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Enhanced Saliency Based Ulcer Detection Model Using Multigraph Clustering Algorithm

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***Abstract**: Image segmentation is the process of obtaining particular regions from the images. Edge detection identifies the edge points around the needed objects. Contour extraction refers to outlining the segmented portion from the image. In order to make the method practically useful in hospital clinical trials, further tests using a much larger number of datasets are critical to validate the effectiveness and the robustness of the WCE images. Furthermore, this study is proposed to implement efficient ulcer recognition task for the WCE images such as bleeding, ulcer using different dataset. In this paper, analysis a novel saliency estimation method that takes advantage of the superpixel segmentation method and the image contrast information (texture and color contrasts). In this proposed method is based on the multi-level superpixel representation to avoid deficiency of pixel representation in the saliency region detection. The proposed multi-level superpixel segmentation method is considered as a superior alternative to the traditional WCE image segmentation method since it can outline abnormal region correctly and compactly. The paper segments image by keying in any point location inside the object or segments the WCE image automatically starting from the center point. In this paper anlayis the statistical data such as number of objects found during segmentation and similar objects within the WCE image are also calculated. The gray scale conversion of the particular segments is also carried out so that the output WCE image partitions the image into different objects. Suppose the image may be WCE images which could identify the cell information; the collection of rises in the plate in which the coarse and finer size rice particles are distinguished out.*
***Keywords:** Image segmentation, Digital Image Processing, Superpixel Segmentation, Clustering, K-Fuzzy Logic.*

I. Introduction

Digital Image Processing is a component of digital signal processing .The area of digital image processing refers to dealing with digital images by means of a digital computer. Digital image processing has several advantages above analog image processing and it allows a considerably wider collection of algorithms to exist apply to input data and can keep away from troubles for example the increase of sound and signal buckle during processing. Digital Image Processing involves the modification of digital data for improving the image qualities with the aid of computer.The processing helps in maximize the clarity, sharpness of image and details of features of interest towards extraction of information and further analysis.

II. Literature Survey

Sae Hwang[1] Wireless Capsule Endoscopy (WCE) is a relatively new technology (FDA approved in 2002) allowing doctors to view most of the small intestine. One of the most important goals of WCE is the early detection of colorectal polyps. We introduce "Bag-of-Visual-Words" method which has been successfully used in particular for image classification in non-medical domains. Initially the training image patches are sampled and represented by speeded up robust features (SURF) descriptor, and then the bag of words model is constructed by K-means clustering algorithm. Subsequently the document is represented as the histogram of the visual words which is the feature vector of the image. Finally, a SVM classifier is trained using these feature vectors to distinguish images with polyp regions from ones without them. Our preliminary experiments on our current data set demonstrate that the proposed method achieves promising performances.Duzhen Zhang and Chuancai Liu**[2]** A novel automatic salient object detection algorithm, which integrates context-based saliency with location computation based on the boundary priors, is proposed. Input image is expressed as a close-loop graph with superpixels as nodes and salient object of image has a well-defined graph-based manifold ranking location. The saliency of the image elements is defined based on their relevances to the given seeds or queries. Saliency object location is carried out in a two-stage scheme to extract background regions and foreground salient objects efficiently. We introduce a location weight to measure the relationship of superpixels and the centroid of the detected salient regions to eliminate the background. Saliency map is computed through context analysis and location computing based on multi-scale superpixels.**Alexandros Karargyris and Nikolaos Bourbakis[3]** Over the last decade, wireless capsule endoscopy (WCE) technology has become a very useful tool for diagnosing diseases within the human digestive tract. Physicians using WCE can examine the digestive tract in a minimally invasive way searching for pathological abnormalities such as bleeding, polyps, ulcers, and Crohn's disease. To improve effectiveness of WCE, researchers have developed software methods to automatically detect these diseases at a high rate of success. This paper proposes a novel synergistic methodology for automatically discovering polyps (protrusions) and perforated ulcers in WCE video frames. Finally, results of the methodology are given and statistical comparisons are also presented relevant to other works.

III. Methodologies

3.1 Superpixel Segmentation

A super pixel is defined as the meaningful entity by grouping spatially neighboring pixels with the similar property. Simple Linear Iterative Clustering (SLIC) is the state-of-the-artsuperpixel algorithm that outputs a desired number of regular, compact super pixels with a low computational overhead.The propose system apply a SLIC super pixels as a pre-processingmethod for WCE image saliency detection. Because it not only provides good segmentation results, but also generates suitable size of super pixels for WCE image analysis. In the SLICmethod, the local K-means clustering is first performed on the pixels based on the color space and spatial distances. Then the isolated small clusters are merged with the largest neighbor clusters to obtain the specific number of the superpixels.

