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Automatic Detection of Tumor in Wireless Capsule Endoscopy Images Using Energy Based Textural Features and SVM Based RFE Approach

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ABSTRACT

This paper deals with processing of wireless capsule endoscopy (WCE) images from gastrointestinal tract, by extracting textural features and developing a suitable classifier to recognize as a normal or abnormal /tumor image. Images obtained from WCE are prone to noise. To reduce the noise, filtration technique is used. The quality of the filtered image is degraded, so to enhance the quality of the image, discrete wavelet transform (DWT) is used. The textural features (average, energy) are obtained from DWT for three color spaces (RGB, HSI, Lab). Feature selection is based on support vector machine- recursive feature elimination approach.

Keywords- Discrete Wavelet Transform (DWT), Feature selection, Support Vector Machine (SVM), Texture, Wireless Capsule Endoscopy (WCE).

I. INTRODUCTION

Tumors in digestive tract greatly threaten human's health. Push gastroscopy and colonoscopy are common technologies to diagnose GI tract diseases [1]; however, neither of them can reach the small intestine due to its complex structure. In 2000, a novel technique of endoscopy, wireless capsule endoscopy (WCE), was introduced. It possesses a breakthrough since it can directly view the whole small intestine for the first time. Due to this advantage, WCE is rapidly applied in hospitals.Until today, this new imaging device has been utilized to inspect bleeding, ulcer, and other diseases in the GI tract [2]. Ithas also been reported that over 1,000,000 patients worldwidehave been examined with WCE.

Fig. 1. Wireless capsule for endoscopy

As shown in Fig. 1, a WCE capsule resembles a pill in appearance.It consists of a short-focal-length CMOScamera, lightsource, battery, and radio transmitter. After it is swallowed by apatient, the capsule moves through the esophagus, stomach, andfinally reaches the intestines. It is excreted with the patient'sfeces. The camera takes photos of the GI tract at two framesper second, producing a large number of images in each examination.It would be tiring and time consuming for physiciansto spend about two hours [3] on average for each case on reviewingall the images in order to identify areas with abnormalconditions, such as bleeding or tumor.

Therefore, it is greatly desired that computerized approachesbe designed and implemented to provide support for physicians. Substantial effort has been invested to design computational methodologies that could potentially assist in understanding WCE images and help clinicians to make decisions. Two clues, lumen and illumination highlight, are extracted for navigation of active endoscopic capsule [4]. Hu *et al.* proposed a new compact and panoramic image representation for WCE images. Recently, Bejakovic *et al.* [5] put forward a scheme using colour, texture, and edge features to analyse the Crohn's disease lesion for WCE images. Hwang and Celebi [6] introduced an unsupervised detection of polyps in WCE images based on Gabor texture features and *K*-means clustering. We have investigated bleeding and ulcer region detection for WCE images in our previous works [7]–[8], which mainly concentrate on features that are suitable for detecting bleeding and ulcer in WCE images.

This paper studies a computerized tumor detection system for WCE images, which exploits textural features and support vector machine (SVM) based feature selection. A feature selection approach i.e. recursive feature elimination based on SVM (SVM-RFE), are employed to refine the set of proposed features.Extensive experiments on WCE images show that the proposed scheme achieves a promising performance for tumor recognition in WCE images.

In the remainder of this paper, three colour spaces to describe noiseless WCE images are discussed in Section II, followed by a discrete wavelet transformin Section III. Obtaining textural features in Section IV. Section V describesthe classification with SVM-RFE. Experimental results showed in Section VI and the paper concludes in Section VII.

II. NOISELESS WCE IMAGES WITH THREE COLOR SPACES

In this paper, median filter is used because it preserve edges from random noise. Median filtering is a nonlinear process useful in reducing impulsive or salt-and-pepper noise. Impulsive or salt-and pepper noise can occur due to a random bit error in a communication channel. In a median filter, a window slides along the image, and the median intensity value of the pixels within the window becomes the output intensity of the pixel being processed.The median filter preserves brightness differences resulting in minimal blurring of regional boundaries.

