Proceeding of the IEEE
International Conference on Robotics and Biomimetics
Dali, China, December 2019

Research on a New Feature Detection Algorithm for Wireless Capsule Endoscope Bleeding Images Based on Super-pixel Segmentation

Zengcao Liu[1]
Department of Control Science and Engineering,
Zhejiang University ,
310027,Hangzhou,China,
21832157@zju.edu.cn

Chao Hu[2,*]
Ningbo Institute of Technology,
Zhejiang University,
315100,Ningbo,China
huchao@nit.net.cn

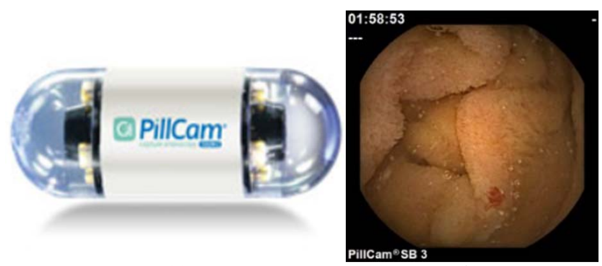
Zheng Shen[2]
Electrical Engineering and Automation
Jiangxi University of Science and Technology ,
341099,Ganzhou,China,
879322358@qq.com

***Abstract* - Gastric hemorrhage is the manifestation of many digestive tract diseases. The traditional gastroscope detection has the disadvantages of insecurity, discomfort and unsanitary. As a new type of detection technology, wireless capsule endoscope (WCE) overcomes the defects of traditional gastroscope detection. But in the process of detection, due to the frequency of 2 frames per second, a huge amount of pictures will be generated. It is unreasonable to rely on doctors to manually screen images of gastric bleeding from massive pictures. Therefore, there is an urgent need for a high standard of computer-aided medical technology. Based on this purpose, our paper proposes a new detection feature, the RG coefficient of variation of super-pixel block, which is used to automatically detect gastric hemorrhage. Firstly, the super-pixel segmentation method SLIC is used to segment the images, which preserves the homogeneity and edge information of the pixels in the region. Secondly, the new detection features are extracted from the super pixel blocks, compared to the traditional color features and the currently widely used color detection features. K-fold cross validation is performed on our data set. Finally, by using the new detection features proposed in our paper, the accuracy of the detection is improved by 4.13%, the sensitivity is improved by 7.5% and the miss detection rate is actually reduced. Achieve the automatic screening of suspicious bleeding images under the condition of ensuring high standards, and reduce the diagnosis time.**

Index Terms - wireless capsule endoscope; gastric hemorrhage; SLIC; coefficient of variation.

I. INTRODUCTION

With the development of society and fast-paced lifestyle, most people are facing environmental pollution, work pressure and unreasonable eating habits, which will damage their health and cause digestive tract diseases. Gastric hemorrhage is the manifestation of many gastrointestinal diseases. As a new type of gastrointestinal disease detection technology, wireless capsule endoscope (WCE), as shown in Figure 1 (a), is similar in size to ordinary capsules, and moves with the help of gastrointestinal peristalsis, overcoming the defects of traditional mechanical endoscopy. It's safe and sanitary, avoiding the pain brought to patients. It has been used in many hospitals. However, since the frequency of the image captured by the wireless capsule endoscope is 2 frames per second, 50,000 to 60,000 images will be generated during the operation. And the number of pathological pictures is very small, accounting for about 5% - 10% of the total number of pictures. Therefore, it is a time-consuming and tedious job to diagnose by doctors alone, and the eyesight fatigue of working for a long time will easily lead to misdiagnosis and missed diagnosis. In order to reduce the labor intensity and avoid the waste of medical resources, it is a key problem to be solved to study a set of computer-aided detection software which can accurately and automatically screen the image of gastric hemorrhage. The purpose of our paper is to study a detection algorithm of gastric hemorrhage image based on wireless capsule endoscope.



