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Bleeding Detection In Wireless Capsule Endoscopy Images Using Clustering Algorithm

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Abstract - Wireless Capsule Endoscopy (WCE) is a great breakthrough for Gastro Intestinal (GI) Tract diagnoses, and it can view the entire gastrointestinal tract, especially the small intestine without invasiveness and sedation. However, a tough problem associated with this new technology is that too many images to be inspected by naked eyes cause a huge burden to physicians, so it is significant to find an automatic diagnosis method. In this paper, a new automatic algorithm for bleeding detection in WCE images is proposed. This new approach mainly focuses on color feature which is also a very effective clue used by physicians for diagnosis. We propose six color features in HIS color space to discriminate between bleeding and normal status. Then we use support vector classifier to verify the performance of the proposed features and judge the status of the images. Experimental results show that the proposed features and classification method is effective and the average accuracy can achieve approximately 97%.

Keywords - Wireless Capsule Endoscopy, Bleeding, ColorFeatures, Support Vector Classifier (SVC).

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1. INTRODUCTION

Bleeding in the gastrointestinal (GI) tract result from a number of etiologies, including vascular lesions, vascular tumors, ulcers and inflammatory. The general approach to diagnose the bleedings is to directly view the GI tract by different manners. However, the traditional imaging techniques such as push entoroscopy, sondeenteroscopy are not only painful and invasive, but also technically difficult to reach the small intestines.

In rapid bleeding detection they grouped pixels through the super-pixel segmentation procedure and used the red color ratio in the RGB color space to represent the features of these super-pixels. It utilized six color features (mean and variance of H, S and V value) in the HSI color space to discriminate between bleeding and normal status. The Pyramid of Hue Histograms (PHH) to characterize the bleeding WCE images, incorporating color and spatial information by combining illumination invariant color histograms and the spatial pyramids method. Although these methods can detect the bleeding frames from the normal ones in some degree, majority of them extract the complete color features from a WCE image, ignoring the specific color range of WCE images.

In this method color histogram for bleeding detection in WCE images. The proposed method is an extension of Bag of Words method. In order to make the most of the color information of the bleeding images to calculate the color words by applying K-means clustering procedure to the pixel represented WCE images in the specific color space. Then each WCE image is characterized as histogram of the cluster centers (named words based color histogram) to represent the feature vector. Finally, Support Vector Machine (SVM) and K Nearest Neighbor (KNN) are utilized as classifiers to detect bleeding frames.

1.1 IMAGE PROCESSING

Image processing covers a vast area of scientific and engineering knowledge. It is built on a foundation of one- and two-dimensional signal processing theory and overlaps with such disciplines as artificial intelligence (scene understanding), information theory (image coding), statistical pattern recognition (image classification), communication theory (image coding and transmission), and microelectronics (image sensors, image processing hardware). Broadly, image processing may be subdivided into the following categories: enhancement, restoration, coding, and understanding. The goal in the first three categories is to improve the pictorial information either in quality (for purposes of human interpretation) or in transmission efficiency. In the last category, the objective is to obtain a symbolic description of the scene, leading to autonomous machine reasoning and perception.

Image Processing and Analysis can be defined as the "act of examining images for the purpose of identifying objects and judging their significance". A major attraction of digital imaging is the ability to manipulate image and video information with the computer. Digital image processing is now a very important component in many industrial and commercial applications and a core component of computer vision applications. Image processing techniques also provide the basic functional support for document image analysis and many other medical applications. The field of digital image processing is continually evolving. Transform theory plays a key role in image processing. Image and signal compression is one of the most important applications of wavelets.

1.2 OBJECTIVE OF THE STUDY

Our main contributions can be summarized in the following two aspects.

1) The propose method the words based color histogram to represent the image to make use of middle level features rather than low level features influence of the color spaces, cluster centers and different classification methods in terms of the classification performance.
2) The two-stage saliency extraction method to localize the bleeding areas in WCE images. Since these two-stage saliency maps highlight the bleeding regions and separate bleeding mucosa from the uninformative parts, we could obtain the bleeding area candidates successfully.

For more than 30 years, the first step in diagnosis or treatment of acute gastrointestinal bleeding has been upper endoscopy/enteroscopy (EGD) and colonoscopy. Approximately 80% of patients do not have a source of bleeding detected, possibly because the source of bleeding is outside the range of EGD or colonoscopy or because the bleeding has already stopped by the time the procedure is performed. We conduct a pilot study to obtain preliminary information on whether capsule endoscopy can improve detection of a source of acute gastrointestinal bleeding in the Emergency Department (ED) setting.