Noiseless RGB WCE images to be converted to HSI and Lab color spaces [9]. RGB stands for Red Green and Blue. This model represents how your computer sees color. HSI represents, Hue: Describes a pure color (pure yellow, orange or red) Saturation: Gives a measure of the degree to which a pure color is diluted by white light. Brightness: Subjective descriptor practically impossible to measure. Embodies the achromatic notion of intensity => intensity (gray level), measurable. The Lab color space is: Colorimetric (colors perceived as matching are encoded identically). Perceptually uniform (color differences among various hues are perceived uniformly). RGB to HSI conversions are carried out using the below mentioned equations (1) (2) (3) & (4). For RGB to Lab conversion, equation (5) (6) are used.

A. RGB to HSI Conversion

$$H = \begin{cases} \theta & \text{if } B \le G \\ 360 - \theta & \text{if } B > G \end{cases} \qquad (1)$$

$$\theta = \cos^{-1}\left\{ \frac{\frac{1}{2}[(R-G)+(R-B)]}{[(R-G)^2+(R-B)(G-B)]^{1/2}} \right\} \qquad (2)$$

$$S = 1 - \frac{3}{(R+G+B)}[\min(R,G,B)] \qquad (3)$$

$$I = \frac{1}{3}(R+G+B) \qquad (4)$$

B. RGB to Lab Conversion

RGB to XYZ

[X] = [3.240479 -1.537150 -0.498535] * [R]
[Y] = [-0.969256 1.875992 0.041556] * [G]
         (5)
[Z] = [0.055648 -0.204043 1.057311] * [B]
XYZ to Lab

CIE-L* = (116 * var_Y) - 16
CIE-a* = 500 * (var_X - var_Y)
         (6)
CIE-b* = 200 * (var_Y - var_Z)

III. DISCRETE WAVELET TRANSFORM

Wavelet transform is a useful tool for multiresolution analysis of an image [10]. As for WCE images, wavelet transform may provide local characterization to better analyse the mucosa of the inner GI tract, leading to more capable image analysis using information at different scales. Moreover, wavelet transform may obtain information along different orientations in an image. In addition, our previous preliminary work has demonstrated that wavelet-based texture provides more information for tumor detection in WCE images. Due to the aforementioned reasons, we utilize the wavelet transform to build the textural descriptor for WCE images. For 2-D images, wavelet transform is implemented through discrete wavelet transform (DWT) with a separable filter bank, and an image is convoluted with a low-pass filter L and high pass filter H recursively. An image is then decomposed into four subimages, which are generally denoted as LL, LH, HL, and HH. The LL subimage is derived from low-pass filtering in both directions on original image and it is the most like the original picture, therefore, it is called the approximation component. The remaining subimages are detailed components. The HL is derived from high-pass filtering along the horizontal direction and low-pass filtering along the vertical direction. The other two subimages LH and HH have similar explanations.

IV. OBTAINING TEXTURAL FEATURES

Here total 34 wce images are taken. Each one will be in RGB format. These are converted in to HSI and Lab color spaces. Thus all images are converted and collected as RGB, HSI and Lab colors. In our study, taking into account the size of WCE images and the region of interest (ROI), which will be clarified in details in the experiments, we apply two levels DWT to each channel of a WCE image, yielding seven subimages for each channel. We choose all such seven subimages as the basis for the

textural feature analysis. The features are extracted from those DWT applied images. To extract feature, Mean and Energy [11] is calculated in 34(wce images)*3(color spaces) DWT images.

$$Mean = \sum_{x=1}^{M} \sum_{y=1}^{N} I(x,y) \qquad (7)$$
$$M*N$$

$$Energy = \frac{1}{M^2 N^2} \sum_{x=1}^{M} \sum_{y=1}^{N} I(x,y)^2 \qquad (8)$$

Mean is calculated for Approximation and Diagonal components. Energy is calculated for Horizontal and Vertical components. Thus extracted features are given for training.