(a) (b)
Fig. 1 Wireless capsule endoscope and gastric bleeding image

At present, research methods for gastric hemorrhage detection are roughly classified into three types: image-based detection method, pixel-based detection method, and image block-based detection method. The image-based detection method is to extract features from an entire image. Cui et al. [1] calculated the low-order color moments of the H, S, and I channels of the entire image in the HSI color space, and classified them as features using SVM. Although the image-based method has a faster detection speed, when the abnormal area occupies a small image area, there will be a missed detection of the abnormal image. Pan et al. [2] extracted the color features of each pixel in the RGB and HSI color spaces, and used the probabilistic neural network to classify the pixels. Huang et al. [3] obtained the RGB color features of each pixel and used EM clustering to classify the pixels. But only for a 240×240 image, the number of pixels is 57600, which will lead to high computational complexity and long recognition time. In order to reduce the missed detection of small images of bleeding area, image block-based detection method is adopted.

*Corresponding author: Chao Hu

978-1-7281-6321-5/19//$31.00 ©2019 IEEE

Baopu Li et al. [4, 5] divided the image into 30*30 image sub-blocks and selected 36 sub-blocks with the most valid information to study. However, this method simply divides the image into a fixed number of rectangular blocks, which will lose the edge semantic information and local feature information of the image itself.

Ren et al. [6] proposed the concept of super-pixel in 2003. Super pixel refers to the image block composed of adjacent pixels with similar texture, color, brightness and other characteristics. As a key technology in the field of vision, there are many methods of super-pixel segmentation. Achanta et al. [7] proposed the SLIC algorithm, which clusters the pixels into super pixels according to the relationship between the color similarity and the distance between pixels. The smaller the distance between pixels and the closer the color information, the more likely the two pixels are to be divided into one super pixel. It is mainly realized by two steps of initialization seed point and pixel point clustering, which avoids the curve evolution to find similar pixel points and reduces the time cost and obtains good segmentation effect.

II. SLIC And Color Features Analysis

Super-pixel segmentation based on SLIC algorithm. For the size of super-pixel, if the size of super-pixel is too large, the bleeding symptoms of small areas cannot be detected. If the size of super-pixel is too small, the time of super-pixel block produced by each image will increase, which will affect the processing speed of the whole algorithm. In our paper, multi-dimensional experiments are carried out on multiple images. Among them, the segmentation effect of gastric bleeding image in Fig. 1 (b) is shown in Fig. 2:

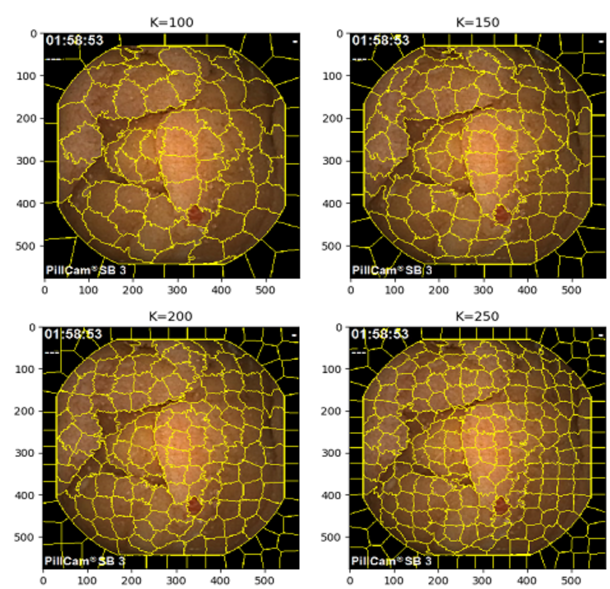


Fig. 2 The rendering of gastric bleeding image using the SLIC algorithm

It can be seen that the bleeding area divided by K = 100 and K = 150 still contains other components, while the bleeding area divided by K = 200 is a single area. The effect of K = 250 is the same as that of K = 200, but the number of the whole super-pixel blocks will increase. So in our paper, each image is divided into 200 super-pixel blocks, which can effectively segment the bleeding area, and better maintain the boundary information of the image, so that the pixels in each super-pixel block have homogeneity. Fig. 3 is a partial bleeding super-pixel block after segmentation, and Fig. 4 is a partial non-bleeding super-pixel block after segmentation.


