Scientific Journal of Impact Factor (SJIF): 3.134
e-ISSN (O): 2348-4470
p-ISSN (P): 2348-6406

International Journal of Advance Engineering and Research Development

Volume 2, Issue 12, December -2015

WCE Image Enhancement and Disease Detection Using Classification

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Abstract-- *The wireless capsule endoscopy (WCE) has been widely used to detect the diseases in gastrointestinal tract. However, the quality of acquired images during endoscopy degraded due to factors such as environmental darkness and noise. Hence, decrease in quality also resulted into poor sensitivity and specificity of ulcer and diagnosis. The image quality of WCE is not satisfactory for medical applications since some of them are dark and low-contrast. The WCE image enhancement is a challenge task, mainly because the diversity of the WCE images of different people and the need to preserve the local fine details of WCE images. So image enhancement is not a sufficient to detect disease. In this paper we proposed a new method which include image enhancement followed by segmentation and classifier. The results show improved WCE images quality which is beneficial for automatic detection of diseases and aids clinicians to better visualize images and ease the diagnosis.*

Keywords--*Wireless capsule endoscopy (WCE), Gamma correction, Maximum likelihood, Confusion matrix.*

I. INTRODUCTION

Video capsule endoscopy provides visualization of the GI tract by transmitting images wirelessly from a disposable capsule to a data recorder worn by the patient. The first capsule model for the small intestine was approved by the Food and Drug Administration (FDA) in 2001. The WCE system consists of 3 components: (1) a capsule endoscope; (2) a sensing system with sensing pads or a sensing belt to attach to the patient, a data recorder, and a battery pack; and (3) a personal computer workstation with proprietary software (RAPID v 6.5, Given Imaging; WS-1 Endo Capsule, Olympus America; MiroView, IntroMedic) for image review and interpretation. All 3 systems include handheld viewers that allow real-time review of images during WCE examinations (RAPID Real-Time, Given Imaging; Real Time Viewer, Olympus America; Miro-View Express, Intro Medic). All capsule endoscopes have similar components: a disposable plastic capsule, a complementary metal oxide semiconductor or high-resolution charge-coupled device image capture system, a compact lens, white-light emitting diode illumination sources, and an internal battery source. The mode of data transmission is either via ultra-high frequency band radio telemetry (PillCam, Endo Capsule) or human body communications (MiroCam). The latter technology uses the capsule itself to generate an electrical field that uses human tissue as the conductor for data transmission. Currently PillCam SB2 and MiroCam are available with extended battery life, which may be beneficial in patients with delayed small-bowel transit[1].

Fig. 1 describes WCE pill-shaped device. It is swallowed by the patient after about 12 hours fasting. This miniature device propelled by peristalsis of GI tract begins to work and record images at 2 frames per second while moving forward along the GI tract. At the same time, images are sent to a data recorder attached to the patient's waist wirelessly.

The whole inspection process takes about 8 hours, before the image data can be processed. Finally, a physician performs analysis by watching the recorded data in the form of either video or images. However, the diagnosis process is time consuming due to the huge amount of data (about 50,000 useful images per inspection)[1]. Therefore, the diagnosis is not a real-time process, making this situation a potential breakthrough for off-line post processing and computer aided detection. Furthermore, the resolution of WCE image is only 256×256 due to volume limitation of encapsulation, especially power limitation, whereas traditional endoscopy has a superior performance on this aspect since no power limitation exists. Moreover, bad imaging conditions such as low illumination and complex circumstances in the GI tract will further deteriorate the quality of produced images. The proposed method aims to enhancing the WCE images by image filtering and gamma correction and disease detection by classification. Section II describes noise removal and contrast enhancement process. Section III includes flow chart for enhancement and classification. Section IV dedicated to simulation results. Finally, Section V and VI conclude the paper and presents future works as well as references[3].

Fig. 1. Wireless capsule endoscopy capsule and its component

II. METHODS FOR NOISE REMOVAL AND CONTRAST ENHANCEMENT

Digital images are prone to a variety of types of noise. Noise is the result of errors in the image acquisition process that result in pixel values that do not reflect the true intensities of the real scene Mostly, the encountered noise in the acquired data exhibits a Gaussian-like distribution. Gaussian noise is characterized by his additive and zero-mean distribution property. Basically, the zero-mean property of the distribution allows such noise to be removed by locally averaging pixel values[4].

Contrast enhancements techniques improve the perception of objects in the scene by strengthen the brightness difference between objects and background. Contrast enhancements are typically performed as a contrast stretch followed by a tonal enhancement, although these could both be performed in one step. A contrast stretch improves the brightness differences uniformly across the dynamic range of the image, whereas tonal enhancements improve the brightness differences in the shadow (dark), midtone (grays), or highlight (bright) regions at the expense of the brightness differences in the other regions.

