HOOKWORM DETECTION IN WIRELESS CAPSULE ENDOSCOPY IMAGES USING EDGE MORPHOLOGICAL OPERATOR

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Abstract: Wireless capsule endoscopy (WCE) has become a widely used diagnostic technique to examine inflammatory bowel diseases and disorders. Automatic hookworm detection is a challenging task due to poor quality of images, presence of extraneous matters and diverse appearances in terms of color and texture. To improve the quality and the contrast of the image a preprocessing using noise removal is implemented and an Artificial Neural Network classifier based normal or abnormal classification is applied. An artificial neural network–Back Propagation Network is used here as classifier. Feature selection is embedded in the hierarchical framework that chooses the most relevant feature subsets at each node of the hierarchy. With help of this feature we can design contrast, correlation and entropy features and can get classified result more accurately than existing result (without coloring model). It clearly demonstrates promising classification performance and also adaptive histogram to enhance the contrast of capsule endoscopy images. Also this method has better discriminatory power and low computational complexity.

Keywords - Artificial Neural Network (ANN), Back propagation Network (BPN).

I. INTRODUCTION

Hookworms are estimated to infect more than 740 million people around the world, but most people who are infected are asymptomatic. Hookworm usually lives in the upper part of small bowel. Iron deficiency anaemia secondary to loss of iron into the gut is the most significant risk of hookworm. Diarrhoea, chronic abdominal pain, anorexia and weight loss are also frequent symptoms seen. The prevalence of infection is as high as 80% in tropical areas within developing countries, and only 20% in drier climates. Definite diagnosis is made by seeing hookworm eggs during stool examination, however sometimes its diagnosis can be missed. A human digestive system consists of a series of several different organs including the oesophagus, stomach, small intestinal (i.e., duodenum, jejunum, and ileum) and colon. Standard endoscopy has been playing a very important role as a diagnostic tool for the digestive tract. For example, various endoscopies such as gastroscopy, push enteroscopy, colonoscopy have been used for the visualization of digestive system. However, all methods mentioned above are limited in viewing small intestine. To address the problem, Wire- less Capsule Endoscopy (WCE) was first proposed in 2000, which integrates wireless transmission with image and video technology.

The Wireless Capsule Endoscopy (WCE) is a non-invasive technique that enables the visualization of the small bowel mucosa for diagnosing purposes. The WCE is swallowed by the patient and it is passively propelled by peristalsis. The most common indication for capsule endoscopy is for evaluation of obscure gastrointestinal bleeding. Wireless capsule endoscopy, measuring 26mm × 11mm, is a pill-shaped device which consists of a short-focal-length CMOS camera, light source, battery and radio transmitter. We first introduce how it works briefly. After a WCE is swallowed by a patient who has a diet for about 12 hours, this little device propelled by peristalsis starts to work and record the images while moving forward along the digestive tract. Meanwhile, the images recorded by the camera are sent out wirelessly to a special recorder attached to the waist. This process continues for about eight hours until the WCE battery ends. Finally, all the image data in the special recorder are downloaded into a personal computer or a computer workstation, and physicians can view the images and analyse potential sources of different diseases in the gastrointestinal (GI) tract. It should be noted that the diagnosis process exerted by physicians is very time-consuming due to the large amount of video, so the diagnosis is not a real-time process.

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II. EXISTING SYSTEM

A pre-processing using noise removal or green plane process in Curve let Transform is implemented, 10 features with our data set trained images on 50 images using NN (neural network) training and applying ANN classifier based Normal or Abnormal. An artificial neural network –Back Propagation Network is used here as classifier. Feature selection is embedded in the hierarchical framework that chooses the most relevant feature subsets at each node of the hierarchy. With data set trained image features we can get classified result on more accuracy than existing result (without colouring model).

III. PROPOSED METHODOLOGY

The Proposed method was evaluated on a publicly available dataset and clearly demonstrated promising classification performance and also adaptive histogram for enhance the contrast of capsule endoscopy images. The block diagram consists of various techniques that are used to detect and enhance the edges of the hookworms.