1.3 PROCESS DESCRIPTION

Wireless capsule

Patient must fast for 12 hours before the process and should not take any medicines that could delay gastric emptying. Bowel Preparation is not necessary. Then, at the medical center the sensors, data recorder, and battery pack are attached. After swallowing the capsule with a small amount of water the patients are free to leave for their usual activities. They are allowed to drink clear liquids 2 hours after capsule ingestion and to eat a light meal 4 Hours later. The Patients returns to the hospital after 8 hours. Then the data recorder is removed, and the images are downloaded and are processed. Patients can resume their regular diet and activities afterwards. They are advised to avoid Magnetic Resonance Imaging (MRI) and radio transmitters until the disposable Capsule passes in the stool, typically within 10 to 48 hours. They are asked to notify the physician if they develop nausea, vomiting, or abdominal discomfort or if they do not see the capsule passed in the stool within 1 week.

Traditional endoscopy and colonoscopy procedures give your doctor the ability to examine the upper and lower portions of your gastrointestinal tract, but seeing the middle portions, including the duodenum, jejunum and ileum of the small intestine was once unreachable to cameras. Capsule endoscopy sheds light on the middle regions of the gastrointestinal tract without exploratory surgery. Swallowing the tiny camera can reveal the source of gastrointestinal bleeding, detect bowel inflammation from Crohn's disease, find tumors and see ulcers.

People who may have celiac disease can benefit from this type of endoscopy to get a definitive diagnosis and monitor intestinal inflammation without an invasive procedure. Some gastroenterologists are also using colon capsule endoscopy to screen for colorectal abnormalities such as polyps and precancerous neoplasms.

The diagnostic procedure is almost as simple as swallowing a pill the size of a large vitamin tablet, but this capsule contains lights, a wireless transmitter and a camera housed in clear plastic. Your doctor will fit you with a monitoring device to wear as the pill moves through you. Some monitors are connected to adhesive patches the doctor will place on your abdomen. For the next 8 to 12 hours, you will wear the monitoring device as the capsule moves slowly through your gastrointestinal tract.

You will not feel any unusual sensations during the test, but the camera you have swallowed will be working overtime. During a typical test, the camera takes about 50,000 pictures of your stomach and intestinal walls. Like a camera flash, the LED lights in the capsule provide light for the images the camera takes and transmits to the compact monitoring device you wear.

After the wireless camera completes its tour of your stomach, small intestine and colon, it is expelled. The capsule may emerge after a few hours, or it may not make its reappearance for up to 72 hours; both possibilities are normal. The camera is disposable and can be flushed, so you do not need to retrieve it. The information it gathered is stored in the monitoring device, not the capsule.

1.4 TECHNIQUES STEPS

Pre-processing

In image preprocessing, image data recorded by sensors on a satellite restrain errors related to geometry and brightness values of the pixels. These errors are corrected using appropriate mathematical models which are either definite or statistical models. Image enhancement is the modification of image by changing the pixel brightness values to improve its visual impact. Image enhancement involves a collection of techniques that are used to improve the visual appearance of an image, or to convert the image to a form which is better suited for human or machine interpretation.

Classification

Once the features are extracted from a frame in question, the decision has to be made whether it is bleeding or not. The most popular classification mechanisms are simple thresholding and machine learning based techniques. Thresholding is simple but the results depend heavily on the threshold chosen and the thresholds are not often robust to variations in input images. Well known classifiers like Neural Networks and Support Vector Machines offer a more sophisticated mechanism for arriving at the decision. Using a classifier necessitates a training phase and a proper database of images to be used in the training phase. Various configurations including multilayer perceptron neural networks, probabilistic neural networks and different kernels for SVMs are used in literature. Some algorithms also use K-Nearest neighbour classification with good results. In cases where the feature vector size is large, feature selection techniques could also be used. Methods like Principal Component Analysis (PCA) are often used in order to assist the classification by initial reduction of redundant data from the feature vector. It is to be noted that C4.5 Decision Trees are considered by some as the best decision mechanism for bleeding detection, compared to SVM and Neural Networks.

Feature Extraction

For any pattern recognition problem, feature extraction is the most challenging task. Therefore, the performance of a bleeding detection scheme like any pattern recognition problem highly depends on quality of the extracted features. However, one of the major obstacles in extraction of quality features is that the bleeding zone in a bleeding frame may attain any arbitrary shape covering very small to very large areas. This random nature of bleeding zones creates problem when overall statistics of the entire image like mean pixel value and minimum, maximum, or median values are used as features when ROI is not available, therefore, often results in contamination of extracted features where small bleeding zones are surrounded by large nonbleeding zones. However, when the extracted ROI is available, one may consider that feature normalization with respect to the target area can overcome the problem of varying sizes of the region under feature extraction. But, the major concern here is the number and the choice of statistical features required for better discrimination between bleeding and nonbleeding images.