Thus Mean and Energy Features are calculated for the image of each color format. So with an image three color formats total twelve features are extracted. With total 34 images, 34*12 features are obtained. Then those features are said to trained feature.

V. CLASSIFICATION WITH SVM-RFE

Support vector machines [12]are supervised learning models with associated learning algorithms that analyses data and recognize patterns used for classification and regression analysis. The basic SVM [13] takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier.Classification accuracy is computed.SVM [14] maps input vectors to a higher dimensional vector space where an optimal hyper plane is constructed.Among the many hyper planes available, there is only one hyper plane that maximizes the distance between itself and the nearest data vectors of each category.This hyper plane which maximizes the margin is called the optimal separating hyper plane and the margin is defined as the sum of distances of the hyper plane to the closest training vectors of each category.

A. SVM-RFE

The extracted feature [16] values are passed to the classifier to find the presence of Tumor in the image. For classification Support Vector Machine Recursive Future Elimination is used. SVM Recursive feature elimination eliminates the reoccurring values in the feature extracted. It takes a set of input data and predicts, for each given input, which of two possible classes forms the output, making it a non-probabilistic binary linear classifier. Given a set of training examples, each marked as belonging to one of two categories, an SVM training algorithm builds a model that assigns new examples into one category or the other. An SVM model is a representation of the examples as points in space,

mapped so that the examples of the separate categories are divided by a clear gap that is as wide as possible. New examples are then mapped into that same space and predicted [17] to belong to a category based on which side of the gap they fall on. For simple understanding of SVM concept, algorithm for Support vector machine based Recursive feedback elimination is written. Here 't' represents the training sequence that obtained from 34*12 features. And 'T' represents the target, the trained images are arranged in sequence as different classes as that the output will chose the class the image depends on.

SVM-RFE (T, F, f, s)
Initialize
      T:={training dataset}
      F:={all input features}
      f:=filter_out_factor
      S:=the size of final informative gene subset

Begin
      While (the size of F>s)
            Train linear SVM on T in the feature space defined by F
            Rank the features of F by w_i^2 in the descending order
              if f<0
                   F2:=F-{f bottom ranked features in F}
              else if f=0
                   F2:=F-{a number of features with largest ranks are removed so that the size of F2 is the closest smaller number of power of 2}
              else
                   F2:=F-{f*100% of features in F with largest rank}
              end
              if the size of F2<s
                 Adjust F2 to be composed of s top ranked features in F
              end
              F=F2
      end
      return F
end

Fig.2.SVM-RFE Algorithm

As in the above explanation, in this paper for all wce images are to be trained. Then the trained features are stored. After training, images are arranged as normal and abnormal by target fixed. When a new image is passed through the classifier, it checks with the trained samples and target and shows whether the image is an abnormal or normal image. For more trained images, more the accuracy obtained.

VI. EXPERIMENTAL RESULTS AND ANALYSIS

A. WCE Images: Normal and Abnormal image

Fig.2. Normal and Abnormal Image

In this paper a new wireless capsule endoscopy image with and without tumor are taken for analysis. The new 18 images are given apart from trained images. Those are shown in above figure.
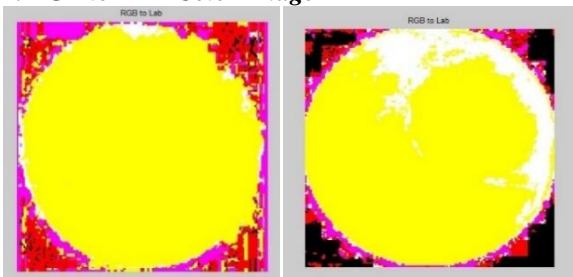
B. RGB to LAB Color Image

Fig.3. Normal and Abnormal for Lab Image

Figure 3 represents the RGB to Lab color space conversion for normal image and abnormal image.