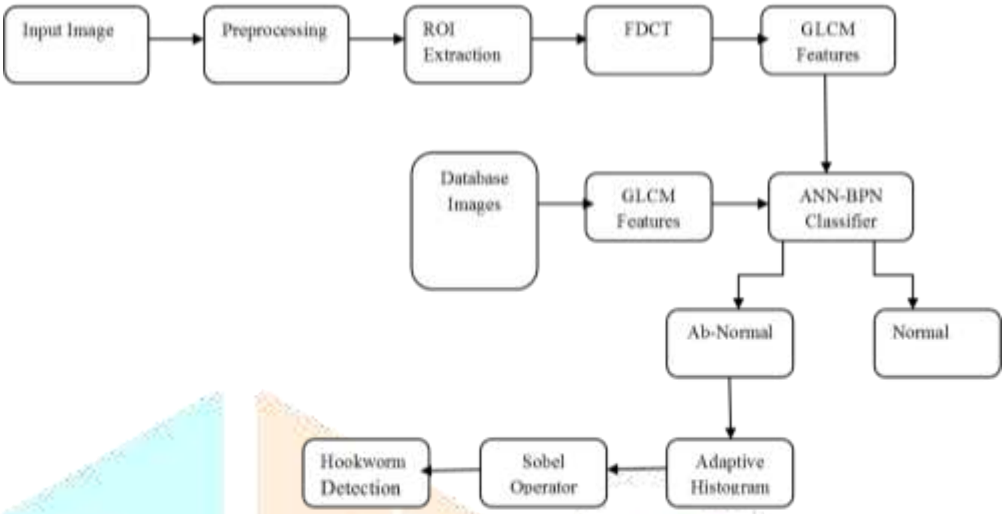

Fig. 3.1 Block Diagram

The given image is in RGB color which must be converted into gray-scale images. The ROI is extracted, that is the area where the hookworm is present. This image is decomposed into several subbands using fast discrete curvelet transform. Now the co-occurrence matrix is constructed, based on the orientation and distance between image pixels. Then the meaningful statistics are extracted from the matrix as the texture representation. Artificial Neural Networks (ANN) forms an appropriate internal feature extractors and classifiers based on the input images. The classifiers get the GLCM values of the input image and then these images are compared with the images present in the database. The database images consist of several images whose GLCM values are been calculated. By comparing these images the hookworm is detected from it. Adaptive histogram improves local contrast and enhancing definition of edges in each region of the image. Sobel operators detect all the edges present in the input image and it is futher processed in order to detect the edges of the hookworm. The resultant image the hookworm is detected. The area occupied by the hookworm is also calculated.

3.1 Input Image

The input image obtained from the wireless capsule endoscopy and stored in the database. This image is sent for pre-processing where the image data is improved by suppressing the undesired distortions and by enhancing some features of the image. Here, an RGB image is converted into its corresponding gray scale image. Also, the image is converted into its standard size of 256x256 pixels.

3.2 Region of Interest Extraction

In medical image analysis segmentation is the first step to be followed, to avoid distortion of ROI. The goal of segmentation is to divide entire medical image in to sub regions i.e. (white and gray matter). In addition, this helps in classifying image pixels in to anatomical regions (such as bones, muscles and blood vessels). Defining the borders of ROI in medical image can simplify the procedure of segmentation.There are different approaches (for segmenting the image) defined for the different imaging technologies such as CT, MRI, US, colonoscopy, wireless capsule endoscopy etc. Segmentation is semi-automatic procedure and we need to define a seed point in an image.

3.3 Fast Discrete Curvelet Transform

The curvelet transform is proposed for image denoising and has shown promising performance over DWT. Since curvelet transform captures curvilinear information perfectly, it has shown promising results in content based image retrieval, character recognition, face recognition etc. The curvelet transform has been divided into two generations. It involved ridgelet analysis and hence is extremely slow. Therefore, the algorithm was modified where the ridgelet analysis has been removed (redundancy reduction) to increase the speed. The curvelet has a frequency support in a parabolic- wedge area due to the anisotropic scaling law as width = length2.

This operator searches over the image domain *(x, y)* for the maximum change in the blurred partial derivative with respective to increasing radius *r* of the normalized contour integral of *I(x, y)* along a circular arc of radius *r* and center coordinate (x_0,y_0). In this, G_σ is a smoothing function such as a Gaussian of scale σ ,*r* is a small increment in radius, and θ is the angular sampling interval along the circular arcs.