In order to overcome these problems, it is to be ensured that the characteristics of the bleeding zone, no matter how small or large, must contribute independently in the feature vector. Hence, in this paper, histogram of normalized planes at the ROI is proposed as features. Histogram-based features can clearly reflect the bleeding areas no matter how small or large in certain bins, and the property of bleeding is also preserved. In the proposed method, all the pixels of ROI extracted from a normalized plane of a WCE image are taken to perform histogram and frequency in each bin is measured. Therefore, this histogram-based representation of image pixels should ensure the presence of any group of bleeding pixels, no matter how small it is, independently in the feature vector. As this type of representation reflects the presence of any group of bleeding pixels in the feature vector, therefore, it is better to utilize histogram-based feature than to take only the total number of pixels inside the ROI as feature. As bleeding is determined through human perception of colors, it is expected that the histogram representation of bleeding and nonbleeding images should differ significantly and ensure the extraction of quality features.

2. MATERIALS AND METHODS

2.1 EARLIER RESEARCH WORK

In existing system an automatic analysis of bleeding patterns in WCE images is implemented. It implements a blood detection algorithm based on color modeling, edge masking and RX detection. The core of the proposed algorithm is the RX detector, which is implemented on pre-processed images. The simulation results reveal that the algorithm is effective at achieving a satisfactory PoD along with a relatively low FAR. Therefore, it is expected to substantially reduce the number of images to be manually analyzed to provide a diagnose proposal, allowing a more widespread use of WCE. It is worth noticing that the used sequences are compressed, and as a consequence the obtained results can be impaired by the distortion introduced by compression. Future developments will include the algorithm validation on uncompressed data, and the exploitation of the correlation between adjacent frames in order to improve the performance of the RX detection stage.

2.2 PROPOSED RESEARCH WORK

Bleeding in the gastrointestinal (GI) tract result from a number of etiologies, vascular tumors, ulcers and inflammatory lesions the general approach to diagnose the bleedings is to directly view the GI tract by different manners. The existing methods detect the bleeding frames from the normal ones in some degree. Majority of them extract the complete color features from a WCE image, ignoring the specific color range of WCE images

The proposed model designed with word based color histogram for bleeding detection in WCE images. It will find the most of the color information of the bleeding images. It calculates the color words by applying K-means clustering in WCE images in the specific color space. Then each WCE image is characterized as histogram of the cluster centers to represent the feature vector. Finally, SVM and K nearest neighbor are utilized as classifiers to detect bleeding frames. Secondly localization of the bleeding areas in the bleeding frames is focused. Inspect the bleeding images under different color spaces like RGB, HSI/HSV, CMYK, CIELAB, YUV, and XYZ and select the components that highlight the bleeding areas. Then create the first stage saliency map by combing these components together to strengthen the suspicious regions. Then combine all the saliency features of finding the color area. And predict the most red situated area and fix that region.

The wireless capsule endoscope is a swallowable medical device equipped with a miniature camera enabling the visual examination of the gastrointestinal (GI) tract. It wirelessly transmits thousands of images to an external video recording system, while its location and orientation are being tracked approximately by external sensor arrays. In this paper we investigate a video-based approach to tracking the capsule endoscope without requiring any external equipment. The proposed method involves extraction of speeded up robust features from video frames, registration of consecutive frames based on the random sample consensus algorithm, and estimation of the displacement and rotation of interest points within these frames. The results obtained by the application of this method on wireless capsule endoscopy videos indicate its effectiveness and improved performance over the state of the art. The findings of this research pave the way for a cost-effective localization and travel distance measurement of capsule endoscopes in the GI tract, which could contribute in the planning of more accurate surgical interventions

