filter bank, 2) Feature extraction using a nonlinear sigmoid and a Gaussian smoothing functions, and 3) Clustering using the k-means algorithm.

Depending on the process of texture segmentation using Gabor filters, I propose a texture segmentation system which is contained the following steps:

1) **Decomposition of the input image using a Gabor filter bank,**
2) **Feature extraction using anisotropic diffusion filter, and**
3) **Clustering using the k-means algorithm.**

2.1 Gabor Filter

As mentioned above, Gabor filters have the ability to perform multi-resolution decomposition due to its localization both in spatial and spatial frequency domain. Texture segmentation requires simultaneous measurements in both the spatial and the spatial-frequency domains. Filters with smaller bandwidths in the spatial-frequency domain are more desirable because they allow us to make finer distinctions among different textures. On the other hand, accurate localization of texture boundaries requires filters that are localized in the spatial domain. However, normally the effective width of a filter in the spatial domain and its bandwidth in the spatial-frequency domain are inversely related according the uncertainty principle. That is why Gabor filters are well suited for this kind of problem. A

Gabor function in the spatial domain is a sinusoidal modulated Gaussian is given by [2, 3, 4]:

$$g\,l\,q\,y\,s\,g\,(x,y) = \exp\left(-\frac{x'^2 + g^2 y'^2}{2s^2}\right)\cos\left(2p\,\frac{x'}{l} + y\right) \qquad \textbf{... (1)}$$

where $x' = x\cos(\theta) + y\sin(\theta)$,

$y' = y\cos(\theta) - x\sin(\theta)$.

In this equation, λ represents the wavelength of the cosine factor, θ represents the orientation of the normal to the parallel stripes of a Gabor function in degrees, ψ is the phase offset in degrees, and γ is the spatial aspect ratio and specifies the elliptically of the support of the Gabor function, and σ is the standard deviation of the Gaussian determines the (linear) size of the receptive field.

The parameter λ is the wavelength and $f = 1/\lambda$ is the spatial frequency of the cosine factor. The ratio σ/λ determines the spatial frequency bandwidth of simple cells and thus the number of parallel excitatory and inhibitory stripe zones which can be observed in their receptive fields. The half-response spatial frequency bandwidth b (in octaves) and the ratio σ/λ are related as follows:

$$b = \log_2 \frac{\frac{s}{l}p + \sqrt{\frac{\ln 2}{2}}}{\frac{s}{l}p - \sqrt{\frac{\ln 2}{2}}},\quad \frac{s}{l} = \frac{1}{p}\sqrt{\frac{\ln 2}{2}}\,\frac{2^b + 1}{2^b - 1} \qquad \textbf{… (2)}$$

ψ=0^o and ψ = 90^o returns the real part and the imaginary part of Gabor filter respectively. The real part of Gabor filter is an even-symmetric filter was used. The filter parameters were particularly selected so that it can properly capture texture information as recommended in [4]: θ: 0^o, 30^o, 60^o, 90^o, 120^o, 150^o

the values of frequencies: $F_L(i)=0.25 - 2^{i-0.5}/N_c$

$F_H(i)=0.25 + 2^{i-0.5}/N_c$

where i =1, 2,..., $\log_2(N_c/8)$, N_c is the width of image which is a power of 2. Note that $0 < F_L(i) < 0.25$ and $0.25 \leq F_H(i) < 0.5$.

For an image with 256 columns, for example, a total of 60 filters can be used -6 orientations and (5 + 5) frequencies. Note that in this paper we set the value of the bandwidth b of the Gabor filter to 1 octave.

2.2 Feature Extraction Using Anisotropic Diffusion Filter

Filter outputs by default are not appropriate for identifying key texture features. A number of feature extraction methods were proposed to extract useful information from the filter outputs. Some of the feature extraction methods include: using a non-linear sigmoidal function [2, 4], using the magnitude response [3], and also using pixel adjacency information [2, 3]. Each filter output is smoothed using a Gaussian smoothing function that matches the corresponding filter spatial Gaussian curve. The

smoothing Gaussian is selected to be wider than the matched Gabor modulated Gaussian [2].

