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Tumor Recognition in Wireless Capsule Endoscopy Images

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Abstract: *This paper implementation of simple algorithm for detection of tumor in endoscopy images. Tumor is an uncontrolled growth of tissues in any part of the body. Tumors are of different types and they have different characteristics and different treatment. The wireless capsule endoscopy (WCE) image is visually examined by the physician for detection and diagnosis of gastrointestinal (GI) tract tumor. However this method of detection resists the accurate determination of tumor. To avoid that, this project uses computer aided method for segmentation (detection) of endoscopy tumor based on the combination of algorithms. This method allows the segmentation of tumor tissue with accuracy and reproducibility comparable to manual segmentation. In addition, it also reduces the time for analysis. At the end of the process the tumor is extracted from the gastrointestinal tract image. The wireless capsule endoscopy images, are extracted by gray level co-occurrence matrix (GLCM) & principal component analysis (PCA) and wavelet transform (DWT) which are characterize multi resolution property of images. After performing, the probabilistic neural network (PNN) based feature selection classify the type of tumor.*

Index Terms: *Feature selection, Probabilistic Neural Network (PNN), texture, tumor recognition, wireless capsule endoscopy (WCE) image.*

I. Introduction

The prototype capsule endoscope was developed at the Royal London Hospital in the UK by Professor Paul swain. Modern endoscopic or capsule endoscopic technique has revolutionized the diagnosis of the diseases and also treatment of the upper GI tract. ie. esophagus, stomach, duodenum and colon. The last remaining digestive system part is the small intestine. The small intestine has been a difficult organ in digestive system which is to make diagnoses and treat without performing any kind of surgery. The technique requires three main components, an ingestible capsule, a portable data a workstation equipped with image processing data software.

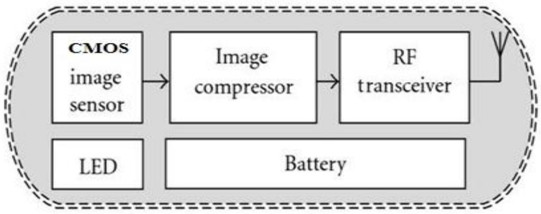


Fig. 1 Block diagram of Pill Cam

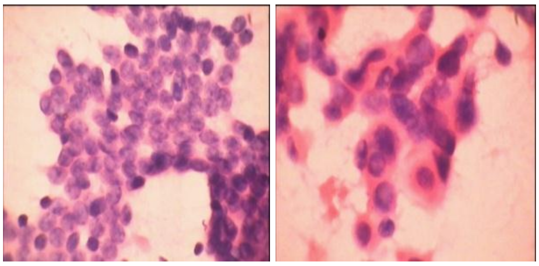
The capsule consists of an optical dome and lens, light emitting diodes, a processor, a battery, a transmitter and an antenna encased in a resistant coat the size of large vitamin pill shows the Fig. 1 It acquires video images during natural propulsion through the digestive system that it transmits via a digital radio frequency communication channel to the recorder unit worn outside the body, this also contains sensors which allow basic localization of the site of image capture within the abdomen. Upon completion of the examination, the physician transfers the accumulated data to the workstation is a modified personal computer required for off line data storage, interpretation and analysis of acquired images, and report generation. Clinical trials have been performed to evaluate the safety and efficacy of the system as a tool in the detection of small bowel disease. Preliminary results show that the small bowel capsule provides good visualization from mouth to colon with a high diagnostic yield. It compares favorably with the gold standard techniques for the localization of cryptic and occult GI bleeding and the diagnosis of small bowel Crohn's disease. Use of the capsule endoscope is contraindicated in patients with known small bowel strictures in which it may impact, resulting in acute obstruction requiring retrieval at its use. Some units advocate a barium follow through to exclude structuring disease in all patients before in all patients before capsule endoscopy. Wireless Capsule endoscopy is used as a less-invasive procedure in placement of a traditional endoscope. Old technique endoscopy is a long, thin tube inserted into the rectum and colon or into the oral cavity. The standard capsu**le** is the measures 11 mm (width) x 26 mm (height) and weighs less than 4 grams. In the WCE it contains of an imaging device and light-source on one-side or using also both sided and the transmits images at a rate of per second 2 images, generating more than 40,000 pictures over an 7-hour period. We have investigated GI tract tumor, bleeding and ulcer region detection for WCE images in our previous works.