3. ALGORITHM DESCRIPTION

3.1 K-MEANS CLUSTERING

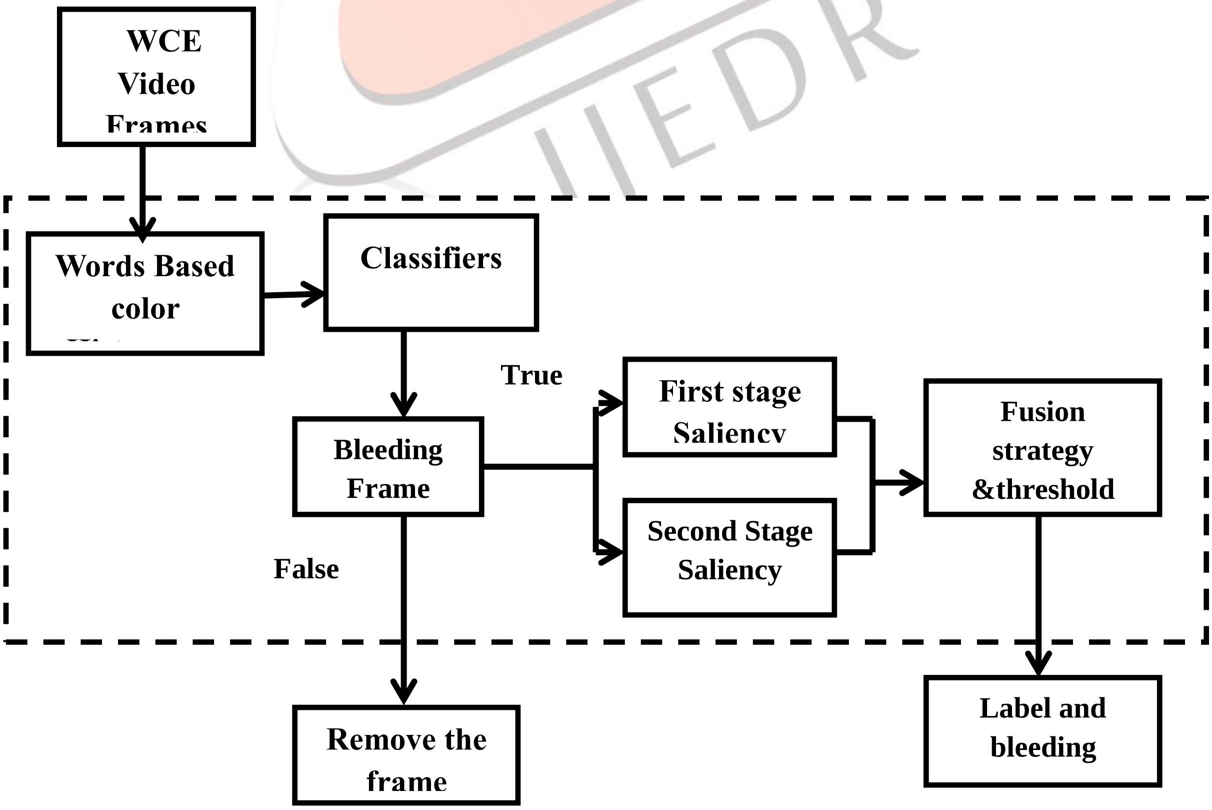
K-Means clustering is a method of vector quantization, originally from signal processing, that is popular for cluster analysis in data mining. k-means clustering aims to partition *n* observations into k clusters in which each observation belongs to the cluster with the nearest mean, serving as a prototype of the cluster. This results in a partitioning of the data space into Voronoi cells.

The problem is computationally difficult (NP-hard); however, there are efficient heuristic algorithms that are commonly employed and converge quickly to a local optimum. These are usually similar to the expectation-maximization algorithm for mixtures of Gaussian distributions via an iterative refinement approach employed by both k-means and Gaussian Mixture Modeling. Additionally, they both use cluster centers to model the data; however, k-means clustering tends to find clusters of comparable spatial extent, while the expectation-maximization mechanism allows clusters to have different shapes.
The algorithm has a loose relationship to the k-nearest neighbor classifier, a popular machine learning technique for classification that is often confused with k-means because of the k in the name. One can apply the k-nearest neighbor classifier on the cluster centers obtained by k-means to classify new data into the existing clusters. This is known as nearest centroid classifier or Rocchio algorithm
The K-means clustering is used for classification of object based on a set of features into K number of classes. The classification of object is done by minimizing the sum of the squares of the distance between the object and the corresponding cluster.

THE ALGORITHM FOR K –MEANS CLUSTERING
The most famous partitional clustering algorithm is k-means clustering. The steps of k-means clustering are as below.
Step 1: Determine the number of clusters we want in the final classified result and set the number as N. Randomly select N patterns in the whole data bases as the N centroids of N clusters.
Step 2: Classify each pattern to the closest cluster centroid. The closest usually represent the pixel value is similarity, but it still can consider other features.
Step 3: Recompute the cluster centroids and then there have N centroids of N clusters as we do after Step1.
Step 4: Repeat the iteration of Step 2 to 3 until a convergence criterion is met. The typical convergence criteria are: no reassignment of any pattern from one cluster to another, or the minimal decrease in squared error.