2.1 Geometric mean filter

A geometric mean filter achieves smoothing comparable to the arithmetic mean filter, but it tends to lose less image detail in the process. It separates the red, green and blue channels. It is followed by introducing a gain to compensate the attenuation resulting from the filter. Each filtered channel is then combined to form resulting colored image[1].

Let’s Sxy represents the set of coordinates in a sub-image window (neighborhood) of size m x n where m and n are equal, centered at point (x, y). The local image function f(x, y) is filtered image and g(s,t) is input image. In Geometric mean filter each restored pixel is given by the product of the pixels in the sub-image window, raised to the power 1/m×n

$$f(x, y)=[\pi(s,t)\epsilon\, S_{xy}\, g(s,t)]^{1/mn} \qquad (1)$$

2.2 Gamma Correction

Gamma correction, gamma nonlinearity, gamma encoding, or often simply gamma, is the name of a nonlinear operation used to code and decode luminance or tristimulus values in video or still image systems. Gamma correction is, in the simplest cases, defined by the following power-law expression

$$V_{out}=AV_{in}^{\gamma} \qquad (2)$$

where *A* is a constant and the input and output values are non-negative real values; in the common case of *A* = 1, inputs and outputs are typically in the range 0–1. A gamma value $\gamma < 1$ is sometimes called an encoding gamma, and the process of encoding with this compressive power-law nonlinearity is called gamma compression; conversely a gamma value $\gamma > 1$ is called a decoding gamma and the application of the expansive power-law nonlinearity is called gamma expansion.

III. IMAGE ENHANCEMENT & CLASSIFICATION

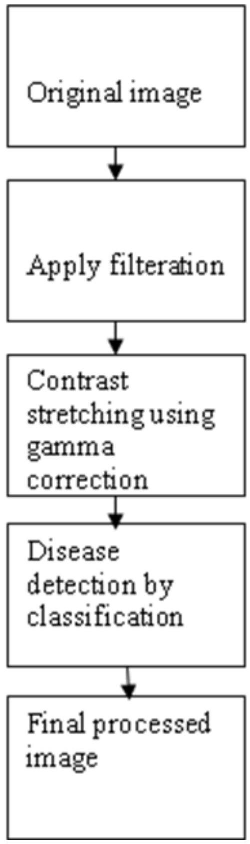

Fig.2 Flow chart of image enhancement and classification for WCE image

3.1 Classification

The goal of classification is change the representation of an image into something that is more meaningful and easier to analyze[5]. Classification approaches can be used to classify the total scene content into a limited number of major classes.
In literature numbers of algorithms are available for classification. In this paper we have considered Maximum likelihood algorithm

3.2 Maximum Likelihood / Bayesian Classifier

It applies the probability theory to the classification task. A statistical decision rule that examines the probability function of a pixel for each of classes, and assign the pixel to class with the highest probability[6].
First choose training pixels from each class of image using ground truth image, then find mean, covariance matrix, inverse covariance matrix and determinant of Covariance matrix for training pixels for each class of image.

Let the classes for an image be represented by Ci, i = 1, 2, ... , M. Where M is the total number of classes. X is measurement vector of candidate pixel. $P(Ci/X)$ and the $P(X/Ci)$ which is estimated from training data are related by Bayes theorem.

$$P(Ci/X) = P(X/Ci)P(Ci)/ P(X) \quad i=1,2,.....,M \tag{3}$$

Where $P(Ci/X)$ gives the likelihood that the correct class is Ci for a pixel at position X, where $P(Ci)$ is the probability that class Ci occurs in the image, $P(X/Ci)$ give the probability that the pixel belongs to each available class, $P(X)$ is the probability of finding a pixel from any class at location X.

$$P(X) = \sum_{i=1}^{M} P\left(\frac{X}{Ci}\right) P(Ci) \tag{4}$$

Classification rule for maximum likelihood $X \epsilon Ci$ if $P(Ci/X) > P(Cj/X)$ for all $j \neq I$ i.e., the pixel at x belongs to class Ci if $P(Ci/X)$ is the largest.

According to equation (3) $P(X/Ci)P(Ci) > P(X/Cj)P(Cj)$ for all $j \neq i$ where $P(X)$ has been removed as a common factor. Likelihood function is

$D = ln\{P(X/Ci)P(Ci)\}$

$$D = ln\ P(X/Ci) + ln\ P(Ci) \tag{5}$$

where ln is the natural logarithm.