In this paper mainly concentrate on software part suitable for detecting tumor, bleeding and ulcer in WCE images, in this paper tumor recognition use MATLAB software. The wireless capsule endoscopy images using tumor detection, which exploits textural features and probabilistic neural network (PNN), based feature selection. The features for WCE images which are robust to the illumination change and characterize multi resolution property of WCE images are extracted by GLCM and wavelet transform (DWT). Because such features may not necessarily yield a high classification performance.

The WCE images shown in Fig. 2 and preprocessing, Transformation DWT in Section II, Textural Feature Analysis GLCM & PCA in section III, PNN Based Feature selection Section VI, presents discussions of this study and the paper concludes in Section VI.

II. Implementation Flow

Wireless Capsule Endoscopy Images



(a) (b)

Fig. 2 several representative WCE images. (a) Benign tumor. (b) Malignant tumor.

A. Preprocessing

The first part of implementation is preprocessing. Preprocessing images commonly involves removing low-frequency noise, normalizing the intensity of the individual particles images, removing reflections of images, and masking portions of images. Image preprocessing is the technique of enhancing data images and its computational processing.

B. Wavelet Transform

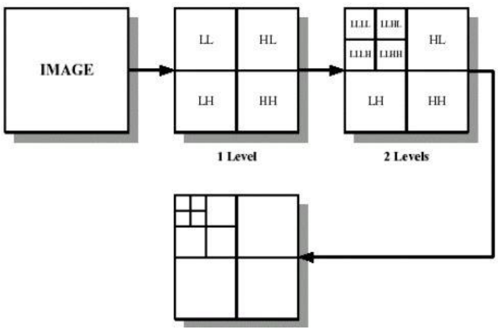


Fig. 3 2-D DWT for Image

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. The Fig. 3 shows 2D DWT separable filter bank. The wavelet transform uses multi-resolution technique. The DWT uses multi resolution technique by which different frequencies are analyzed with different resolutions. The DWT gives good frequency resolution and but its also poor time resolution. The wavelet transform provides a time-frequency representation of the discrete signal. The discrete wavelet transform, which is based on sub-band coding, is found to the fast computation of DWT.

III. Textural Features

There are different types of tumors are available in GI tract. There are two types of tumor. Non cancerous tumor called as a benign tumor and cancerous tumor called as a tumor physicians malignant mainly use color and texture pattern to judge and discriminate status of the mucosa of inner tract in the GI tract. Therefore, we study

A. Texture feature extraction based on GLCM

The gray level co-occurrence matrix (GLCM) is a feature extraction classifier. The GLCM creates a symmetry matrix with the distances and directions between pixels, and then extracts meaningful statistics from the matrix as texture features extraction. GLCM texture to recognize tumor WCE images. The GLCM is a symmetry matrix, it is level determined by the image gray-level. Elements in the matrix are computed by the equation showed as follow GLCM expresses the texture feature according the correlation of the couple pixels gray-level at different positions. It is quantificational describes the texture feature. In this paper, four features is selected, include energy, contrast, entropy, inverse difference.

Energy:

$$E = \sum_x \sum_y p(x,y)^2 \qquad (1)$$

The energy is feature texture measure in a gray-scale image of, reflecting the distribution of image gray-scale uniformity of weight and homogeneity changing and texture.

Contrast:

$$I = \sum \sum (x-y)^2 p(x,y) \qquad (2)$$

The contrast is the main diagonal near the moment of inertia, which measure the value of the matrix is distributed and images of local changes in number, reflecting the image clarity and texture of shadow depth. Contrast is large means texture is deeper.

Entropy:

$$S = -\sum_x \sum_y p(x,y) \log p(x,y) \qquad (3)$$

Entropy measures image texture randomness, when the space co-occurrence matrix for all values is equal, it achieved the minimum value; on the other hand, if the value of co-occurrence matrix is very uneven, its value is greater. Therefore, the maximum entropy implied by the image gray distribution is random.

Inverse Difference:

$$H = \sum_x \sum_y \frac{1}{1+(x-y)^2} p(x,y) \qquad (4)$$

It measures in image texture number of local changes. Its value in large is illustrated that image texture between the partial very evenly and different regions of the lack of change. Here gray-level value p(x, y) at the coordinate (x, y).

B. Principal Component Analysis

Principal component analysis (PCA) is one of the statistical techniques frequently used in signal processing to the data decorrelation or to the data dimension reduction PCA is a useful statistical technique its use such as face recognition and image compression, and is a common technique for finding patterns in data of high dimension.