I propose to use the Anisotropic Non-Linear diffusion filter which was introduced by Perona and Malik(1990) [5] with the following criteria:-

1) Immediate Localisation: **At each resolution, the region boundaries should be sharp and coincide with the semantically meaningful boundaries at that resolution.**

2) Piecewise Smoothing: **At all scales, intraregional smoothing should occur preferentially over interregional smoothing.**

Anisotropic diffusion equation with the anisotropic diffusion coefficient *c(x,y)* where t is the time [6]:-

$$\frac{\partial I}{\partial t} = div(c(x,y,t)\nabla I) = c(x,y,t)\nabla^2 I + \nabla c \nabla I \qquad \text{… (3)}$$

Where *div* = divergence operator

***c(x,y,t)*=diffusion coefficient**

∇ **= gradient operator**

This anisotropic is discretised by a moving operator with a four-pixel neighborhood though also other pixel neighborhoods are possible [6]:

$$I_{i,j}^{t+1} = I_{i,j}^{t} + l(c_N.\nabla_N I + c_S.\nabla_S I + c_E.\nabla_E I + c_W.\nabla_W I). \qquad \text{… (4)}$$

Where $I_{i,j}^{t+1}$ **= new gray value.**

$I_{i,j}^{t}$ **= current gray value.**

l **= weight value (0.25 for four pixel neighborhood).**

C_x = **directional diffusion coefficient, subscript *x* indicates direction (North, South, East, and West), function of the directional gray value gradient.**

$\nabla_x I$ = **directional gray value gradients (gray value of neighboring pixel minus current pixel)**

The location of edges is unknown. As a simple estimate, the directional gray value gradients C_x **are used, denoted as *c(s)*, where *s* =** $\|\nabla I\|$**, termed "edge-stopping" function; the behavior of the anisotropic diffusion depends heavily on the choice of the edge-stopping function. There are many edge-stopping function forms have been introduced, the most common diffusivity function form is introduced by Perona and Malik (1990) [5]:**

$$c\ (s) = e^{-\left(\frac{s}{K}\right)^2} \qquad \dots (5)$$

Where *K* = determine the magnitude of the edges to be preserved and rate of diffusion. With low values of *K*, small gradients can block diffusion, whereas high values admit diffusion in areas with relatively big gradients. The exponential form privileges high-contrast edges over low-contrast ones.

2.3 k-means Clustering

The *k*-means clustering algorithm was used in the segmentation process [2, 4, 7]. It was the most common algorithm used to cluster pixels into number of clusters representing the texture regions.

- **k-means algorithm:**
  - **Begin with an initial set of cluster means.**
  - **Every element in the set is assigned to the nearest cluster center.**
  - **The center of each cluster is re-averaged based on its constituents.**

The process of reassignment and re-averaging repeats for some predefined number of iterations or until the number of reassignments falls below some threshold.

3. Evaluation

Image segmentation is an important process of image analysis. It consists of subdividing an image into its constituent parts and extracting these parts of interest (objects). To characterize the quality of segmented image and the performance of applied algorithms, certain judging criteria are needed. In this paper the objective and quantitative criteria as discussed in [8, 9] are used. Let R_f denote the feature value obtained from a reference image and S_f denote the feature value measured from the segmented image, the performance criteria, which are called Ultimate Measurement Accuracy of an object feature (UMA) can be computed by:

$$UMA = | R_f - S_f | \qquad \dots (6)$$

Zhang [8] has been shown that among all group of existing criteria for segmentation evaluation and comparison, the group with UMA is the best to precisely judge the quality of segmentation results. The values of UMA are inversely proportional to the segmentation results: the smaller the value, the better is the quality (regarding to the feature used). I select the energy measure for the feature measure. Energy measures texture uniformity. High energy values occur when the gray level distribution over the window has either a constant or a periodic form. The energy equation from [7] is:

$$ENE = \sum_{i=1}^{N}\sum_{j=1}^{N} p^2(i,j) \quad \text{... (7)}$$

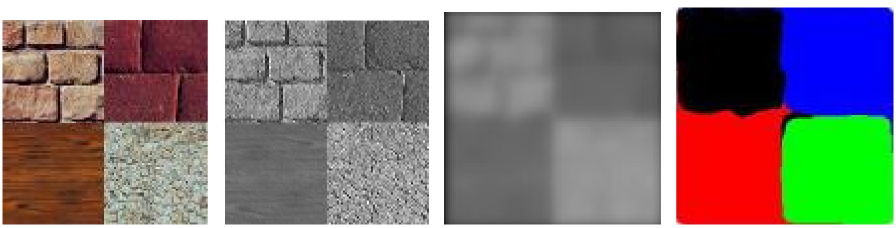
Where, $N \times N$ iis the size of image *p(i,j)*.