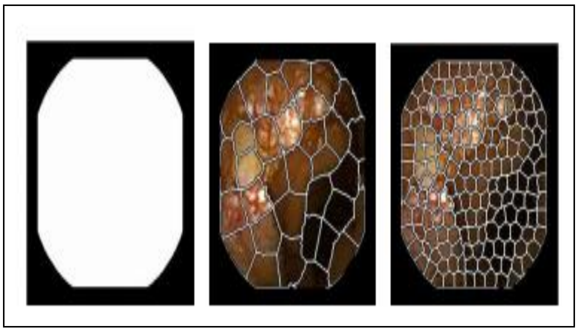

Fig 3.1 Superpixel Segmentation

Choosing a suitable number of superpixels for the WCE image is empiric and case-specific. This is because that too many numbers of superpixel lead to over-segmentation, whiletoo few superpixels result in loss of the boundary information of the objects. In addition, using a single superpixel size to do segmentation may not be able to describe the boundarywell for some cases. Therefore, we propose a multi-level superpixel method that first segments the image by using multiple different numbers of superpixels (a.k.a., multiple levels of superpixels), then fuses all superpixel segmentation in all levels later. The number of superpixels K we tested in this paper is set to be 50, 100, 150, 200, and 250 in each level, which results in level number L = 5.

3.2 Multiple Graph Region Clustering Algorithm

Given a set of N data points X = { xi } , a set of kernel functions { K_k }, and the desired number of clusters C, output a membership matrix U = { uic }, s { w_k } for the kernels.

1. Procedure MGRCA (Data X, Number C, Kernels { K_k }
2. Initialize membership matrix U(0).
3. repeat calculate normalized memberships
4. Calculate Co-Efficient
5. for (i=1..N;c=1..Ck=1..M) doN
6. Calculate Co-Efficient
7. for (k = 1..M) do N
8. □ □ □ □ □ □ □ □ □ (u (t)) m □ ick
9. end for
10.Update Weights for (k = 1..M) do 1/ □
11. □ □ □ □ □ □ □ □ □ □ □ □ □ □ □ 1/ □ + ...
12. end for
13. Calculate Distances for (i = 1..N;c = 1..C) do

14. D□ □ □ □ □ □ □ □ □ □ □ ick(□ k(t))2
ic k=1
15. 1end for
16. Update Memberships for (i = 1..N;c = 1..C) do U
17. end for
18. until || U(t) _ U(t-1) || □

The above Algorithm summarizes the MGRCA algorithm, which starts by initializing a random membership matrix satisfying nonnegative and unity constraints. Optimal weights are calculated by fixing the memberships, and optimal memberships are updated assuming fixed weights. The process is repeated until the amount of change per iteration in the membership matrix falls below a given threshold.

Fig 3.2 Graph Based Image Segmentation With Various Thresholds

3.3 Source Image Selection For Recognition

The image selection is made through open file dialog control and there is no need to type file path. JPG Images are filtered in the control but other image types can also be selected. The source image is converted in to .Net Bitmap class and then pixels are retrieved.

Fig 3.3 Sources Image Selection for Recognition

3.4 Pattern Image Selection

In the paper, the image selection is made through open file dialog control and there is no need to type file path. JPG Images are filtered in the control but other image types can also be selected. The pattern image is converted in to .Net Bitmap class and then pixels are retrieved.

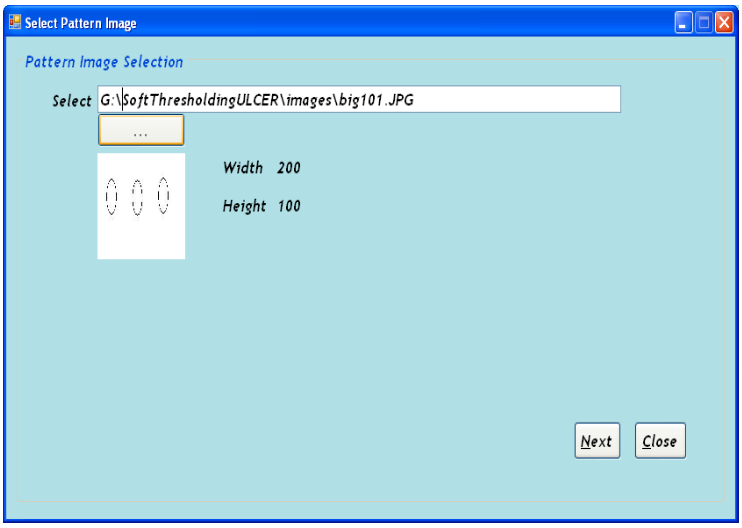

Fig 5.4 Pattern Image Selection

IV. Performances Analysis

The following table 4.1 shows the experimental results for precision and recall values for Multi level Superpixel and Multi Graph Region Cluster model. The table contains number of pixel count, Number of iteration level and MLS-SEM and MGRCA-SEM precision recall values.