Fig. 3 Partially bleeding super-pixel block after segmentation


Fig. 4 Partially non-bleeding super-pixel block after segmentation

Super-pixel segmentation is the first step of our paper. In order to accurately detect the super-pixel blocks of bleeding and recognize the images of gastric bleeding, it is necessary to extract the relevant description features of the super-pixel blocks as input for the machine to learn. There are many features to describe the super-pixel block. However, as the basic unit of classification, the size of each super-pixel block fluctuates between dozens to hundreds of pixel points. Considering the small size, irregular shape and lack of texture information, it is difficult to describe the super-pixel block with ordinary features. Therefore, when selecting the description features, we should try to select the statistical features that are independent of the shape and size of the super-pixel block. Considering that most doctors diagnose bleeding by color, our paper uses the color feature of super-pixel block as the description feature.

In different color spaces, the color features extracted from the image will make a difference. Therefore, it is necessary to find a color space that conforms to the human vision system, and the features extracted in this color space can better describe the images. RGB is the most basic and commonly used color space in the practical application of image processing. Many other color spaces are converted by RGB color space. And the RGB color space represents an image with three basic colors: red (R), green (G), and blue (B).

In the RGB color space, which statistical feature of the color can be very descriptive to the image. In [8], the first-order histograms of statistical features such as mean, standard deviation, entropy, skewness, and energy values are used to represent various performance index values of the image. These statistical features in [9] show a good description for image classification and analysis. Therefore, we first consider the color mean of bleeding and non-bleeding super-pixel blocks as the feature in each channel of RGB. Figure 5 shows the distribution of the color mean of each bleeding and non-bleeding super-pixel block under each RGB channel. It can be seen that, whether in R channel, G channel or B channel, the color mean of bleeding super-pixel block overlaps the color mean of non-bleeding super-pixel block. So it is meaningless to consider the color mean of each RGB channel as the detection feature.

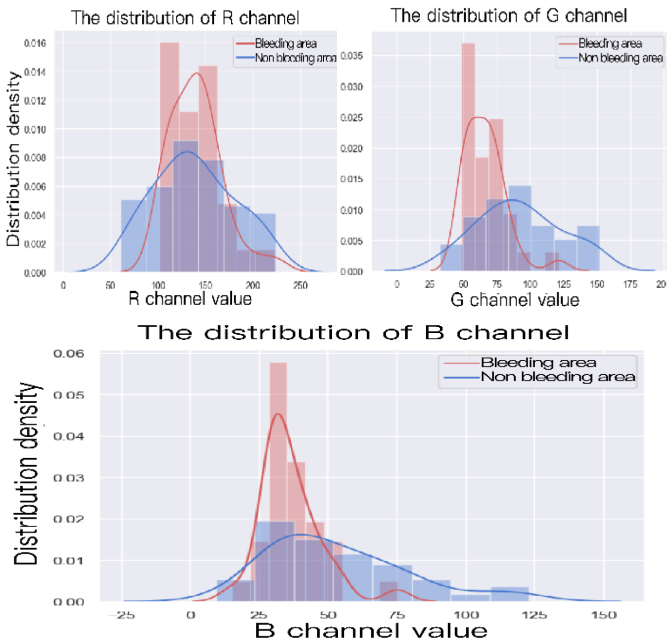


Fig. 5 Average pixel frequency distribution of super-pixel blocks for each RGB channel

