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Lesion Area Detection (LAD) using Superpixel Segmentation

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Abstract

Nowadays, in biomedical field, imaging techniques are used to discover the abnormalities in the particular region. Lesion is an area in an organ or tissue, which has suffered from damage through injury or disease, such as a wound, ulcer, abscess, or tumor. Lesion area of the tissue is detected using source images. Wireless capsule endoscopy image of the gastrointestinal tract is used to find the lesion. Preprocessing of image is done using denoising by multidimensional filter. Denoised image is edge detected during which the edge points in an image differentiation is highlighted by Sobel edge detection. The value of each pixel in the edge detected image is evaluated based on the comparison of corresponding pixel in the input image with its neighboring pixels by the morphological operation. Erosion and dilation operation erodes and adds pixels respectively to the edge detected image, so that the value of the output pixel has the maximum pixel value. During segmentation, the pixels are grouped using superpixel algorithm to reduce the complexity while maintaining high diagnostic accuracy. As a final point, the Correlation coefficient test finds the spoiled area between healthy tissue and abnormal tissue by color encoding. This intends to identify the suspected abnormal areas (lesion) from the source images.

Keywords: Correlation Coefficient, Lesion Area, Morphological Operation, Multidimensional Filter, Sobel Edge Detection, Superpixel Segmentation

1. Introduction

In the field of Biomedical and Health Informatics, Detection of lesions is always problematic due to similar intensity between lesions and normal tissues. Lesions can occur anywhere in the body that consists of soft tissue found in the mouth, skin, intestinal tract and the brain. Lesions can also be caused by metabolic processes, like an ulcer, cancer, or autoimmune activity. Many researchers used different techniques to detect the lesion area in the targeted tissue. Manual detection of lesion area is slow and difficult; therefore automatic multiple sclerosis lesion detection is used to find the multiple lesion in the targeted region. A fast and accurate method for evaluating the size of MS lesions in the damaged region is used to diagnose the disease and helps the doctors in treatment decision.

Due to the food practice and emotional stress, ulcer in stomach is the emerging problem nowadays. These ulcers are developed from the lesions which occur in the soft tissues of the stomach. An endoscopy is considered the best procedure for diagnosing digestive ulcers, Wireless Capsule endoscopy images shows the clear view of the gastrointestinal tract as in Figure 1. The lesions and ulcers developed in the intestinal region should be detected using the scanned image before it leads to cancer. Early detection of lesion helps in further treatment.

2. Scope of the Research

In medical field computational time is the most important parameter for analysis of any diseases and their treatment. Detection of lesion area reduces computational time for

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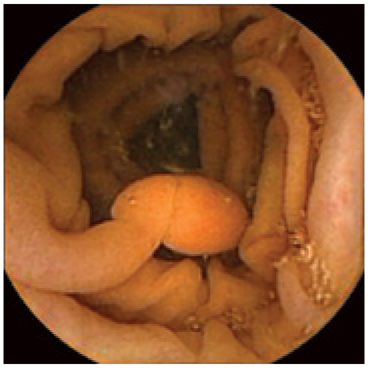

Figure 1. Wireless capsule endoscope image of intestine.

clinical diagnosis. In large datasets, manual lesion detection is required and it takes more time to diagnose the abnormality. Many techniques have been developed for the identification of infected region in terms of voxels segmentation, but still it needs an improvement in terms of accuracy and computational complexity. Hence LAD using superpixel segmentation and Pearson's correlation coefficient detect the lesion area automatically and reduces the computational complexity.

3. Related Works

3.1 Pre-processing

Preprocessing of images commonly involves removal of low frequency noise, removing reflections of images, normalizing the intensity of the individual voxels of the image, and masking portions of images. Therefore input image must be preprocessed. All medical images contain some form of noise due to environment, where the scan is taken. This noise should be removed using filters based on the nature of the noise present in the input scan image. The goal of image denoising is to remove the noise while retaining the important image features like edges, details as much as possible. Denoising of image includes smoothening of images; reduce noise, and preserving edges. A Guided multidimensional filter must be used to perform smoothing, reducing and preserving edges of the image without the loss of original information[13].

Medical image contains the signal subspace and the noise subspace is very close such that all the useful information is difficult to extract. This leads to artifacts and loss of spatial resolution in the restored HIS[2]. Multidimensional Filtering is used to denoise the intestinal image where signal subspace and noise subspace are difficult to filter. Hence the signal subspace dimension is reduced as well as signal to noise ratio is enhanced.