SVM-based method
Fu et. al describes a basic SVM-based method that operates on segments rather than pixels or image as a whole. Here, the image is first converted to CIE Lab space and the pre-processing involves edge detection in L channel. The detected edge regions are dilated and then masked. The images are then smoothened a bit by Gaussian filtering and divided into meaningful segments using super-pixel segmentation algorithm. Super-pixel segmentation takes into account closeness of adjacent pixels in spatial and color domain. The segments are then manually marked as bleeding and normal. Feature vector used is red ratios: R/G, R/B and R/(R+G+B), where R, G and B are the mean values of R, G and B values of pixels in a segment. The feature vectors extracted from these segments are then fed to SVM learning and the learned model is then used for classification. In testing phase, the feature set extracted from the super-pixels of a pre-processed frame are classified using the learned SVM model as bleeding or normal.

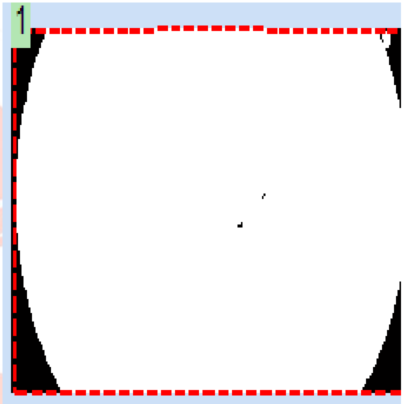
ARCHITECTURE DIAGRAM



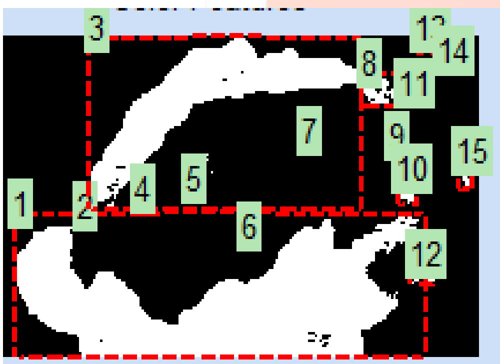
WCE CAPSULE CAMERA

4. Experimental Result

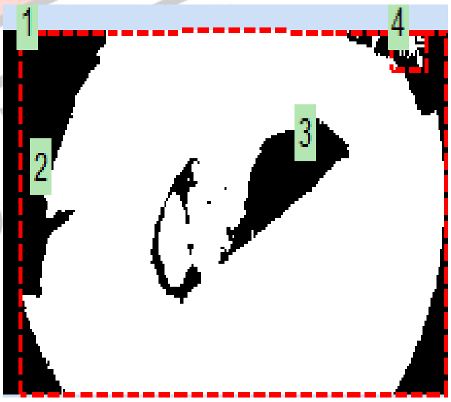
INPUT VIDEO



CLUSTER1



CLUSTER2



CLUSTER3

5. CONCLUSION

Compared to traditional endoscopy, the WCE technology suffers certain disadvantages like inability to carry out controlled inspection, biopsy, targeted load delivery etc. but its ability to potentially image the GI tract in its entirety and detect obscure symptoms ensures that WCE technology is here to stay. Among the various methods proposed in literature for the automated analysis of WCE videos, classifier based methods promise a better specificity and robustness without much compromise in sensitivity, compared to simple thresholding based methods. Pre-processing the WCE images using various image processing techniques improves the accuracy of detection in general but does not come without its share of problems. Techniques like edge masking can mask genuine bleeding regions since changes in color are also often detected as edges. Similarly, some endoscopy capsules have text and other data overlaid on the images and this may not be completely removed in pre-processing. Such pixels will cause potential problems in segmentation and may affect the classification. Lack of standard annotated WCE databases in public is another impediment in developing learning-based methods and reliably comparing their performances.

In this paper proposed a novel method for bleeding frame detection and region localization in WCE images. The extensive experiments demonstrate that the best classification performance could be obtained with SVM classifier, YCbCr color space and cluster number of 80. The proposed features could obtain accuracy 95.75%, sensitivity 92% and specificity 96.5%, and the corresponding AUC is 0.9771. In the second step, we extracted two stage saliency maps to locate the final bleeding areas. The quantitative result indicates the best bleeding localization performance could be obtained by the weight 0.8 for the first stage saliency map and 0.2 for the second stage saliency map. The corresponding localization precision archives 95.24%.

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