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A Computer Aided Detection Technique for Early Detection of Gastrointestinal Polyps and Tumor in Wireless Capsule Endoscopy Images

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Abstract: Wireless Capsule Endoscopy (WCE) is an omnipotent noninvasive and painless diagnostic method for capturing digital images of entire Gastrointestinal (GI) tract. In this paper, we propose a method to detect colonic polyps and tumors from WCE images. Extractions of textural features are not only from single key point by utilizing single scale-invariant feature but also from neighborhood key points. Haralick texture features are extracted from each of patch size of 16*16 around the key points. For the best classification performance, the SIFT feature strategy is integrated with 22 Haralick textural features. In our prospective system, feature based classification is performed using Neural Network (NN) classifier for detecting colonic polyps and tumors accurately from the WCE images with an accuracy of about 97.5%.

Index Terms: Wireless Capsule Endoscopy(WCE), colonic polyp and tumor detection,SIFT,Haralick texture features,NeuralNetwork(NN),SupportVector Machine(SVM).

I. INTRODUCTION

Wireless Capsule Endoscopy (WCE) is an omnipotent non-invasive and painless diagnostic tool for direct visualization by capturing digital images of patient's gastrointestinal tract. In 2001, by Given Imaging Inc. a novel technique of endoscopy, WCE [1] was first introduced in USA. Now it is available throughout the world and has evolved into an imperative diagnostic method for detecting colonic polyps, tumor, bleeding, ulcer, and crohn's in Gastointestinal (GI) tract [2].The WCE is similar to a disposable pill in its size, has length of 26mm and diameter of 11mm as shown in Fig.1 (a).

It is a method of recording digital images and consists of a tiny camera, protecting dome lens, illuminating LED, batteries, Radio Frequency (RF) transmitter and an antenna. In the examination procedure, after capsule being swallowed by a patient it moves along digestive tract and camera records images for doctors to examine and provide accurate diagnostic decision [3].

Polyp is one among the common disease in intestinal mucosal layer as a result of growing mass protrusions of mucosa by disproportionate tissue procreation [4] in stomach, colon, and urinary bladder.

Some polyps are benign and others are non beginin. Virtually all colon and rectal cancer starts from beginin polyps. Histologically polyps are classified into the neoplastic, hyperplastic, hamartomatous, inflammatory.

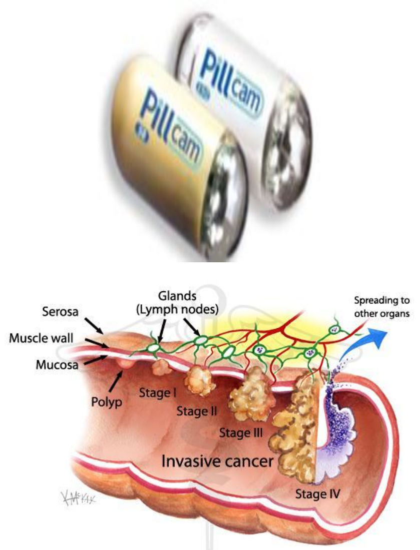

Fig.1. (a) Wireless capsule endoscopy (Given Imaging Ltd)
(b) Colonic polyp to cancer

Most of neoplastic polyp evolves into cancer as shown in Fig1. (b). But majority of neoplastic polyp evolve into adenomatous polyp as shown in Fig2.(a),(b),(c). More risky polyp is adenomatous polyp which can be again divided into tubular adenomas (<1 cm) and Villous tissue (>1) based on size. Hence early detection of polyp is important [5].

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Fig.2. (a) Polyp (b) Neoplastic polyp (b) Adenomatous polyp in WCE images

The major limitation of WCE is that images captured by WCE exceed over 50,000 images for examining one patient's whole Gastrointestinal (GI) tract. Among entire WCE images recorded abnormal images will be only a slight portion. The automatic disease detection is the best solution to scale down the great duty of a doctor to examine images frame by frame to locate abnormalities and diagnose the disease.

In Paper [6] authors Karargyris and Bourbakis introduced Log-Gabor filter based segmentation along with SUSAN edge detector, curvature clusters, and active contour segmentation to identify polyp frames. In [7] authors put forward a region based Active Contour Method (ACM) along with a new technique for geometric shape based polyp detection. Li.et.al [8] work is based on textural features. They integrated the better features of wavelet transform for multi resolution analysis and uniform binary pattern. In [9] authors used an improved bag of feature methodology for automatic detection of polyp. In [10] authors proposed segmentation based on combination of algorithm for automatic detection of tumor. Weston and Guyon [11] used an analytical method for gene selection for cancer classification using support vector machine.

