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ORIGINAL RESEARCH

Bleeding Frame and Region Detection in Wireless Capsule Endoscopy Video

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Abstract – Wireless capsule endoscopy (WCE) enables non-invasive and painless direct visual inspection of a patient's whole digestive tract, but at the price of long time reviewing large amount of images by clinicians. Thus an automatic computer-aided technique to reduce the burden of physicians is highly demanded. Here propose a novel color feature extraction method to discriminate the bleeding frames from the normal ones, with further localization of the bleeding regions. The proposed method is based on a twofold system. First method provides full use of the color information of WCE images and utilize K-means clustering method on the pixel represented images to obtain the cluster centers, with which the characterize WCE images as words based color histograms. Then the methods judge the status of a WCE frame by applying support vector machine (SVM) and *K* nearest neighbor (KNN) methods. Comprehensive experimental results reveal that the best classification performance is obtained with YCbCr color space, cluster number 80 and the SVM. The achieved classification performance reaches 95.75% in accuracy, 0.9771 for AUC, validating that the proposed scheme provides an exciting performance for bleeding classification. The second method propose a two-stage saliency map extraction method to highlight bleeding regions where the first stage saliency map is created by means of different color channels mixer and the second stage saliency map is obtained from the visual contrast. Followed by an appropriate fusion strategy and threshold, localize the bleeding areas. Quantitative as well as qualitative results show that our methods could differentiate the bleeding areas from neighborhoods correctly.

Index Terms – Support Vector Machine (SVM), Wireless capsule endoscopy (WCE), region detection, KNN, characterization process

I. INTRODUCTION

Biomedical image processing has experienced dramatic expansion, and has been an interdisciplinary research field attracting expertise from applied mathematics, computer sciences, engineering, statistics, physics, biology and medicine. Computer-aided diagnostic processing has already become an important part of clinical routine. Accompanied by a rush of new development of high technology and use of various imaging modalities, more challenges arise; for example,

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how to process and analyze a significant volume of images so that high quality information can be produced for disease diagnoses and treatment. The principal objectives of this course are to provide an introduction to basic concepts and techniques for medical image processing and to promote interests for further study and research in medical imaging processing. 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 enteroscopy, sonde enteroscopy are not only painful and invasive, but also technically difficult to reach the small intestines.

In the existing method for 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 th`ese 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 proposed 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. The second stage focus on localization of the bleeding areas in the bleeding frames. Since the components of various color spaces possess different information, to 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 to create the first stage saliency map by combing these components together to strengthen the suspicious regions. In addition, natural saliency lies in the visual contrast. To the second stage saliency map from the prior that if the color information of the region shows large similarity to the red color, then this region should possess high saliency value. Finally applying an appropriate fusion strategy of these two conspicuity maps and automatic threshold, find the localization of bleeding area.

II. LITERATURE SURVEY

In R. Achanta, F. Estrada, P. Wils, and S. Süsstrunk.(2008) "Salient region detection and segmentation," et al[1], describes that the detection of salient regions useful for applications like image segmentation, adaptive compression, and region based image retrieval. In this paper a novel method to determine salient region sin image using low level features of luminance and color. The method is fast, easy to implement high quality saliency maps of same size and resolution as input image. Here a demonstration using algorithm in the segmentation of semantically meaningful whole objects from digital images.

In F. Conversano, E. Casciaro, R. Franchini, S. Casciaro, and A. Lay-Ekuakille.(2008) "Fully automatic 3D segmentation measurements of human liver vessels from contrast-enhanced CT," et al[2],describes that the present work was to evaluate the performance of a novel fully automatic algorithm for 3D segmentation and volumetric reconstruction of liver vessel network from contrast-enhanced computed tomography (CECT) datasets acquired during routine clinical activity. Three anonymized CECT datasets were randomly collected and were automatically analyzed by the new vessel segmentation algorithm, whose parameter configuration had been previously optimized on a phantom model. The same datasets were also manually segmented by an experienced operator that was blind with respect to algorithm outcome. Automatic segmentation accuracy was quantitatively assessed for both single 2D slices and 3D reconstruction of the vessel network, accounting manual segmentation results as the reference "ground truth". Adopted evaluation framework included the following two groups of calculations: 1) for 3D vessel network, sensitivity in vessel detection was quantified as a function of both vessel diameter and vessel order; 2) for vessel images on 2D slices, dice similarity coefficient false positive ratio, false negative ratio, Bland-Altman plots and Pearson correlation coefficients were used to judge the correctness of single pixel classifications. Therefore, the tested method showed significant robustness and accuracy in automatic extraction of the liver vessel tree from CECT datasets. Although further verification studies on larger patient populations are required, the described algorithm has an exciting potential for supporting liver surgery planning and intraoperative resection guidance.

