International Journal of Information Technology, Vol. 11, No. 7, 2005

Automatic Detecting Particle Objects in Image

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Abstract

The aim of urine clinical examination is to identify the pathology components and diagnose diseases of the urology system. It is necessary to realize automatization in the field of microscopic analyzer of urine solution. Detecting particles in the microscopic image is much more difficult because the particles has irregular shape and blur edge. This paper briefly discusses image segmentation and the particles detecting. We present a new robust method for the problem of automatically detecting the particles' location in images. We use Gabor-based feature to enhance the edge information and present a region potential term based on the classical iterative combining iterative method. Following an edge-linking procedure, the regions of objects can be bounded by closed boundaries.

Keyword: Gabor-based filter, image segmentation, detecting particles, microscopic analyzer.

1 Introduction

The urine clinical examination is to check the quantity and sorts of urinary sediments under the microscope. Its aim is to identify the pathology components such as white cells, red cells, casts, crystals, and other particles in urine. And this can help to diagnose the diseases of the urology system. In clinic diagnosis, the traditional examining method is that checkers watch particles in microscopic image under the microscope and judge the kinds and amounts of particles. Usually, the results are estimated because the quantity of checked samples is very large and the examination is burdensome and tend to be made mistakes.

Nowadays there is growing interest in the automatic object detection. People make great progress in automatically detecting human face and iris images. With the development of artificial intelligence and computer technology, especially the development of automatic recognition technology, automatic microscopic analyzer of urine solution in the medical field will certainly instead of the manual work.

With the automated urine microscopic analyzer, you don't centrifuge the urine sample, so you don't have to go through a lot of preparation and have no pollution.

The only thing you should do is to put the sample on the analyzer. The particles will be detected and classified by the automatic recognition system. The IRIS Company of American has invented the IQ200 automated urine analyzer to realize it [1]. But its effect is not as good as it predicts. Some particles such as long casts, bacteria etc. will be difficult to be detected and acquired complete silhouette from image. This will have a severe problem in automatic microscopic analyzer of urine examination.

The study of detecting and recognition in microscopic images is becoming of increasing practical importance [2], [3]. The researchers have made great progress in particles recognition. They focused on measurement and identification of various features such as area, eccentricity, compactness, area of central pallor, nucleus position, number of nuclear lobes, nucleus cytoplasm ratio and color of nucleus and cytoplasm. But detecting special particles is more important than recognition in the microscopic field, because no detecting no recognition. The urine sediments in microscopic image are very small and possess irregular shape. The image itself is fuzzy and illumination is not uniform. The edge of urine sediment particles (especially helical cast, see Fig2.) is not very clear.

In this paper we use Gabor-based combining iterative method to segment the particles from the image. The Gabor wavelet representation captures salient visual properties such as spatial localization, orientation selectivity, and spatial frequency characteristic. Gabor filters [4] are very attractive due to their optimal localization properties both in spatial and in spectral domain. According to the well-known uncertainty principle, the product of the spatial and the spectral support of a filter have a lower bound. Because Gaussians and modulated Gaussians (Gabor functions) [5] can achieve such a lower bound, they are very useful in many spectral analysis tasks such as image representation. Chengjun Liu [6], [7] based on the 2D Gabor wavelet representation and the labeled elastic graph matching has recently shown that the Gabor wavelet representation is optimal for classifying facial actions. This paper succeeds in detecting particles image by Gabor feature combining iterative segmentation.

Section 2 of the paper concentrates on the Gabor-based principle. In section 3, we underline the idea of iterative segmentation algorithm. In section 4, we show the experiment results of segmentation and detecting in microscopic image. We draw a conclusion in section 5.

2 Principle

2.1 Garbo Filter

Gabor wavelets were introduced to image analysis due to their biological relevance and computational properties. The Gabor wavelets, whose kernels are similar to the 2D receptive field profiles of the human cortical simple cells, exhibit desirable characteristics of spatial locality and orientation selectivity, and are localized optimally in the space and frequency domains.
The Gabor wavelets can be defined as follows [3], [6]:

$$\psi_{m,l}(z) = \frac{\|k_{m,l}\|^2}{\sigma^2} \exp(-\frac{\|k_{m,l}\|^2 \|z\|^2}{2\sigma^2})(\exp(ik_{m,l}z) - \exp(-\sigma^2 / 2)) \tag{1}$$

where m and v define the orientation and scale of the Gabor kernels, $\|\cdot\|$ denotes the norm operator, and the wave vector $k_{m,l}$ is defined as follows:

$$k_{m,l} = k_m e^{i\phi_l} \tag{2}$$

where $k_m = k_{\max} / f^m$ and $\phi_l = \pi l / 8$. $k_{\max}$ is the maximum frequency, and f is the spacing factor between kernels in the frequency domain.