As one of the common statistics in data analysis, coefficient of variation has the advantage of statistical characteristics. The coefficient of variation can reflect the relative change degree of a group of data, and it is an important measure index to reflect the dispersion degree of sample data. It is often used to compare the difference of relative quantity between the same type of things. Standard deviation can objectively and accurately reflect the dispersion degree of a group of data, but for different items, or different samples of the same item, standard deviation is lack of comparability. As a relative variation index, the coefficient of variation can solve this problem very well. Moreover, as a dimensionless variable, when comparing the data with different dimensions or different mean values, the coefficient of variation can reflect the characteristics of different color mean values in each bleeding and non-bleeding area. Therefore, the color features of coefficient of variation for super-pixel block have generalization and robust adaptability. The formula for the coefficient of variation is as follows:

$$\mu_{ki} = \frac{1}{n}\sum_{j=1}^{n} h_{kij} \tag{1}$$

$$\gamma_{ki} = \frac{\left(\frac{1}{n}\sum_{j=1}^{n}(h_{kij}-\mu_{ki})^2\right)^{\frac{1}{2}}}{\frac{1}{n}\sum_{j=1}^{n} h_{kij}} \tag{2}$$

Where, μ_{ki} and γ_{ki} respectively represent the mean and coefficient of variation of the super-pixel block under the i -th color channel of the k -th super-pixel block, and h_{kij} represents the color value of the j-th pixel in the i -th color channel of the k -th super-pixel block. n represents the total number of pixels in the super-pixel block. The distributions of coefficient of variation for bleeding and non-bleeding super-pixel blocks in RG, RB, GB two-dimensional space are shown in Figure 6. It can be seen from the figure that the coefficients of variation of bleeding and non-bleeding super-pixel blocks in RG two-dimensional space are basically not coincident. So we consider to extract the coefficients of variation of super-pixel blocks in RG two-dimensional space as detection features.

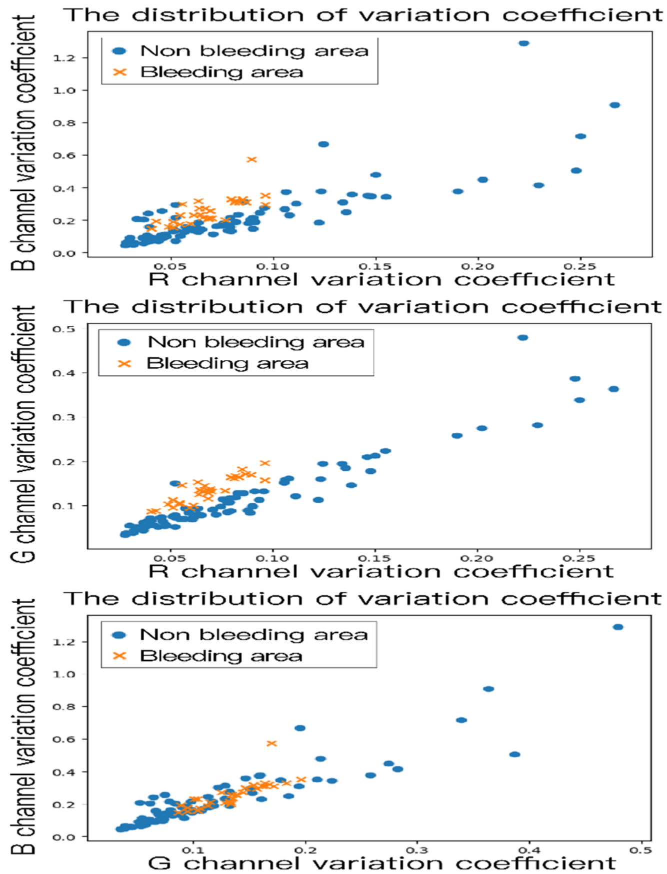


Fig. 6 Distribution of variation coefficients of bleeding and non-bleeding super-pixel blocks in RB, RG, GB two-dimensional space

At the same time, we compare the coefficient of variation and variance in RG two-dimensional space as detection features. Among them, if the RG coefficient of variation is used as the feature, the classification accuracy rate on the test set is 87.597%. And if the RG variance is used as the feature, the classification accuracy rate on the test set is only 62.791%, which is significantly lower. The advantage of the coefficient of variation as the detection feature is further verified.