3.2 Edge Detection

The edge detection process serves to simplify the analysis of images by drastically reducing the amount of data to be processed, while at the same time preserving useful structural information about object boundaries[5]. Edge detection is used to view, particularly in the areas of feature detection and extraction.

The aim of the edge detection is to identify points in a digital image in which image brightness that changes sharply or, more formally, the points where discontinuities are present. The points at which image brightness changes sharply are typically organized into a set of curved line segments termed edges. The edge detection operation is performed by forming a matrix centered on a pixel chosen as the center of the matrix area. If this matrix area value is higher than a given threshold value, then the center pixel is regarded to be as an edge. Gradient based edge detectors are Sobel, Canny and Prewitt operators. The gradient based algorithms have kernel operators that calculate the strength of the slope in directions which are orthogonal to each other, generally vertical and horizontal. Afterward the diverse components of the slopes are combined to give the total value of the edge strength. In Intestinal area the lesion may found in all the edges, in these case canny edge detector cannot be used. Lesion detection consists of high intensity images, Sobel operator is used to detect the edges in this case.

The Sobel operator performs a multidimensional spatial gradient measurement[3] on an image. It is used to find the approximate absolute gradient magnitude at each point in an input grayscale image. The operator consists of a pair of 3×3 convolution masks is shown in Figure 2, and Sobel convolution masks are shown in Figure 3,

The detector uses the masks to compute the first order derivatives G_x and G_y, is given in Equation 1(a) and 1(b),

$$G_x = Z_7 + 2Z_8 + Z_9 \qquad 1(a)$$

$$G_y = Z_1 + 2Z_2 + Z_3 \qquad 1(b)$$

Z_1	Z_2	Z_3
Z_4	Z_5	Z_6
Z_7	Z_8	Z_9

Figure 2. Image neighborhood of Sobel operator.

G_x

-1	0	+1
-2	0	+2
-1	0	+1

G_y

+1	+2	+1
0	0	0
-1	-2	-1

Figure 3. Sobel convolution masks.

The advantage of Sobel operator is intuitiveness and easiness. The Sobel edge detection is used for edge detection and finding directions of gradient magnitude as the approximation of gradient magnitude is easy. Hence Sobel edge detection detects the edges of the gray converted image and the direction of gradient magnitude is found in the intestinal image.

3.3 Morphological Processing

Morphological processing is an operation that process images based on shapes. Morphological operation is one in which the value of each pixel in the output image is based on a comparison of the corresponding pixel in the input image with its neighboring pixel. The most important morphological operations are dilation and erosion. Dilation adds pixels to the boundaries of objects in an image, whereas erosion removes pixels on object boundaries. Enhancement of images with poor contrast and detection of background is done using morphological transformations[14]. Image enhancement has been carried out by the two methods. Information from image background analysis by blocks is used by the first method employs, whereas the second transformation method utilizes the opening and closing operation, which is engaged to define the multi background grayscale images. The basic effect of the erosion operator on a binary image is to erode away the boundaries of regions of foreground pixels (i.e. white pixels, typically). Thus areas of foreground pixels get smaller in size, and holes within those areas become bigger. The basic effect of the dilation operator on a binary image is to gradually enlarge the boundaries of regions of foreground pixels (i.e. white pixels, typically). Thus areas of foreground pixels grow in size while holes within those regions become smaller.

In a binary image, if any of the pixels is set to the value 1, the output pixel is set to 1 based on the correlation of eroded and dilated image. The purpose of the morphological operators is to separate the abnormal part of the image. The separated part of the image has the highest intensity than other regions of the image. Perform a morphological opening on each segment subtract the opening from the original segment to obtain regions to be reassigned to neighboring segments of the intestinal image.

3.4 Superpixel Segmentation

Segmentation is the process of partitioning an image into dissimilar segments. These segments correspond to various tissues, pathologies, or other biologically significant structures in the field of medical imaging. Medical image segmentation is made intricate by noise, and other imaging ambiguities. Even though preprocessing technique by image segmentation were exists[11], some are being used distinctively for medical image computing. Detection of the corresponding area in image by Thresholding is the simplest method. Thresholding is the simplest non contextual segmentation technique[1]. With a single threshold, it transforms a grayscale or color image into a binary image considered as a binary region map. This map contains two probably disjoint regions, one region containing pixels with input data values smaller than a threshold and another relating to the input values that are at or above the threshold.