Here we propose an automatic method to detect colon polyps and tumor from WCE images. Further portions of the paper are formulated as pursued. Section II presents the polyp and tumor frame detection. Section III describes the experimental results and discussion. Section IV concludes the paper.

II.POLYP AND TUMOR FRAME DETECTION

A. Pre-Processing

1)Video to Frame Conversion

The duration of WCE videos are about eight to twelve hours long. In the pre-processing stage WCE video is converted to frames. For the analyzing the properties of any video, we need to study the characteristics of the frames. Hence at first video files are uploaded from the Pillcam^{R}SB in the. Wmv file format. Then these videos are converted into frames of dimension 576X576.This can be done using MATLAB [12].

2) ROI Extraction

As depicted in Fig.3. WCE images have black color background and visible boundaries. By extracting features from the whole WCE frames there may chances for visual defilements in each of the image. For solving this problem, maximum square is marked within circular shaped image can be considered as required Region of Interest (ROI).Thus the significant image information loss can also be avoided. It is satisfactory enough to describe about significant image features and it also provides detailed description and characterization of WCE images. Thus feature extraction procedure; processing can be made much easier.

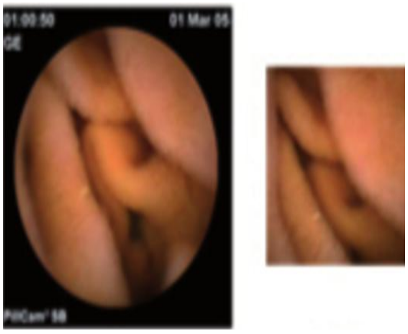

Fig.3. Illustration of ROI extraction

3) Gray Scale Conversion and Resizing

By Converting the color WCE images to gray scale images (Intensity) that is same as removing the hue and saturation information and retaining luminance. The Matlab function rgb2gray converts an RGB image to Intensity using the formula 0.2989*R + 0.5870*G + 0.1140*B, and these weights for each channel account for approximately how "strong" these colors are to the human eye. In the resizing stage, the image was resized to half its size (288×288) pixels from the original (576×576), and to avoid significant loss of quality.

B. Patch Based Method

In our proposed method, features from neighborhood key points are combined instead of extracting features from Whole WCE image. This is the method of detecting salient, stable feature points in an image. The other key point detectors includes Laplacian of Gaussian(LOG),Difference of Gaussian(DOG),Harris Laplace(HL), FAST detector, Harris Affine(HA) and SIFT[13].The proposed method uses SIFT key point detector for scale and rotation invariant key point detection. SIFT algorithm proposed by David Lowe in 1999 then developed by the same author in 2004 is used in computer vision tasks for local feature detection and description in images. SIFT key points extraction consists of two steps such as key point's detection and description.

To describe WCE images different patch sizes are selected around the key points. In this work, selection of patch sizes 4×4, 8×8, 16×16 based on polyp, and tumor size. It is done for testing the impact on patch size for the classification of WCE images. Normally in image

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processing field the size of patch selected as 2^n to obtain SIFT related features.

C. Haralick Feature Extractions

The WCE images with or without polyps and tumors will have textural feature variations in lumen and intestinal mucosal surfaces. Hence we have selected a texture based feature extraction method. Based on richness in texture information the co-occurrence matrix based method is most commonly used technique to extract textural features from patches. In our proposed method, we extract 22 Haralick features from each of the co-occurrence matrix generated. Textural features are also extracted from all neighborhood key points also. The textural features are based on pixel intensities defined by distance-angular relationship of a Co-occurrence matrix suggested by Haralick et.al [14].

D. Feature Concatenation

By subsequently acquiring the distinct textural features, a new approach is evolved to concatenate these features as a group to define colonic polyps and tumor in detail. We consider $p_i(x, y)$as the key point identified by SIFT detector. Here $(x, y)$is considered as position of pixelp_i within the actual image. Along the given patch size a region has to be considered in such a way that p_i is the center.

Then the SIFT+ Haralick texture feature descriptor combination is used. For describing key point p_i indicated as in the image, a 128 dimensional $(SIFT)_i$ descriptor is used. Then by selecting a particular patch size around the key point p_i and computed Haralick textural features. Then $(SIFT)_i$ and textural features are concatenated as a group to create an array having a dimension of 150 to describe the entire patch. The normalization has to be performed before concatenation; SIFT+ Haralick texture feature =Concatenation [$(SIFT)_i$, Haralick Feature]. Thus evaluation of the classification performance is done.