IV. Probabilistic Neural Network

A. Neural Network

Probabilistic neural networks (PNN) are a kind of radial basis network. It’s suitable for classification problems. The PNN creates a two-layer network. The first layer neural network has radbas neurons, and the radbus neurons calculate its weighted inputs with dist and its net input with netprod. The second layer has compet neurons, and the compet neurons calculate its weighted input with dotprod and it is net inputs with netsum. The first layer has only biases.

B.Architecture of a PNN:

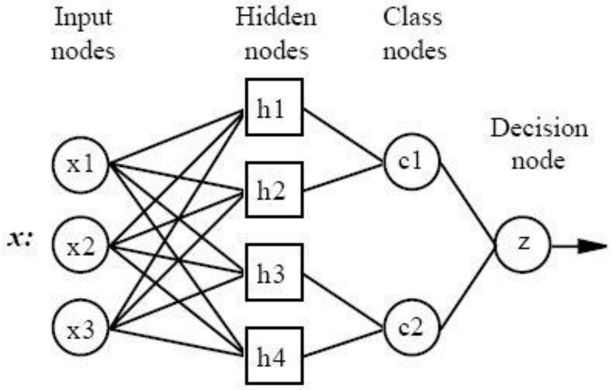


Fig. 4 Architecture of a PNN

All PNN networks have four layers:

Input layer — The input layer each predictor variable the one neuron present. In the case of input layer one neuron categorical variables, N-1 neurons are used where N is number of categories. The processing before the input layer or input neurons standardizes the range of the values dividing by the interquartile range and by subtracting the median. The input layer neurons then feed the values to each of the neurons in the second type of layer is hidden layer.

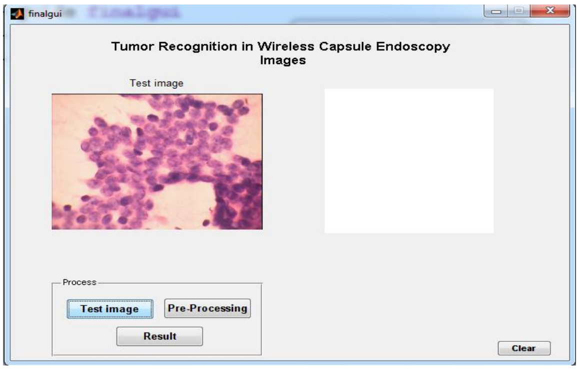
Hidden layer — For each case in the training data set this layer has one neuron present. The hidden layer neuron stores the values of the predictor variables for the case along with the target value. When the presented with x vector of input values from the first layer or input layer, a hidden neuron computes the Euclidean distance of the test case from the neuron's center point and then applies the sigma value (s) with RBF kernel function. The resulting value is passed to the neurons in the third layer is the pattern layer.

Pattern layer / Summation layer — The pattern or summation layer in the network is different for PNN networks and for GRNN networks. For probabilistic neural networks there is one pattern neuron for each category of the target categorical variable. The GRNN networks, there are only two neurons in the pattern layer and they pattern layer represent pattern neuron. The one neuron is denominator summation unit and the other is numerator summation unit. The denominator summation unit adds up the weight values coming from each hidden neurons. The numerator summation unit adds up the weight values multiplied by the actual target value for each of the hidden neuron.

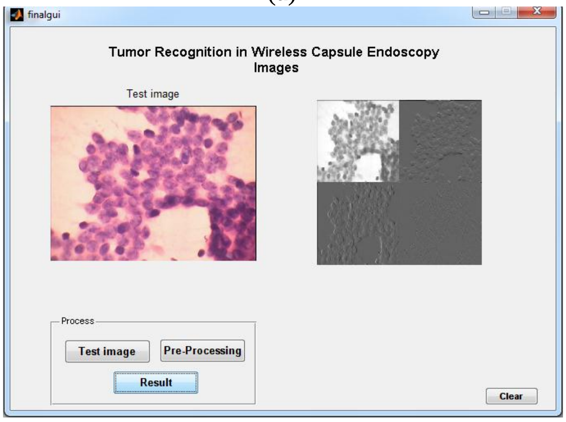
Decision layer —the decision layer is different for Probabilistic Neural Networks and GRNN networks. For Probabilistic Neural Networks, the decision layer compares the weighted votes for each target category accumulated in the pattern layer. And the pattern layer uses the largest vote to predict the target category. For GRNN networks, the decision layer divides the value accumulated in the numerator summation unit by the value in the denominator summation unit and uses the result as the predicted target value.