The Gabor kernels in Eq.(1) are all self-similar since they can be generated from one filter, the mother wavelet, by scaling and rotation via the wave vector $k_{m,l}$. Each kernel is a product of a Gaussian envelope and a complex plane wave, while the first term in the square brackets in Eq.(1) determines the oscillatory part of the kernel and the second term compensates for the direct current(DC) value. The effect of the DC term becomes negligible when the parameter σ, which determines the ratio of the Gaussian window width to wavelength, has sufficiently large values.

In most cases one would use Gabor wavelets of five different scales, $m \in (0,1,2,3,4)$, and eight orientations, $l \in (0,1,2,3,4,5,6,7)$. We can show the real part of the Gabor kernels at five scales and eight orientations and their magnitude, with the following parameters: $\sigma = 2\pi$, $k_{\max} = \frac{\pi}{2}$, $f = \sqrt{2}$ and the kernels exhibit desirable characteristics of spatial frequency, spatial locality, and orientation selectivity.

2.2 Feature Representation

Let $I(x, y)$ denote an input image, the Gabor wavelet representation of the image is the convolution of the image with a family of Gabor kernels as defined by Eq. (1). The convolution of the gray level distribution of an image $I(x, y)$ and a Gabor kernel $\psi_{m,l}(z)$ is defined as follows:

$$O_{m,l}(z) = I(z) \otimes \psi_{m,l}(z) \tag{3}$$

Where $\otimes$ denotes the convolution operator, and $O_{m,l}(z)$ is the convolution results corresponding to the Gabor kernel at orientation m and scale l. Therefore, the set $S = \{O_{m,l}(z) : m \in (0,1,2,3,4,5,6,7), l \in (0,1,2,3,4)\}$ forms the Gabor wavelet representation of the image $I(z)$.

In order to select spatial scales, spatial localities, and orientation selectivity, we should normalize $O_{m,l}(z)$ to zero mean and unit variance.

We derive a feature vector χ , we down sample each $O_{m,l}(z)$ by a factor ρ , the Gabor feature vector $\chi^{(\rho)}$ is then defined as follows:

$$\chi^{(\rho)} = \left(O_{0,0}^{(\rho)^t}, O_{0,1}^{(\rho)^t}, \cdots, O_{4,7}^{(\rho)^t} \right)^t \tag{4}$$

where t is the transpose operator.

We select features of the images based on Gabor filter. It has two steps as follows:

1. Estimate the approximate range of eigenvalue by testing some samples.
2. Determine scales and orientations. Set $l = 8, m = 5$, in the series of Gabor filters, there are different scales and orientations which are about 5×8=40 filters.

3 Detecting Particles in Image

Generally, the gray distribution of the original background is not uniformity, and the contrast between the object and background may vary in the image. The edge of particle objects in image is fuzzy. After processed by the Gabor amplitude filter, the particles in image can be segmented based on iterative method as followings.

3.1 Initial Segmentation

A threshold is determined from the average intensity of high gradient pixels in the obtained intensity image. This threshold is used to find approximate object boundaries.

First we should judge whether the pixel point is the border point of object. If we know it’s a border point but we don't know which border point of four borders it should belong to. In order to do this, we can search for steep points along the image edge. When the border point was found along the X-axis and Y-axis respectively, we will keep the coordinates of point. If the point is not found, our aim is to decide whether it is a border point of the region which the objects locate. Through determining the coordinates of a single object region, we mainly find pixel value distributing inside the region. Initial segmentation is ended which draw outline around the object.

3.2 Region Restriction

Let T_0 denote the value which is the medium range of image as initial threshold.

$$T_{i+1} = \frac{1}{2}\left\{ \frac{\sum_{k=0}^{T_i} h_k \cdot k}{\sum_{k=0}^{T_i} h_k} + \frac{\sum_{k=T_i+1}^{L-1} h_k \cdot k}{\sum_{k=T_i+1}^{L-1} h_k} \right\} \tag{5}$$

h_k is the pixel number of which gray value of image is k .And iterative process will be ended at $T_{i+1} = T_i$ .Set the ending value T_i as segment threshold. The iterative times i are determined by the segmentation experiments which detect the border point of object.

A region boundary is refined using edge information in the image. This involves initializing a closed elastic curve at the approximate boundary, and shrinking and expanding it to fit to the edges in its neighborhood. All over the image vertical coordinate and abscissa to do the same things for objects. We can merge the same region into a restriction area. The merge order must select nearest frames through comparing the area of the region. When single region is satisfied with the condition, we may record with pointer data and resume current coordinate. Finally we can segment the image through the steps of finding border points, drawing frame, merging into a region.