4. Experiments

The proposed method was applied against a number of popular textured images in order to demonstrate its performance.

Fig 1 (a) shows origin image (256 × 256) obtained from Brodatz album [10]. Fig 1 (b) shows the filtered image by Gabor filter with the parameters mentioned above. Then the anisotropic diffusion filter was applied to give the image shown in fig 1 (c). The optimal value of parameters (K= 100 and the iteration =20) were searched until a good segmentation result was achieved. Finally fig 1 (d) shows the segmentation result after clustering. From fig (1) it can be seen that the texture boundaries are well localized to some extent. However, we do not get sharp localization due to the smoothing that is done in the anisotropic diffusion filter.

To see if smoothing is really producing a better result, the segmentation of the same image without smoothing was tested. The result is shown in fig (2). The effect is clear and shows that smoothing suppresses the variations in the texture features within the same texture. Non-smoothed segmentation is severely affected by this variation and the result suffers from non-contiguous labeled regions as in the smoothed case.



(a) (b) (c) (d)

Fig 1: (a) Origin image (256×256) containing four natural textures from the Brodatz album. (b) A filtered image using Gabor filter. (c) The image after applying anisotropic diffusion. (d) Four category segmentation.

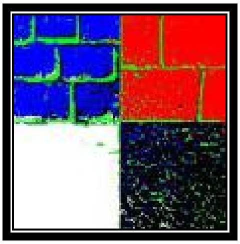


Fig (2) Effect of non-smoothed segmentation

A comparison between Seo [4] texture segmentation method and the proposed method was done against multiple texture images. The segmentation results of the two methods shown in fig (3). From this figure it's clear that Seo method cannot delineate the texture completely. Also Seo method gives noisy segmentation results suffers from non-contiguous labeled regions. While the proposed method gives better segmentation results.

The two methods are unsupervised technique, but they still needed to supervise the number of segments (i.e. choosing suitable starting points for the k-means algorithm). In order to overcome k-means initialization dependent, the two methods will be run several times to obtain good results. The proposed method might resolve this problem by decreasing the number of run times over the Seo method as shown in table (1). This is because of using another feature extraction criterion.

The performance of the proposed method compared with the Seo method can be measured using the Ultimate Measurement Accuracy (UMA) metric (equation 6). Table (1) shows a comparison of the UMA metric results between Seo method and the proposed method. From this table it's clear that the segmented images using the proposed method have the highest quality (smaller values of UMA metric) over the segmented images using the Seo method. This means that the proposed method give results better accurate from the Seo method.

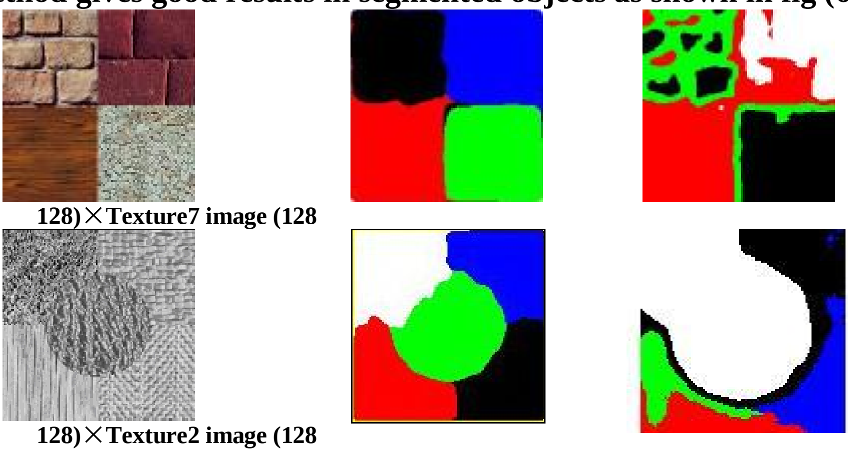
Because of extracting information using different filters, the proposed method is capable of separating a large number of

textures. Also, this creates a better separation of statistical and structural patterns. Fig (4 a) shows two sample images the first is a random mosaics texture image and the second is an area of roofs and ground image, fig (4 b) shows the segmented images using the proposed method .

To evaluate the performance of the proposed method on real images, nuclei in pathological image of the prostate was segmented using the Seo method and the proposed method. A typical sample and its segmentations are shown in Fig (5). From this figure it can be seen that the segmented image using the proposed method (fig 5 (b)) gives accurate segmented result with (UMA= 1.9378×10^{8}) from the segmented image using the Seo method (fig 5 (c)), with (UMA= 2.9213×10^{8}).