E. Classification Method and Criteria

We test our proposed method using two classifiers: Neural Network [15] and Support Vector Machine (SVM).Neural Network (NN) is relatively an advanced machine learning technique established on the basis of statistical learning theory using back prorogation algorithm.

For classification we need to train the model by running the Levin's Berg Back Propagation Algorithm (BPA) on training data and test if accuracy is low, regenerate the model. Then recognize the class label of recently arrived data to classify unknown tuples from the database. For analyzing, forecasted labels are compared to actual labels for classification performance analysis. Applications of SVM are in pattern identification, function approximation, regression analysis.

III . EXPERIMENTAL RESULTS AND DISCUSSION

A. Image Acquisition and Experimental Setup

In this experiment, we have done experiment with a dataset of 435 WCE images that consist of 187 polyps, 100 tumors and 148 normal frames. The WCE images were manually examined by Gastroenterologists from patient's video frame by frame. The images are obtained from Pillcam^{R}SB, device from Given imaging team by a resolution of 576×576. Among 100 tumor samples, 70 samples is used as training set, 15 samples were used as testing set and 15 used as validation set. The training and testing were replicated many times and the mean performance was considered for assessment of classification. Experiments were also carried out several times to attain best validation performance.

B. Experiment Results for Colonic Polyp and Tumor Frame Detection

1) Parameter Selection

First step in the proposed method is to perform and analyze the influence of different feature combination and to select the suitable parameters for classifying WCE images. The key point extraction is carried out and then features from different patch sizes surrounding the key points are extracted, and the feature concatenation is done. For the evaluation of classification performance; main parameter to be considered is patch size. In our experiment different patch sizes {4×4, 8×8, 16×16} are considered. The local textural features extracted is from small patch size {4×4} is not enough to describe key points. For describing key points more accurately and to achieve outstanding performance of colonic polyp and tumor detection patch size of 16×16 is selected. From surrounding key points also experiments are carried out.

2) Patch and Feature Analysis

The proposed method is performed for the analysis of featureconcatenation and classification for the accurate detection of colonic polyps and Tumors. After ROI extractionkey point extraction is done. An analysis of feature extraction and selection has to be done to determine its effectiveness. For analyzing impact of each of the patch size around the key points and to obtain 128 SIFT related features, we apply an SIFT detector based computer vision algorithm for detecting and characterizing local features in WCE image. SIFT key points are at first obtained from the group of reference images and stored in database. It provides a reliable recognition, features extracted from training images be visible even after image scaling, noise, illumination. Those key points will be in immense contrast areas of an image that is boundaries of WCE images. It also reduces additional errors induced by regional variations and can also robustly identify key points even among clutters. By comparing with other key point extraction methods, SIFT is much accurate.

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We further analyzed patch size in relation with the gastrointestinal frame classification through our experiment. The result indicates that for a small patch size (4×4) the extracted local features are not enough to give information about key points. For achieving best performance for disease detection, choose a patch size 16×16 surrounding the key points for implementing the proposed method. To characterize patch features SIFT features are concatenated with 22 Haralick textural features. Local features around every key point with the given training set were enumerated for constructing high dimensional descriptors. This method based on local textural features, could scale down the impact of redundant information and redundant information.

3) Analysis of Different Classification Methods

In our experiment, we need to classify polyp, tumors, and normal frames from the whole WCE images. Normally growing protrusions are polyp in mucosal surface and as the size of polyp becomes larger it leads to tumors. Hence textural based features are used to classify them.

Initially we train dataset to separate polyp and normal frames. By using NN classifier out of 401 frames, 187 frames are classified as polyp and 214 are classified as normal with an accuracy of about 98.8% .While using SVM classifier accuracy from polyp detection accuracy is only about 87.50%. Then we trained dataset to separate tumor and normal frames. Out of 100 frames, 82 frames are tumor and 18 are normal thus NN classifier classified with accuracy of 95.1% and by using SVM tumor detection accuracy is about 82.35%. We also trained polyp and tumor frames together for polyp and tumor classification using NN with an accuracy of about 99.2% and SVM classifier with an accuracy of 83.33%.

In our proposed method, we need to detect polyp and tumor from a given set of WCE images. Instead of separately training polyp vs normal, tumor vs normal and Polyp vs tumor frames. We conducted an experiment by training polyp vs tumor vs normal. After training and validation using classifiers, we analyzed the parameters like performance, training state, error histogram, confusion matrix, Receiver Operating Characteristics (ROC).