3.3 Detecting Pattern

In this case, classify the value space of eigenvalue to fix region, weight region and hiding region. It shows in Fig.1. We use simple combination (such as "or" operator) to determine the eigenvalue at fix region. Certain eigenvalue even has no fix region. It is important to determine this region especial to recognizing process. We should set weight value for other eigenvalue at weight region. We often select most effective eigenvalue to express the samples. We set that it's of insignificance at hiding region. Critical value is the limited value between each two regions. Its value is determined by the test.

Each input image is scanned with a rectangular window to determine whether particles exist in the image or not. The decision rule for deciding whether an input window contains a particle or not is based on maximum likelihood as following:

$$X^* = \arg\max P(y / X_i) \tag{6}$$

To detect particles of different scales, each input image is repeatedly subsampled by a factor and scanned through for a few iterations.

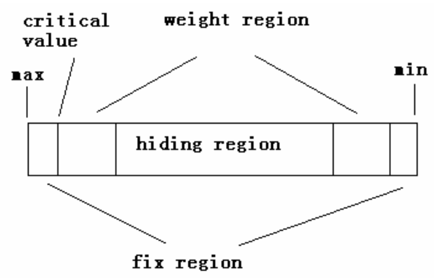


Fig. 1. The eigenvalue region

4 Experimental Results

We focus on the extraction of particles in Fig.2. The interest objects need to be segmented from the background. This is particularly difficult due to the presence of fuzzy edge of cast. Cast boundary may be merged with background. Through the above segmentation algorithm, we can get better segmentation object from the background. A segmentation method is usually designed taking into consideration the properties of a particular class of images.

For training, we select a number of images which contain one or more casts and other particles. In our implementations, all algorithms are programmed in the VC++6.0 language and executed on PIV computer. Experimental results are provided to illustrate the correction of this object detection method. A brief description of these images is given below.

Fig.2 is an original image which contains a cast, an epithelium and a white cell. We adopt general method [8] scanned all the pixels in the image through edge operator with morphologic method. Fig.3 illustrates the result of detecting particles by self-adaptive segmentation method [8] without Gabor-based. From the figure we can see that detecting method can accurately select the locality of epithelium and a white cell. But for cast, it has a bad result. Because cast itself is very complex in its shape and its edge is not very clear. Part of cast edge is fuzzy and confused with background. The rule of detecting particles is to combine much more particles as much as possible. If the outline windows can't cover the particles, it is impossible to segment particles from the image. The recognition rate is determined by whether the segment method is better or not.

Fig.4 shows the result of original image convolution Gabor filter. Its scale and orientation is respectively $l = 1, m = 0$. We select the amplitude image of Gabor filter. Fig.5 illustrates the grey image convert two-value image through threshold 74 adjusting iterative times and range.

Fig.6 shows the detecting result of two-value Gabor image. It selects the silhouette of the cast correctly and completely. From the result we can see that the proposed method is good to detecting long cast particle. Fig.7 is the detecting result of the original image. Though the edge of cast is fuzzy and not uniform, Gabor-based combining iterative method can automatically determine and detect the cast without any manual help.

Fig. 2. The original image

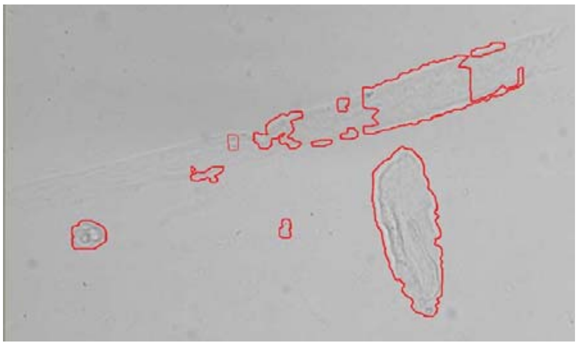


Fig. 3. Self-adaptive segmentation method

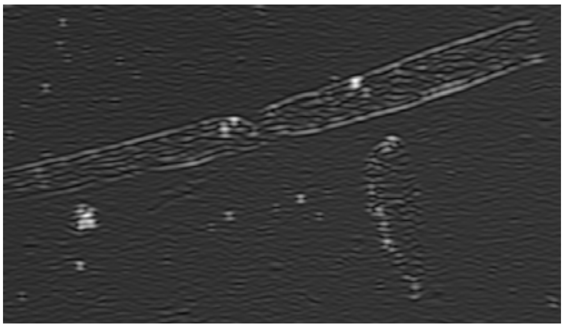


Fig. 4. Gabor-based image(l=1,m=0)