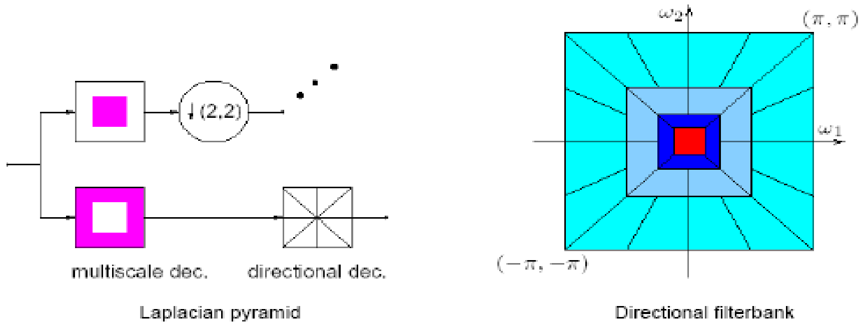

Fig.3.2 Curvelet Transform

The above figure 3.2 shows the operation of the fast discrete curvelet transform in which the image is first subdivided into two sub-bands, the low band and the high band. The low band consists of the region information of the image and the high band consists of the edge information of the image. The low band is further divided into two sub-bands. This process is repeated up to eight sub-bands until we get the clear information about the regions in the image. It involves unwrapping of image and converting it into fixed size. The normalized image has still low contrast and non-uniform brightness which is caused by the position of light sources. In order to obtain well distributed texture image (enhanced image), we have used the background subtraction method proposed.

3.4 GLCM Features

The Grey Level Co-occurrence Matrix (GLCM) method is a way of extracting second order statistical texture features. A GLCM is a matrix where the number of rows and columns is equal to the number of grey levels, G, in the image. The matrix element P (i, j | Δx, Δy) is the relative frequency with which two pixels, separated by a pixel distance (Δx, Δy), occur within a given neighbourhood, one with intensity 'i' and the other with intensity 'j'. The matrix element P (i, j | d, ө) contains the second order statistical probability values for changes between grey levels 'i' and 'j' at a particular displacement distance d and at a particular angle (ө). Using a large number of intensity levels G implies storing a lot of temporary data, i.e. a G × G matrix for each combination of (Δx, Δy) or (d, ө). Due to their large dimensionality, the GLCM's are very sensitive to the size of the texture samples on which they are estimated. Thus, the number of grey levels is often reduced. Here one pixel offset is used (a reference pixel and its immediate neighbour). If the window is large enough, using a larger offset is possible. The top left cell will be filled with the number of times the combination 0,0 occurs, i.e. how many time within the image area a pixel with grey level 0 (neighbour pixel) falls to the right of another pixel with grey level 0(reference pixel). At first the co-occurrence matrix is constructed, based on the orientation and distance between image pixels. Then meaningful statistics are extracted from the matrix as the texture representation. These co-occurrence matrices represent the spatial distribution and the dependence of the grey levels within a local area. Each ***(i,j)*** th entry in the matrices, represents the probability of going from one pixel with a grey level of '***i***' to another with a grey level of '***j***' under a predefined distance and angle.

3.5 Artificial Neural Network – Back Propagation Network Classifier

An artificial neural networks (ANNs) is made up of many artificial neurons which are correlated together in accordance with explicit network architecture. The objective of the neural network is to convert the inputs into significant outputs. A neural network consists of units (neurons), arranged in layers, which convert an input vector into some output. Each unit takes an input, applies a nonlinear function to it and then passes the output on to the next layer. Generally the networks are defined to be feed-forward: a unit feeds its output to all the units on the next layer, but there is no feedback to the previous layer. Weightings are applied to the signals passing from one unit to another, and it is these weightings which are tuned in the training phase to adapt a neural network to the particular problem at hand.

3.6 Sobel Operator

Sobel operator is used in image processing, particularly within edge detection algorithms. It is a discrete differentiation operator, computing an approximation of the gradient of the image intensity function. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector. The Sobel operator is based on convolving the image with a small, separable, and integer valued filter in horizontal and vertical direction and is therefore relatively inexpensive in terms of computations. At each point in the image, the result of the Sobel operator is either the corresponding gradient vector or the norm of this vector.