In addition to the new feature proposed in our paper, there are researches on the detection features of the wireless capsule endoscope bleeding image. At present, the widely used and effective detection feature is the red purity feature proposed by Fu et al. [10]. In this paper, the distribution of some bleeding pixels and non-bleeding pixels in RGB color space is selected for statistics. Through observation, it is found that in RG and

RB two-dimensional space, bleeding and non-bleeding pixels are basically not coincident, while bleeding and non-bleeding pixels are obviously coincident in GB two-dimensional space. Based on this analysis, the red purity is defined as the color feature used to detect the bleeding area. The calculation formula is as follows:

$$F_1 = R(i)/G(i) \tag{3}$$

$$F_2 = R(i)/B(i) \tag{4}$$

$$F_3 = R(i)/(R(i)+G(i)+B(i)) \tag{5}$$

Among them, F_3 is the chroma feature of R channel, and $R(i), G(i), B(i)$ represent the red, green and blue color component values of each pixel point respectively. The chroma feature is adopted to avoid the problem that if the brightness of the light source illuminating the scene is increased, all the amplitudes of all RGB will increase by the same multiple, so that the RGB image is not affected by the brightness [11]. In our experiment, the color features of the super-pixel block are extracted. $R(i), G(i), B(i)$ are respectively represented by the mean value of the color components of each super-pixel block in the red, green and blue channels.

III EXPERIMENTS AND RESULTS

There are many kinds of classifiers, such as SVM, Decision Tree, Random Forest, AdaBoost and so on. In order to select the classifier of our experiment, we select several commonly used classifiers. On the super-pixel block dataset, we have done 5-fold cross validation. And the average accuracy of bleeding detection characterized by RG coefficient of variation is shown in the Table 1 below:

Table 1. Average accuracy of bleeding detection for each classifier - RG coefficient of variation

Classifer	SVM	Logistic	Decision Tree	Random Forest	AdaBoost
Average accuracy	95.42%	66.7%	93.8%	91.7%	93.3%

It can be seen that, with RG coefficient of variation as the feature, SVM has the highest accuracy on different data sets and the best bleeding detection effect. At the same time, refer to [10], with the red purity as the feature, SVM also has the best bleeding detection effect. Therefore, our experiment uses SVM in Sklearn software library based on Python to train and test the classifier. SVM is a machine learning method based on statistical learning theory proposed by Vapnik et al. [12], which can well deal with the recognition of small samples, nonlinear and high-dimensional patterns. For linear separable data sets, linear kernel is used. For non-linear separable data sets, the corresponding kernel functions are selected. Sklearn software library is one of the important machine learning libraries in Python. It has complete documents and has encapsulated a large number of machine learning algorithms, including LibSVM. In our experiment, SVM with radial basis function (RBF) as kernel function is used. The penalty factor is 1 and the γ value is 50. Among them, the penalty factor is the tolerance of the error. The higher the penalty factor, the more intolerable the error, that is, it is easy to over fit. However, if the penalty factor is too small, it is easy to be under fitted and the generalization ability is poor.