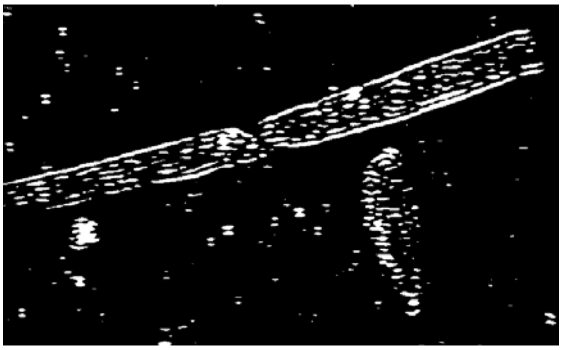


Fig. 5. The two-value Gabor image(threshold is 74)

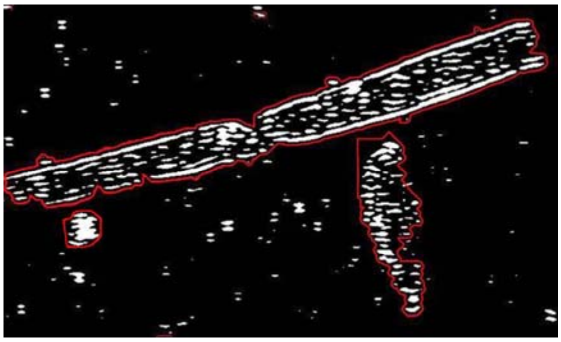


Fig. 6. The Segmentation result of Fig. 5

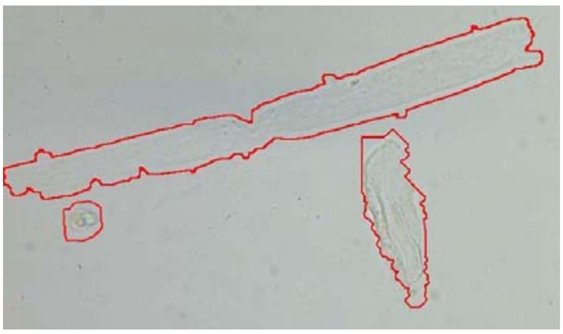
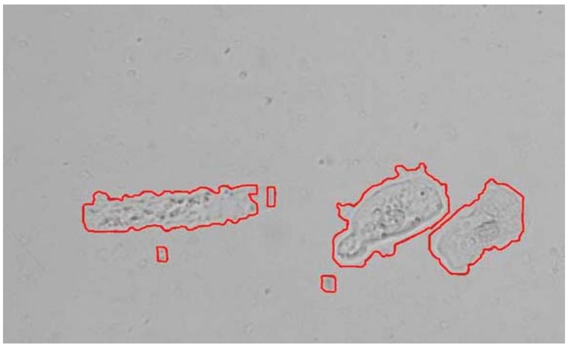
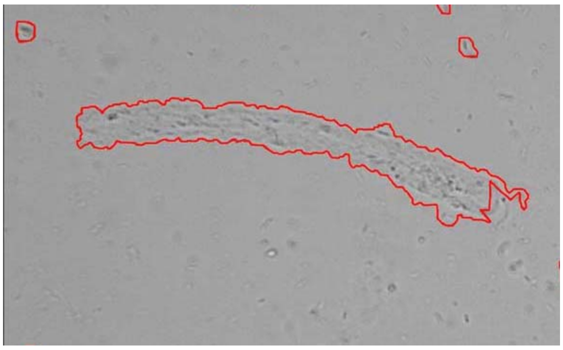


Fig. 7. The detecting result of original image



(a)



(b)

Fig. 8. The detecting result of other images

Fig.8 is the detecting results of other microscopic images. From the image we can see that the particles can be selected very well though the gray distribution is not so good and the edge of particles is not very clear. This segmentation algorithm based on Gabor filter is better than ever and succeeds in detecting particles application.

5 Conclusions

The traditional segmentation techniques such as gray threshold and region growing are based on gray-level or texture similarity of segmented regions. These approaches only work well for images with measurable homogeneous properties. A new robust method using automatic segmentation has been presented in the paper. Through Gabor-based combining iterative method, a threshold is determined from the average intensity of high gradient pixels in the obtained intensity image. We focus on the extraction particles such as long casts in microscopic images. It is proved that the proposed approach to the object detection problem is better than ever.

Experiments on 30 visual images including gray images have shown that the proposed method can achieve correct segmentation. As seen in the figures of section

4, self-adaptive segmentation techniques [8], [9] can't cover long-shape cast in the closed boundaries produced. Using the proposed Gabor-based algorithm should generate much more accurately bounded regions of objects according the size of objects. Overall, the paper segmentation algorithm is a feasible approach for segmenting and detecting particles in images. After the effective segmentation, the particle objects can be easily determined and recognized.

Acknowledgements

This project is supported by the Science and Research Foundation of the Jilin Province. The research described in this paper is corporately carried out with the Dirui Co. of Changchun. The authors wish to express their sincere thanks to Pengfei Qu and Jiuchuan Tang for their programming and experimental assistance.

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