Outstanding validation performance is accomplished at the 3rd epoch where the mean square error (MSE) is minimum. MSE is for stopping training network and if actual error less than or equal to this error then training is desired to be aborted. Then progress of training in our system is analyzed using epoch, time, performance, gradient, validation, and validation check. Number of epochs is about 9 iterations but increasing number of epoch's accuracy of this model can be improved. Training time is about 0.00.24 but testing is faster. Here Gradient is about 1.16, it is the multiplication factor for miscalculation rectification at the time of back propagation. It provides steady learning. Error tolerance is also between 0 and 1. From the confusion matrix sensitivity, specificity, accuracy can be also analyzed.

Here we have both sensitivity and specificity high. ROC determine whether diagnostic classification good or not. In our experiment, most of the points in ROC curve are closer to the ideal co-ordinate thus result is more accurate. As faster the curve approaches to ideal point the test results are more accurate. The Fig.6 represents ROC characteristics, where class 1 to class 3 in this figure refers to polyp, tumor and normal frames respectively. The overall accuracy of our proposed system is about 97.5% by NN and by SVM it is only about 86.50%. Table I represents the classification result comparison analysis and Table II represents Comparison of state of art method with proposed method.

TABLE I CLASSIFICATION RESULT COMPARISON OF PROPSED METHOD

		Polyp Vs Normal	Tumor Vs Normal	Polyp Vs Tumor	Polyp Vs Tumor Vs Normal
Neural Network (NN)	Acc.	98.8%	95.1 %	99.2%	97.5%
	Spec.	94.00%	92.1 %	95.9%	93.4%
	Sen.	99.50%	96.50%	99.7%	98.8%
Support Vector Machine (SVM)	Acc.	87.50%	82.35%	83.3%	86.6%
	Spec.	85.6%	80.2%	81.8%	83.8%
	Sen.	88.7%	83.4%	84.9%	88.9%

TABLE II COMPARISON OF STATE OF ART METHOD WITH PROPOSED METHOD

		Acc.	Sen.	Spe.
Polyp vs Normal detection	Li's Method	88.56%	72.00%	92.7%
	Yuan,Li Meng	93.20%	90.88%	94.5%
	Proposed Method	98.8%	95.1%	99.5%
Tumor Vs Normal detection	Li, Mex.G	84.9%	76.7%	93.2%
	Proposed Method	95.1%	92.1%	96.5%
Polyp vs Tumor detection	Proposed Method	99.2%	95.9%	99.7%
Polyp Vs Tumor Vs Normal detection	Proposed Method	97.5%	93.4%	98.8%

4) Scope for Future Work

Our proposed method has still room for improvement. For practical implementation in hospitals, more tests by large number of datasets have to be carried out. In our experiment, entire processing is carried out in MATLAB at Core i3, Windows 7 workstation with 4 GB memory. Further testing is done using larger dataset are difficult for justifying the robustness and effectiveness of our suggested classification approach. The proposed classification accuracy can be improved by processing

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with high performance systems. The alternative key point selection method and more feature integration methods could be used to achieve better result. Thus abnormal regions can be more precisely detected from the set of whole WCE images.

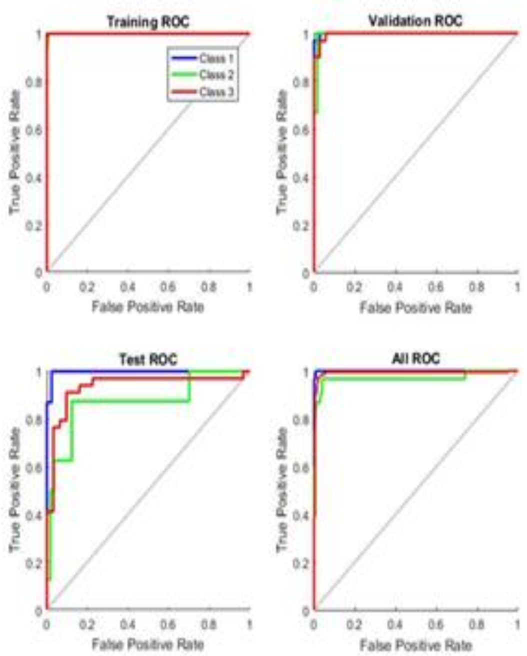

Fig.4. Receiver operating characteristics of our proposed system

IV .CONCLUSION

Thus we developed a Computer Aided Detection (CAD) method for automatic detection of polyp and tumor images from WCE images. Dataset is collected from public database of Given Imaging [16]. Along with SIFT key point extraction method 22 Haralick textural features is concatenated for extracting features from WCE images. The supervised classification is achieved using NN to increase disease detection accuracy. Compared to SVM classification results accurate detection is achieved using NN. Experimental results verify that the proposed method detects colonic polyp and tumors from the WCE images with higher accuracy and thus it is quite suitable for real-time applications.

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