In our paper, the results of bleeding detection are evaluated using evaluation indexes such as accuracy, sensitivity, specificity, missed detection rate and false positive rate. These five evaluation indexes are widely used in the performance evaluation of medical image classification methods. Its definition is as follows:

$$Sensitivity = \frac{TP}{TP+FN}$$

$$Specificity = \frac{TN}{TP+FP}$$

$$Accuracy = \frac{TP+TN}{TP+FP+TN+FN}$$

$$Missed\ Detection\ Rate = \frac{TN}{TP+FN}$$

$$False\ Positive\ Rate = \frac{FP}{TN+FP}$$

Among them, TP represents the correctly classified bleeding area; FN represents the misclassified bleeding area; TN represents the correctly classified non-bleeding area; FP represents the misclassified non-bleeding area. For medical images, the specificity is the ability to find normal samples. The higher the specificity is, the more correct the normal images can be identified. The higher the sensitivity is, the stronger the ability to detect pathological images is, and the probability of missing detection is greatly reduced. Accuracy is the overall expression of sensitivity and specificity. Ideally, the values of accuracy, sensitivity, and specificity would be 100%, but this is very difficult. The main purpose of our paper is to screen out suspicious bleeding images for further diagnosis by the doctor. Therefore, it is necessary to improve the sensitivity as much as possible under the condition of ensuring high accuracy, and at the same time, it is also hoped that the rate of missed detection and false positive rate will be as low as possible.

In our experiment, 60 images of gastric hemorrhage are segmented by SLIC super-pixel method. 80 bleeding super-pixel blocks and 160 non-bleeding super-pixel blocks are selected from the segmented super-pixel blocks to form the experimental data set. The whole data set is randomly and evenly divided into 5 parts as shown in Figure 7, each of which contains 16 bleeding super-pixel blocks and 32 non-bleeding super-pixel blocks. Four parts are selected as training set, one part is test set and SVM is used as classifier to carry out five experiments to obtain the average test results with red purity as feature and RG coefficient of variation as feature, as shown in the following Table 2.

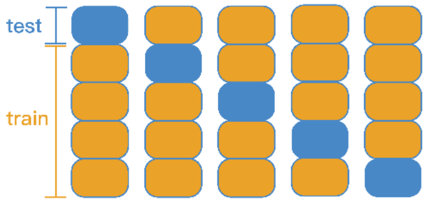


Fig. 7 Training set: test set = 4:1

Table 2. Average test results - red purity and RG coefficient of variation

	Accuracy	Sensitivity	Specificity	Miss detection rate	False detection rate
Red purity	91.67%	80%	97.5%	20%	2.5%
RG coefficient of variation	95.8%	87.5%	98.1%	12.5%	1.9%

It can be seen from the above results that in this experimental data set, five experiments are carried out with training set: test set = 4:1. Compared with the red purity as the detection feature, the accuracy of RG coefficient of variation as the detection feature is improved by 4.13%, the sensitivity is increased by 7.5%, effectively reducing the rate of missed detection and avoiding more bleeding images being identified as non-bleeding areas.

At last, we make missing judgment analysis on several images with incorrect classification. There are two main reasons:

1. There are a large number of bubbles and mucus on the surface of the stomach, which block the red area, resulting in the missing judgment of the bleeding image, as shown in Figure 8.
2. The color of the bleeding area is lighter or affected by the brightness of the surrounding area, which causes the bleeding image to be missed, as shown in Figure 9.

Fig. 8 Case one of missing judgment

Fig. 9 Case two of missing judgment

Ⅳ. CONCLUSION AND FUTURE WORK

Our experiment is based on the gastroscope images taken by wireless capsule endoscope(WCE). Firstly, select the appropriate K value and use the super-pixel segmentation method SLIC to effectively extract the bleeding super-pixel blocks. The homogeneity and edge information of the pixels in the area are preserved. On the basis of the super-pixel block, the coefficient of variation in RG color space is extracted and the contrast experiment is performed with the color mean feature, the color variance feature and the red purity feature. The data set is divided into five parts. Four parts are selected as training set, one part is test set and SVM is used as classifier to carry out five experiments to obtain the average test results of each feature. Taking the coefficient of variation in RG space as the detection feature, the effect of detecting the bleeding images is obviously improved. The accuracy of detection is improved by 4.13%, the sensitivity is increased by 7.5%, and the rate of missed detection is effectively reduced, which achieves the purpose of our research.