S. NO	**Selective Superpixels (Image)**		**Multi-Level Superpixel Saliency Extraction Method (MLS-SEM) (Precision- Recall Values)**	**Multiple Graph Region Cluster Saliency Extraction (MGRCA-SEM) (Precision-Recall Values)**
	Count (N)	**Level (K)**		
1	50	4	12.5	25
2	100	8	25	50
3	150	12	37.5	75
4	200	16	50	100
5	250	18	69.44	138.88

Table 4.1 Precision-Recall for MLS-SEM and MGRCA-SEM

The following Fig 4.1 shows the experimental results for MLS-SEM and MGRCA-SEM precision and recall model. The figure contains number of pixel count, Number of image and MLS-SEM and MGRCA-SEM precision recall average values.

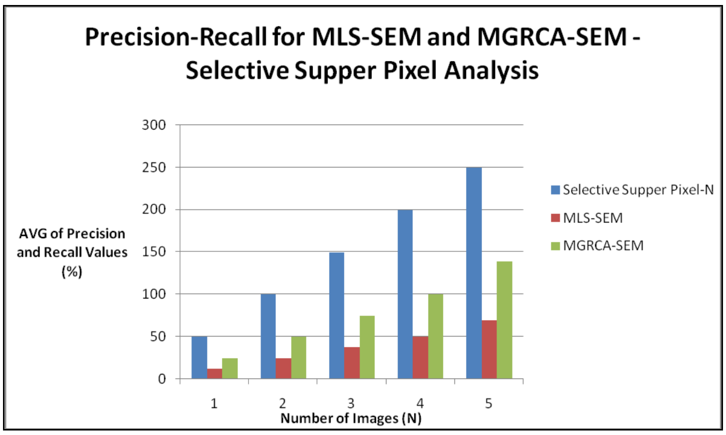

Fig 4.1 AVG- Precision-Recall for MLS-SEM and MGRCA-SEM

The following Fig 4.1 shows the experimental results for MLS-SEM and MGRCA-SEM precision and recall model. The figure contains number of pixel count, Number of image and MLS-SEM and MGRCA-SEM precision recall average values.

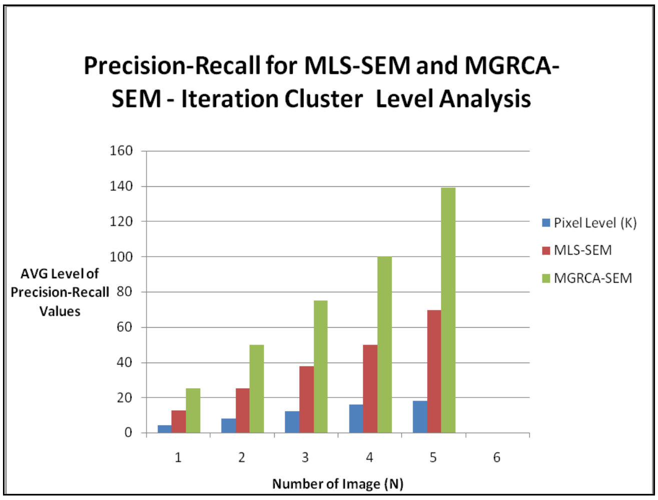

Fig 4.2 Pixel Level- Precision-Recall for MLS-SEM and MGRCA-SEM

The proposed modified LLC image coding method acts as the second stage for WCE image description. The original LLC method gives a compact description to represent WCE images by taking the locality and sparsity into consideration. In our methods, by carrying out max pooling after dividing the original LLC code into salient and non-salient parts, the WCE images can be better encoded to emphasize the salient regions in the recognition process.Since ulcer regions have particular color and texture characteristics, we utilized this important information and extracted salient maps that emphasize the color and texture contrasts of ulcer regions inside the WCE images. We tested many textures to outline the ulcer region and found that the features extracted from LM filter could obtain better performance than the others. This result may be due to the multi-scale and multi-orientation nature of the LM filter. The experimental results shown in fig 6.1 and 6.2 validated the effectiveness of our proposed method and also gave strong evidence to support our arguments.

V. Conclusion And Future Enhancement

The proposed system eliminates the difficulties in the existing system. It is developed in a user-friendly manner. The system is very fast in applying segmentation algorithm. This software is very particular in reducing the difficulty in segmentation algorithms. Through this project, the problem of manual pattern is eliminated. Since very less input is given; any persons can use the application. Once the pixel value is found to be incorrect in given rectangular area, the entire area is ignored for further pixel comparison. This results in fast work and their overall recognition time is reduced.The end users are required to have minimum working experience in systems to run this software. The application reduces recognition time and helps in improving error free and efficient patterns identification. The application is tested well so that the end users use this software for their whole pattern recognition related operationThe thesis has covered almost all the requirement. Further requirements and improvements can easily be done since the coding in mainly structured or modular in nature. Improvements can be appended by altering the accessible modules or adding original modules. Several areas to be developed in future, so the application must be upgraded for the new ones required and it is possible to modifications according to new requirements and specifications. The Future Analysis of this thesis as follows:

1. In future, same thesis will developed in web based application. It should not require software installation.
2. Here the image segmentation only handled, in future plan to add the concept of compression and decompression of image which should reduce the image size proficiently.The images are planned to store in the database without affecting real image

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