In L. Cui, C. Hu, Y. Zou, and M.-H. Meng "Bleeding detection in wireless capsule endoscopy images by support vector classifier," in Information and Automation (ICIA), et al[3],describes image processing algorithm for the diagnosis of ulcers, which is a lesion occurring in the digestive tract, based on endoscopic images. In general, ulcers are visually distinguishable from normal tissues owing to the defective state in the mucosal membrane, cornea or skin tissue. Based on this characteristic, we used different colors to distinguish between ulcer and normal tissues in the proposed method. First, image luminance was adjusted to ensure similar luminance distribution values through a preprocessing stage in which the captured images were normalized to achieve uniform intensity distribution for each channel. Then, we selected distinctive elements for the detection of ulcer tissues with distinct image-associated chromatic characteristics. Because image luminance can affect detection even after preprocessing, we selected elements that were distinguishable from normal tissues based on the distribution of values displayed by ulcers from both RGB and HSV bands. Moreover, most of the digestive tract ulcers occur on the mucosal surface and tend to cluster together to form a specific zone. This implies that a detected ulcer pixel

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is more likely to be surrounded by ulcer tissue than normal tissue. Therefore, we used the intensity of each image channel as an additional detection element and performed ulcerative zone detection. An additional advantage of the zone detection process is the exclusion of errors caused by image-emanated random impulse noise.

III. SYSTEM ANALYSIS AND DESIGN

Proposed System

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.

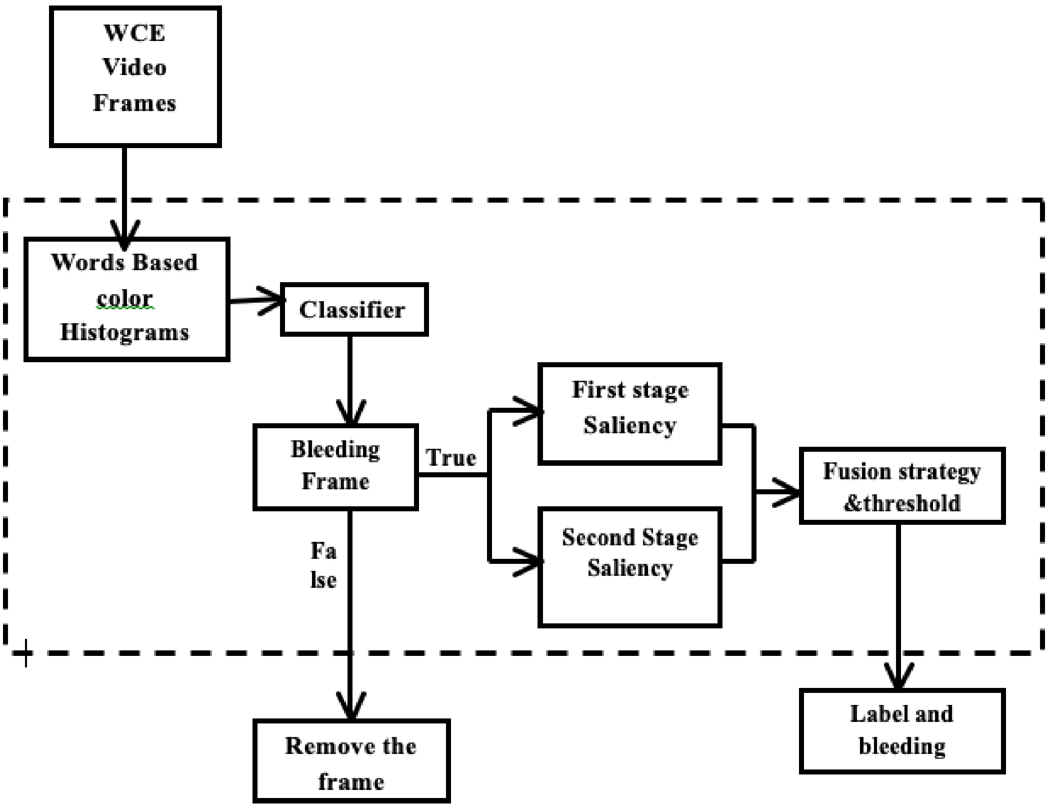

Fig 1: System Architecture Block Diagram

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

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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 WCE Video frames are converted into word based color histograms. A classifier will identify the bleeding frame. If it is a bleeding frame, the bleeding location detection is done using First stage Saliency and Second stage Saliency.

1. First Stage Saliency:

This module is used to localizing the bleeding area. Color is the main hue is used to differentiate the bleeding area. The bleeding area can be classified using the following equation

$$S_{stage}(x, y) = \alpha^* A(x, y) + \beta^* M(x, y)$$

Where A(x, y) denote the A channel and the M(x, y) denote the color space. α and β defined as the pre-defined constant value.