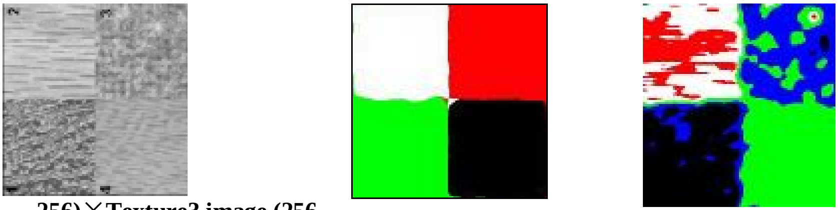
The proposed method worked reasonably fast, 7.201 seconds, for 128×128 sized images, but took 23.9688 seconds for 256×256 sized images. While the Seo method took 6.8906 seconds for 128×128 sized images and 24.6563 for 256×256 sized images.

The distinguishing of objects from background is one of the important fields in segmentation researches. Therefore this method gives good results in segmented objects as shown in fig (6).

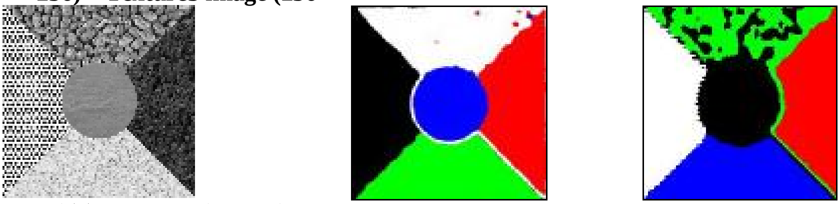


(a) (b) (c)

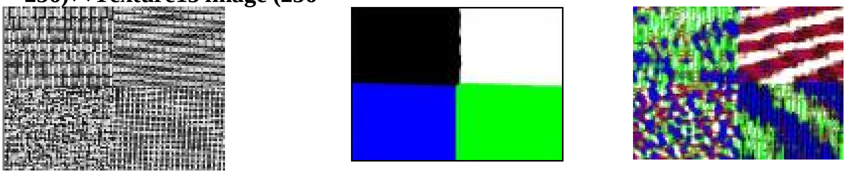
Fig(3):(a)multiple natural textures images from the Brodatz album.(b) segmentation results using the proposed method.(c) segmentation results using Seo method.



256)×Texture3 image (256



256)×Texture15 image (256



308)×Texture1 image (416

165)×Texture10 image (165

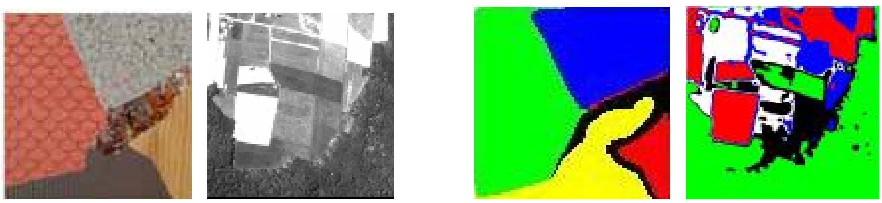
Texture11 image (162×80)

(a) (b) (c)

Fig(3):(a)multiple natural textures images from the Brodatz album.(b) segmentation results using the proposed method.(c) segmentation results using Seo method (continue).

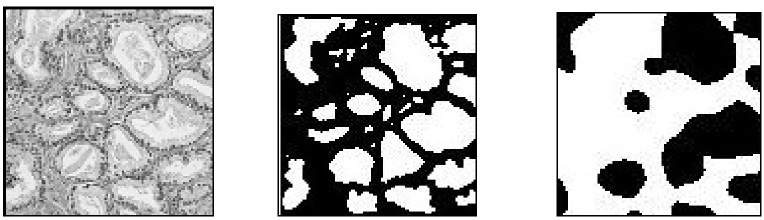
Table (1) a comparison of UMA metric results and no. of run times between Seo and the proposed method.