V. Experimental Result And Discusion

Here, we take the WCE images, firstly preprocessing the image and then apply wavelet transform for good resolution of images. The gray level co-occurrences matrix used as classifier to create a matrix with the direction and distance between pixels and then extracted features. Further applying the classifier probabilistic neural network can be use to classify the tumors types. The following Fig. 5 and Fig. 6 show the tumor images.


finalgui
Tumor Recognition in Wireless Capsule Endoscopy Images
Test image
Process
Test image
Pre-Processing
Result
Clear

(a)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Tumor Recognition in Wireless Capsule Endoscopy Images
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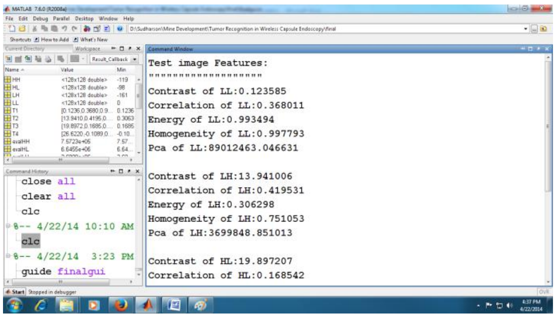
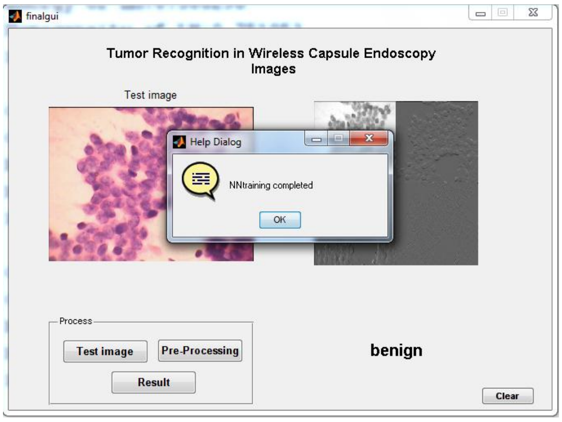
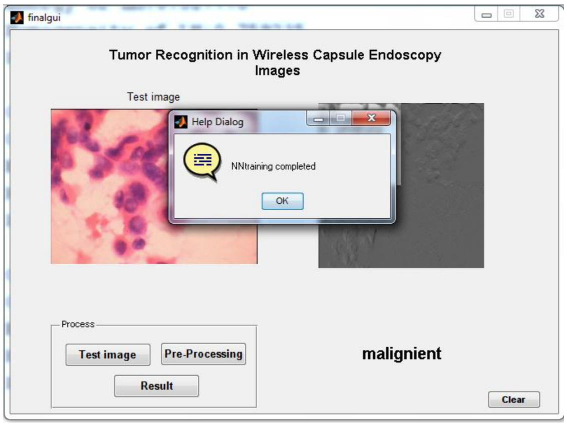
(b)


close all
clear all
clc
%-- 4/22/14 10:10 AM
clc
%-- 4/22/14 3:23 PM
guide finalgui
Test image Features:
Contrast of LL:0.123585
Correlation of LL:0.368011
Energy of LL:0.993494
Homogeneity of LL:0.997793
Pca of LL:89012463.046631
Contrast of LH:13.941006
Correlation of LH:0.419531
Energy of LH:0.306298
Homogeneity of LH:0.751053
Pca of LH:3699848.851013
Contrast of HL:19.897207
Correlation of HL:0.168542

(c)


finalgui
Tumor Recognition in Wireless Capsule Endoscopy Images
Test image
Help Dialog
NNtraining completed
OK
Process
Test image
Pre-Processing
Result
benign
Clear

(d)



(e)

Fig. 5 Benign tumor images (a) input image. (b) Wavelet image. (c) GLCM & PCA Feature ext window. (d) & (e) Neural Network output.

VI. Conclusion

The wireless capsule endoscopy images using tumor detection, this method are a combination of discrete wavelet transform and probabilistic neural network. The PNN has been implemented for classification of endoscopy image. PNN is adopted for it has fast speed on training and simple structure. Twelve images of endoscopy were used to train the probabilistic neural network classifier and tests were run on different set of images to examine PNN classifier accuracy. The extract the textural features (GLCM) of low and high frequency components from wavelet transform in WCE images. In the method only 2 classes of tumors are considered, but this method can be extended to more classes of GI tract tumors.

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