The future work includes the following five points:

First, our paper only analyzes a small number of selected super-pixel blocks. Under the same feature, it may not reach the results based on thousands of pixel analysis. And because the wireless capsule endoscope is passive motion, the speed and motion cannot be controlled. It is difficult to produce many high-quality images in one experiment. In the future work, while designing a better description of features, it is also important to explore ways to control the speed and motion of the wireless capsule endoscope and generate more high-quality pictures.

Second, because our paper is only trying to propose and use a new feature, in the process of machine learning, only the SVM classifier with RBF as the kernel function is simply used. Then in the future work, it is important to better adjust the parameters, find out better methods to produce a complete and high-standard computer-aided medical system.

Third, in view of the two cases of missing judgment, in the future work, we can add image preprocessing methods, such as image enhancement and adaptive threshold, to enhance the non-obvious bleeding area and eliminate the occluded bubbles.

Fourth, our paper introduces RGB color space. In the future work, we can consider the properties of different color spaces, such as HSV, CIEL*a*B.

Fifth. The images of wireless capsule endoscope also have rich texture features. In the future work, it can be considered to combine the color features and texture features to further detect the gastric hemorrhage images.

ACKNOWLEDGMENT

This research was funded by National Natural Science Foundation of China (61273332), Ningbo Sc. & Tech. plan project (2016C50003, and Innovation Team 2014B82015).

REFERENCES

[1]Cui L, Hu C, Zou Y, et al. Bleeding detection in wireless capsule endoscopy images by support vector classifier[C]//Infounation and Automation (ICIA), 2010 IEEE International Conference on. IEEE, 2010: 1746-1751.

[2]Pan G, Yan G Qiu X, et al. Bleeding detection in wireless capsule endoscopy based on probabilistic neural network[J]. Journal of medical systems, 2011，35(6): 1477-1484.
[3]Hwang S, Oh J H, Cox J, et al. Blood detection in wireless capsule endoscopy using expectation maximization clustering[C]//Medical Imaging. International Society for Optics and Photonics, 2006: 61441 P-61441 P-11.
[4]Li B, Meng M Q H. Computer-aided detection of bleeding regions for capsule endoscopy images[J]. Biomedical Engineering, IEEE Transactions on, 2009, 56(4):1032-1039.
[5]Li B, Meng M Q H. Computer-based detection of bleeding and ulcer in wireless capsule endoscopy images by chromaticity moments[J]. Computers in Biology and Medicine, 2009, 39(2): 141—147.
[6]Ren X, Malik J. Learning a classification model for segmentation[C]//Computer Vision, 2003. Proceedings. Ninth IEEE International Conference on. IEEE, 2003:10-17.
[7]Achanta R Shaji A, Smith K, et al .SLIC superpixels compared to state-of-the.Art superpixel methods [J].Pattern Analysis and Machine Intelligence, IEEE Transactions on,2012, 34(11): 2274-2282.
[8]S.Sainju, F. M. Bui, and K. A. Wahid, "Automated bleeding detection in capsule endoscopy videos using statistical features and region growing," Journal of medical systems,vol.38, no. 4, pp. 1-11, 2014.
[9]Sergyan S. Color histogram features based image classification in content-based image retrieval systems[C]// International Symposium on Applied Machine Intelligence and informatics. 2008:221-224.
[10]Fu Yanan. Research on image processing technology of wireless capsule endoscope [D]. Shandong University, 2013,付延安. 无线胶囊内窥镜图像处理技术研究[D].山东大学,2013.
[11]J. Berens, GD Finlayson, and G. Qiu. Image indexing using compressed colour histograms[C]. In IEE Proceedings on Vision, Image and Signal Processing, volume 147, pages 349-355. IET, 2000.
[12]C. Cortes and V. Vapnik. Support-vector networks[J]. Machine learning 20(3):273-297, 1995