2. Second Stage Saliency

The second salient regions as those regions with large similarity to the red color values If a pixel has a greater R value and smaller G, B values, it would be assigned higher saliency value. Hence we derive the second stage saliency map based on the following three steps Utilize a 5*5 Gaussian filter on the original image to eliminate fine texture details as well as noise and coding artifacts. Then the saliency maps for R, G and B color channels are calculated by

$$S_R(x, y) = 1\text{-}\exp\left(-\frac{V_R^2}{\sigma_R}\right)$$

$$S_G(x, y) = \exp\left(-\frac{V_G^2}{\sigma_G}\right)$$

$$S_B(x, y) = \exp\left(-\frac{V_B^2}{\sigma_B}\right)$$

where V**R,** V**G,** and V**B** are the corresponding values in RGB space. The parameters σ_R , σ_G , and σ_B are chosen to adjust the three color saliency map. The region with larger V**R**, and smaller V**G** and V**B** will have higher S_R, S_G and S_B. Finally the second saliency map is for an image I could be formulated as

$$S_{stage2}(x, y) = \frac{1}{3} \times (S_R + S_G + S_B)$$

Finally fusing method is used to join together

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$$S_{final} = w1 * S_{Stgae1} + w2 * S_{Stage2}$$

where S_{final} is the fused saliency map and w1+w2 = 1. Once these two stage saliency maps are fused together, the bleeding regions are likely to be strengthened.

RESULT AND DISCUSSION

In this chapter the data's that are used to form a single and efficient processing is based on the simple format the existing and proposed model is compared to find the efficiency of the manual power for detecting the process.

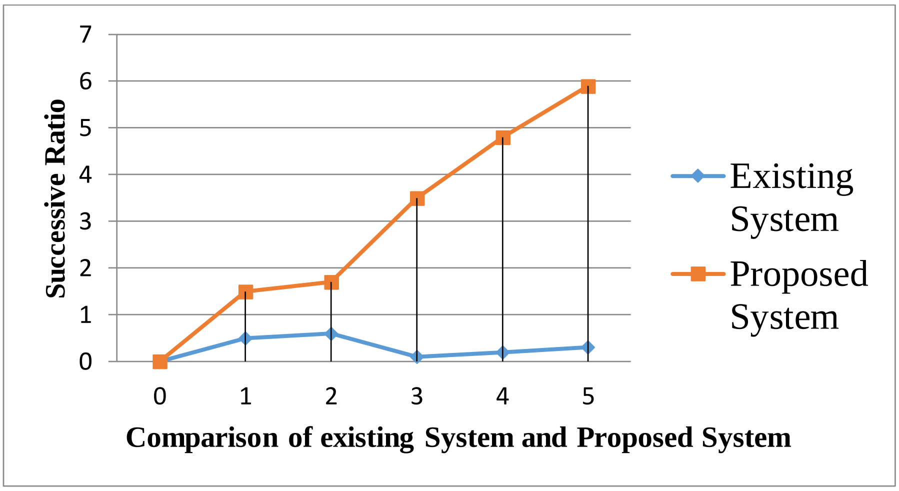

Fig. 2: Comparison of Existing system and Proposed system

This should be efficient for the simple model that can be used to process for the entire process thus it is an efficient process for finding the best methodology of the process to be under different processing mechanism. The data that is used here to compare the various process of the mechanism this should be easily process by the entire mechanism.

Result

The information for bleeding localization is obtained and the bleeding area has been detected accurately.

Quantitative Analysis

After obtaining the bleeding frames, we focused on the localization of the bleeding areas in this part. Our model calculates two stage saliency maps and fuses them together to detect the bleeding areas. Evaluation of the fusion strategy is an important step in the assessment of the model performance. We tested in the Eq. 6 for the values {0, 0.2, 0.4, 0.6, 0.8, 1} to obtain the final saliency maps and then applied the Otsu's threshold method on the calculated saliency maps to obtain the bleeding area 1 w To evaluate the localization performance that was obtained by using different weighting models, three criteria: Precision, FPR, FNR were calculated. The best bleeding localization result with the precision of 95.24% was achieved with weight of 0.8 on the first stage saliency map. This result is inspiring, showing that our proposed saliency method could detect the bleeding area accurately. Moreover, when the weight of the saliency region is set to 0 or 1, the best localization accuracy is not obtained. This result indicates that these two-stage saliency calculation methods complement each other to provide useful information for bleeding localization. Furthermore, the algorithm achieved a good FPR of 0.86%.

Qualitative Analysis

To illustrate our proposed saliency methods visually by the first example image given in Fig. 2. is the saliency map generated through means of channel mixer while obtained by prior knowledge that the region with red color should assign large saliency value. It is obvious that these two saliency maps provide good ability to identify bleeding regions. After the fusion strategy, the final saliency map. In this figure, the bleeding mucosa appears brighter than normal mucosa region; hence it can be easily extracted by an appropriate threshold. The binary bleeding mask image obtained through the Otsu's threshold procedure. 1 0.8 w .

IV. CONCLUSION AND FUTURE WORK

The proposed method for bleeding frame detection and region localization in WCE images is an achievement in medical field. 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. The implementation of the proposed model should be simple and efficient for the protective method that can be used for the secure process. In medical diagnosis there are lots of methods that are used to maintain under the different scenarios.

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