C. RGB to HSI Color Image
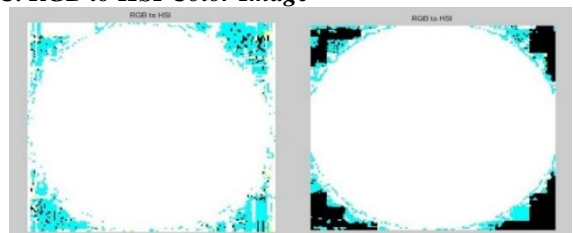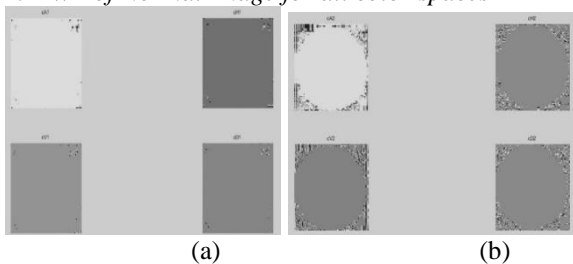

Fig.4. Normal and Abnormal for HSI Image

Figure 4 represents the RGB to HSI conversion.

D. DWT of Normal Image for all color spaces
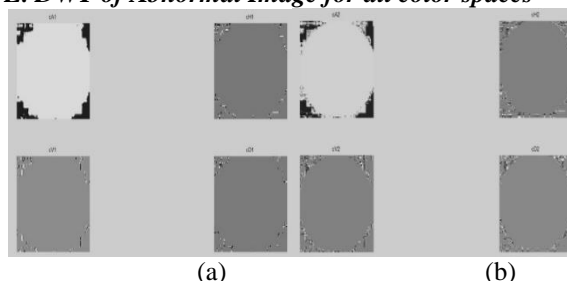

(a)   (b)

(c)

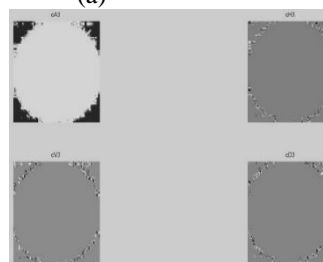Fig.5. DWT of (a) RGB (b) Lab (c) HSI color spaces for Normal Images

For Normal WCE image, DWT is applied to each color space. In above figure(a) represents DWT of RGB image, (b) represents DWT of Lab image and (c) represents DWT of HSI image.

E. DWT of Abnormal Image for all color spaces

(a)   (b)

(c)

Fig.6. DWT of (a) RGB (b) Lab (c) HSI color spaces for Abnormal Images

For Abnormal WCE image, DWT is applied to each color space. In above figure (a) represents DWT of RGB image, (b) represents DWT of Lab image and (c) represents DWT of HSI image.
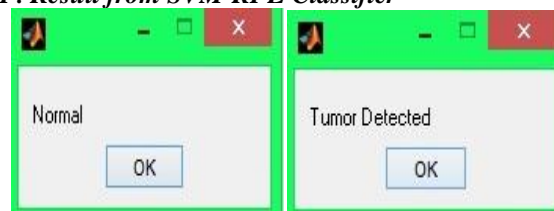
F. Result from SVM-RFE Classifier

Fig.7. (a) 'Normal' displayed in SVM-RFE Message Box
(b) 'Tumor Detected' displayed in SVM-RFE Message Box

In SVM-RFE approach, it classify with all trained wce images and produce the output with the message box as normal or abnormal image. In above figure, (a) represents the normal image (b) represents the abnormal image. Thus for 18 images the SVM-RFE approach will classify. The accuracy for those 18 images are calculated.

VII. CONCLUSION AND FUTURE WORK

Thus a computerized tumor detection system is used for WCE images. The proposed textural features use the advantages of mean and energy in discrete wavelet transform, working much better than traditional features for tumor detection in WCE images. By using SVM-RFE classifier, for 18 images tumor is detected. The classifier shows with 100% accuracy. So to obtain proper classification accuracy, more number of images are to be given in future. Also different classifiers viz. Naive Bayes classifier, Multi SVM will be incorporated and their performances are to be analyzed. As a result, the best classifier is preferred for tumor detection accuracy.

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