Image	Seo method		The proposed method	
	No. of run times	UMA $10^8\times$	No. of run times	$10^8\times$UMA
Texture1	7	9.2934	2	6.0510
Texture2	7	3.1093	2	1.6731
Texture3	6	8.4064	3	6.7043
Texture7	6	0.6360	2	0.3687
Texture10	2	9.3901	1	1.1017
Texture11	2	2.1226	1	1.0231
Texture13	2	3.1713	1	2.9364
Texture14	1	2.7849	1	1.0413
Texture15	6	8.1606	4	4.3556
Average	4.333333	5.230511	1.888889	2.806133



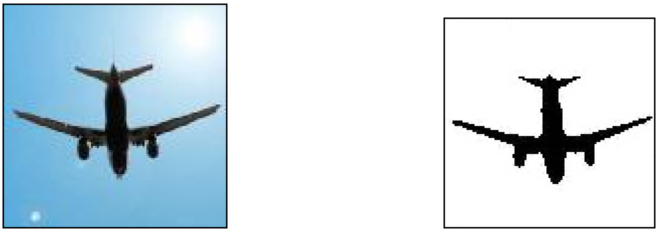
(a) (b)

Fig (4): (a) two original images (512 $\times$512), (b) segmented images using the proposed method.



(a) (b) (c)

Fig (5): (a) Origin image (128$\times$128), (b) segmented image using the proposed method, (c) segmented image using Seo method.



(a) (b)

Fig (6): (a) "airplane" original image (256$\times$256), (b) object segmentation image

5. Conclusions

In this paper the multi-channel method to the texture segmentation problem was demonstrated and evaluated. The multi-channel filtering approach attempts to tune multiple filters at different spatial-frequencies and orientations to capture key texture information through separate channels. Well known classes of filter that have joined spatial and spatial-frequency localization are Gabor filters. Gabor filter bank covering the spatial frequency domain that it can decompose an image into multi-resolutions that correspond to different texture characteristics.

Extraction of texture information from filter responses can be done in several ways. In this paper anisotropic diffusion filter was proposed for feature extraction step. This filter has many characteristics that will success the segmentation process. The nonlinearity characteristic, both the black and light area in the images can be detected. So that it is important to localizing the boundaries between regions. Smoothing resulted in suppressing the variations within the same texture region in the output image, thus enhancing the segmentation process significantly. However, care has to be taken not to over-smooth the outputs so that correct localization of the texture edges can be achieved. Thus diffusing the texture feature space enhances the contrast between the textons, and smoothes the textured areas so that the relative contrast of the real segments increases. k-means clustering algorithm was then invoked to perform the segmentation.

Experimental results show that the proposed method was effective, accurate, and gives better segmentation results as compared with Seo method. The smaller the values of UMA metric, the better are the quality of the segmented images using the proposed method. It can be seen from experiments that the value of UMA metric for the segmented images using the proposed method is less than by 2.424378 as an average from the segmented images using the Seo method. Also the number of run times to get better segmented images using the proposed method is less by 2.444444 as an average from the segmented images using the Seo method.

The performance of the proposed method is effective, because the capability of separating a large number of textures, and of segmented real images, random mosaics texture images, area of roofs and ground images, and to distinguish objects from background.

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تقسيمِ نسيج الصورةِ باستخدام مرشِحِ غابور ومرشِح انتشار أنيزوتروبيك

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المستخلص

تقسيم الصورة عملية مهمة جدا في العديد من تطبيقات تحليل الصور ورؤية الحاسبة. في هذه البحث تم اقتراح طريقةِ تقسيمِ نسيج الصورةِ باستخدام مرشِحِ غابور ,ومرشِح انتشار أنيزوتروبيك ،و خوارزميةً العنقدة k-meanْ. مرشح غابور أستخدم كمرشح متعدد القنوات لتحليل النسيج في الصورة. عملية استخلاص وتحسين خصائص النسيج تم باستخدام مرشِح انتشار أنيزوتروبيك. ثم تم استخدام خوارزمية العنقدة k-mean لتجميع نقاط الصورة إلى عناقيد تمثل مناطق النسيج في الصورة.

نوعية التجزئة باستخدام هذه الطريقةِ تم تقيُيّمه باستخدام مقياس الدقة UMA. التجاربُ ترينا أن انجاز هذه الطريقة فعال وأنها أعطت نتائج تقسيمُ دقيقةُ وأفضل مقارنة مع طريقة Seo من ناحية نوعية التجزئة، عدد مرات التنفيذ، زمن التنفيذ والقدرة على تجزئة عدد كبير من الأنسجة وتجزئة صورة حقيقية، صور الفسيفساء، صور المناطق السقوفِ والصورِ الأرضيةِ، ولتَمييز الأجسامِ مِنْ الخلفيةِ.

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