IV. RESULTS AND DISCUSSION

Fig.4.1 Input Image

Fig.4.2 Gray-Scale Image

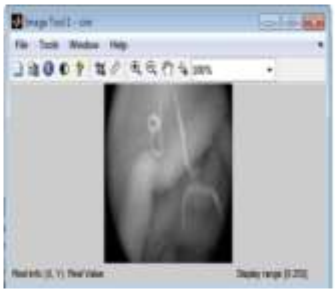

Fig.4.3 ROI Extracted Image

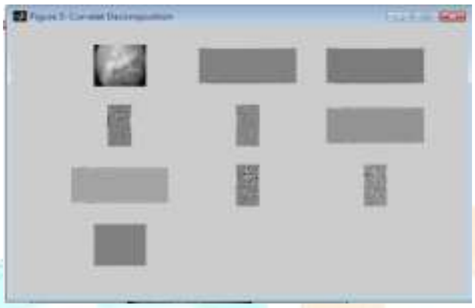

Fig 4.4 Curvelet Decomposed Image

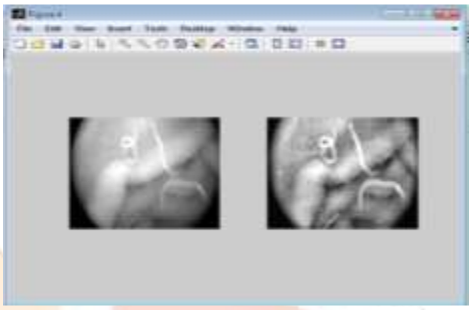

Fig.4.5 Enhanced Image of Hookworm

Fig.4.6 Edge Detection

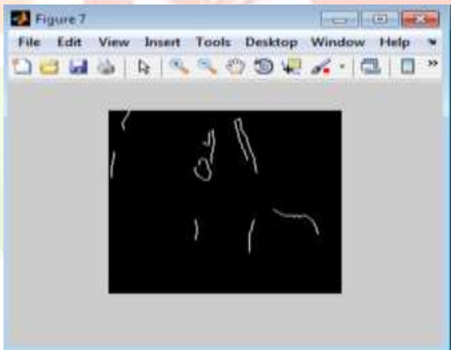

Fig.4.7 Extracting the Hookworm Edges

Fig.4.8 Enhancement of Edges of the Hookworm

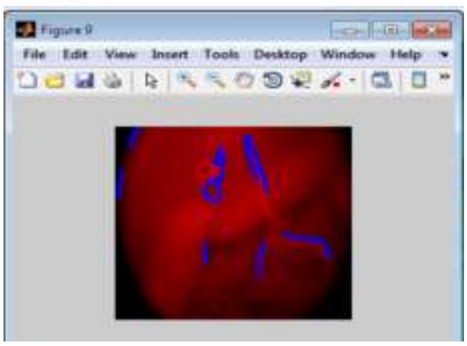

Fig.4.9 Detection of Hookworm

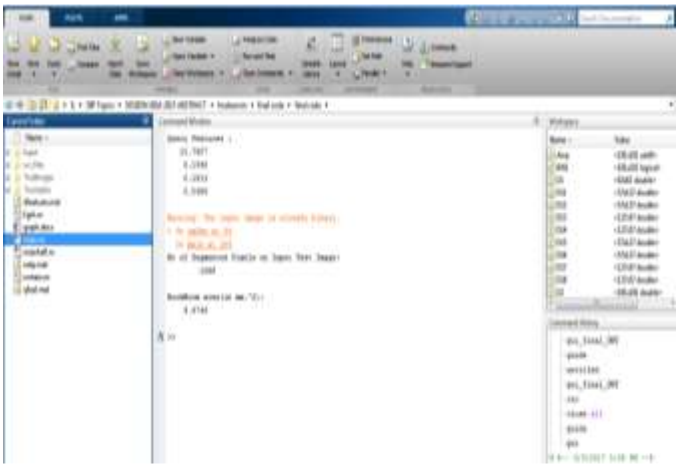

Fig4.10 Area of Hookworm

V. CONCLUSION AND FUTURE SCOPES

The curvelet transform provide a better energy compaction and critically sampled filtering along the image allows to remove the noise more efficiently. GLCM is used to extract the various features from the input and database images. Then these images are compared using Artificial Neural Network-Back Propagation Network (ANN-BPN) as a classifier which clearly demonstrates promising classification performance and also adaptive histogram enhances the contrast of capsule endoscopy images. Also proposed method has low computational complexity. This method of detection of hookworm is less efficient when more number of images should be analyzed at the same time. Future scope of our project using Probabilistic Neural Network (PNN) can be employed to classify the Normal and abnormal images. An efficient algorithm is proposed for detection based on the Spatial Fuzzy C-Means Clustering.

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