Pixel and encompassing features which are the basic data unit of image representation form the key for the qualitative and quantitative output of any image processing step. The result exhibiting similar features within local or global neighborhood is termed as Superpixel. The job of grouping pixels into super pixels by comparing the values of each and every neighborhood pixel within specific connectivity, defining the boundary strength of superpixel, and the midpoint of superpixel called the seed point[10]. The complexity of images from hundreds of thousands of pixels to only a few hundred super pixels reduces the computational cost and increases the image processing speed. Superpixel based image segmentation techniques applies many sophisticated algorithms for fast 2D image segmentation using SLIC[9]. Superpixels are universally defined as constricting and grouping uniform pixels in the image, which are widely used in image segmentation and object recognition. In addition to the above performance, clustering techniques comparison gives extraordinary results[8]. The superpixel map is natural and perceptually meaningful representation of the input image. For that reason, the superpixel representation greatly reduces the number of image primitives and improves the representative efficiency when compared to the traditional pixel representation of the image. The convenience and effectiveness of superpixels to compute the region based visual features provides important benefits for the vision tasks such as object recognition.

Grouping of pixels through superpixel segmentation is to reduce the computational complexity while maintaining high diagnostic accuracy. Red ratio in RGB space extracts the feature of each superpixel which is then fed into support vector machine for classification. To reduce the computational cost and make abnormal tissue detection faster, group the pixels based on color and location first, and the detect abnormalities at superpixel level. Gray image is converted to color image in superpixel segmentation to maintain the intensity. The relative difference between any two colors which is approximated as points in 3-D space[15] with three components (l, a, b) is obtained using the Euclidean distance between them

$$S_{color} = \sqrt{\left(l_i - l_j\right)^2 + \left(a_i - a_j\right)^2 + \left(b_i - b_j\right)^2} \tag{2}$$

Similarity of any two pixels depends not only on color similarity but also on spatial distance as

$$S_{spatial} = \sqrt{\left(x_i - x_j\right)^2 + \left(y_i - y_j\right)^2} \tag{3}$$

Therefore the similarity measure can be obtained by

$$S = S_{color} + \lambda_{\times} S_{spatial} \tag{4}$$

Where S_{color} shown in Equation (2) is the color similarity, $S_{spatial}$ shown in Equation (3) represent the spatial distance between two pixels and λ is the balancing factor between spatial distance and color similarity, shown in Equation (4). Intestinal image is segmented using superpixel, hence the exact geometry of the lesion is segmented using grouping of pixels. The lesion is found based on the inconsistency of spatial location from the segmented part[12]. The segmented region of the intestinal image shows the pixels where the correlation test has to be performed.

3.5 Correlation Coefficient

The correlation coefficient matrix represented in statistical that the normalized measure of the strength of linear relationship between variables[7]. The correlation coefficient r_X, Y between two random variables X and Y with expected values μ_x and μ_y and standard deviations σ_X and σ_Y is their covariance normalized by their standard deviations, is given in Equation 5,

$$r_{X,Y} = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{E\left(\left(X - \mu_x\right)\left(Y - \mu_y\right)\right)}{\sigma_X \sigma_Y} \tag{5}$$

where E is the expected value operator and cov means covariance. Since $\mu_x = E(X)$, $\sigma_x = E(X^2) - E^2(X)$, and likewise for Y, $r_{X,Y}$ is given in Equation 6,

$$r_{X,Y} = E\left(X,Y\right) - \frac{E\left(X\right)E\left(Y\right)}{\sqrt{E\left(X^2\right) - E^2\left(X\right)}\sqrt{E\left(Y^2\right) - E^2\left(Y\right)}} \tag{6}$$

In statistics, the Pearson product moment correlation coefficient is a measure of the linear correlation (dependence) between two variables *X* and *Y*, giving a value between +1 and −1, where 1 denote total positive correlation, 0 is no correlation, and −1 is total negative correlation. This concept is widely used in the sciences as a measure of the degree of linear dependence linking two variables[6]. Pearson's correlation coefficient between two variables is defined as the covariance of the two variables divided by the product of their standard deviations. This form of the description involves a "product moment", that is, the mean (the first moment about the origin) of the product of the mean adjusted random variables; hence the modifier product moment in the name.

Pearson's correlation coefficient can be defined as the covariance of two groups of numbers divided by the product of their standard deviations[4] is given in Equation 7,

$$r = \frac{\text{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{\sum\left(x_i - \bar{x}\right)\left(y_i - \bar{y}\right)}{\sqrt{\sum\left(x_i - \bar{x}\right)^2 \sum\left(y_i - \bar{y}\right)^2}} \tag{7}$$

where r is the Pearson's correlation coefficient, x_i is the *i*th element in X, and $\bar{x}$ is the mean of group X. In the numerator, the raw scores are centered by subtracting out the mean of each variable, and the sum of cross products of the centered variables is accumulated. The denominator adjusts the scales of the variables to have equal units. Thus Equation describes r as the centered and standardized sum of cross product of two variables. Using the Cauchy Schwartz inequality, it can be shown that the absolute value of the numerator is less than or equal to the denominator therefore, the limits of ±1 are established for r.

Correlation technique of the proposed system uses the Pearson's correlation coefficient that detects the similarity between the healthy tissue and abnormal tissue by color encoding and finds the lesion.

4. Proposed Methodology

The major functional blocks of our proposed method shown in Figure 4, explains the proposed system of lesion area detection.

This Methodology helps in detection of lesion using superpixel segmentation; intestinal image is segmented by superpixel segmentation, this method includes the following steps of work:

Step 1: Wireless Capsule endoscope image is converted into M file.
Step 2: Read the input image into the GUI.
Step 3: Apply multidimensional filter to the input image.
Step 4: Denoised image is restored.
Step 5: Denoised image is converted into green intensity image to separate the layers of the image and the damaged region is examined closely using this green intensity image.
Step 6: After the step 6, green intensity image is converted to grey scale image using grey conversion. Luminosity method is used for conversion of green intensity image to Gray image, for human perception as shown in Equation 8,

$$0.21\ \mathrm{R} + 0.72\ \mathrm{G} + 0.07\ \mathrm{B} \tag{8}$$

Step 7: Edge detection is used for feature detection and feature extraction. Sobel operator is used for edge detection using Sobel convolution matrix.
Step 8: Morphological operation using both erosion and dilation is used to enhance the processed image. The value of each pixel in the output image is compared with the corresponding pixel of input image with its neighbors.
Step 9: The enhanced image after the step 8 is segmented using superpixel segmentation which groups the identical pixels using Euclidean distance and helps to detect the exact infected region in the image shown in Equation 2, Pixels are grouped based on the similarity of pixel color and spatial distance.

$$S_{color} = \sqrt{\left(l_i - l_j\right)^2 + \left(a_i - a_j\right)^2 + \left(b_i - b_j\right)^2}$$

Step 10: Segmented image is color encoded and using correlation coefficient lesion is detected using Equation 7,

$$r = \frac{\mathrm{cov}(X,Y)}{\sigma_X \sigma_Y} = \frac{\sum (x_i - \bar{x})(y_i - \bar{y})}{\sqrt{\sum (x_i - \bar{x})^2 \sum (y_i - \bar{y})^2}}$$

where r is the Pearson's correlation coefficient, x_i is the i^{th} element in X, and $\bar{x}$ is the mean of group X. Correlated value differentiates the normal tissue and infected tissue by color encoding.

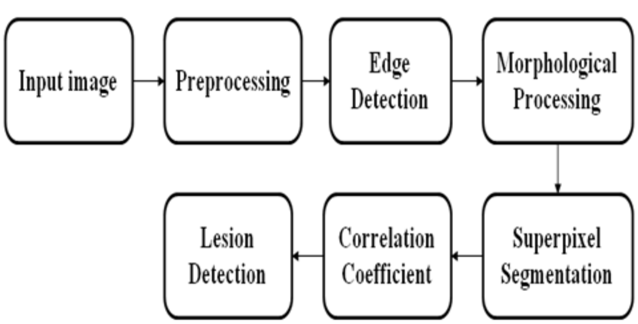

Figure 4. Block diagram of lesion detection.

5. Results and Discussion

Lesion Area Detection (LAD) using superpixel segmentation and the Pearson's correlation coefficient is implemented in GUI. Figure 1 shows the intestinal input image is processed using Denoising, Layer separation, Gray conversion, Edge detection, Morphological operation, Superpixel segmentation and Pearson's correlation coefficient. Lesion is marked as pixels in the last block of Figure 5.

6. Conclusion

The obtained result shows that the detection of lesion in intestinal tract. The supportive systems mainly aim at reducing the time spent at detecting endoscopic images. The fact of good pixel packing and uniformity in size of

Figure 5. Output showing Lesion Area Detection in intestinal image.

pixels in determined to have better performance than the other pixel based algorithm. Pearson's correlation coefficient can detect very small size lesions, with more accuracy which helps in time consumption in clinical diagnosis.

This work may extended by using Spearman's correlation coefficient. Three statistical test can be performed by combining both Pearson's and Spearman's coefficients to get better results for diagnosticians and researchers.

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