$P(X/Ci)$ for multivariate probability distribution is

$$P(X=Ci) = 2\Pi^{(-N/2)} \left| Cov_{ci} \right|^{(-1/2)} \exp\{-1/2(X-M_{Ci})^T (Cov_{ci}^{-1}) (X-M_{Ci})\} \tag{6}$$

P(X/Ci) put in equation 5, so the final Equation for Maximum likelihood / Bayesian classifier as follows

$$D = \ln(a_c) - [0.5\ln(|C_{ovc}|)] - [0.5(X - M_c)^T (C_{ovc}^{-1})(X - M_c)] \tag{7}$$

Where

D = likelihood,

c = a particular class,

X = measurement vector of candidate pixel,

M_c = the mean vector of sample of class c,

a_c = percent probability that any candidate pixel is a member of class c,

C_{ovc} = the covariance matrix of the pixels in sample of class c,

$|C_{ovc}|$ = determinant of C_{ovc},

C^{-1}_{ovc} = inverse of C_{ovc},

Find likelihood for each pixel for each class. Pixel goes to class which has highest likelihood for this pixel, this way classification will be performed[2].

IV. SIMULATION AND RESULTS

- In this paper two WCE images were taken for pre-processing from http://www.capsuleendoscopy.org website.
- On each image, enhancement and classification process have been applied, then find the confusion matrix and overall accuracy from classification results
- Confusion Matrix shows the accuracy of a classification result by comparing a classification result with ground truth information. All diagonal elements in confusion matrix gives percentage of corrected classified pixels means accuracy of each class and all other elements gives percentage of misclassification for each class.
- Figure 3, 5 shows images which are taken for classification. ure3 shows classification of Wireless capsule endoscopy of 16 year old female with Crohn's disease(Small bowel ulceration). Figure5 shows classification of abscure Gastrointestinal bleeding(lesion seen in deep jejunum).Ulcerated area and Bleeding area in classified image shown by eclipse.
- Figure 4, 6 shows accuracy and misclassification of each class
- Using Matlab 7.7 on Intel(R) Core(TM)2 Duo 2 GHz PC, time to enhancement and classification of first image is 3.45 sec and second image is 3.5 sec.

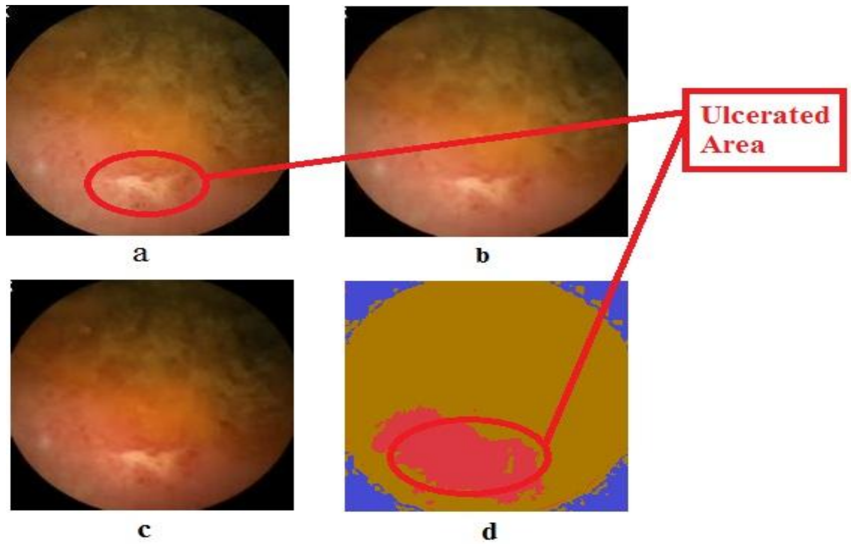

Fig.3 (a) Endoscopy image(b) Filtered image(c) Gamma corrected image(d) Classified image

4.1 Confusion Matrix 1

	Background	**Normal area**	**Ulcerated area**	**Accuracy**
Background	**71.48**	28.3	0.16	
Normal area	0	**84.4**	15.5	**84.92 %**
Ulcerated area	0	1.2	**87.9**	

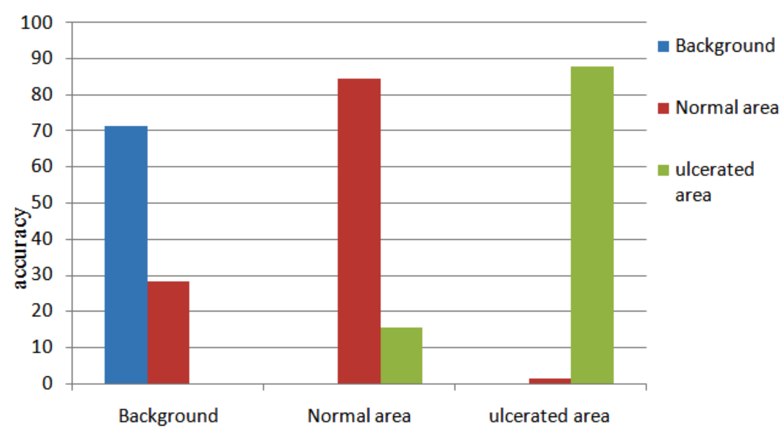

Fig.4. accuracy of each class in classified image

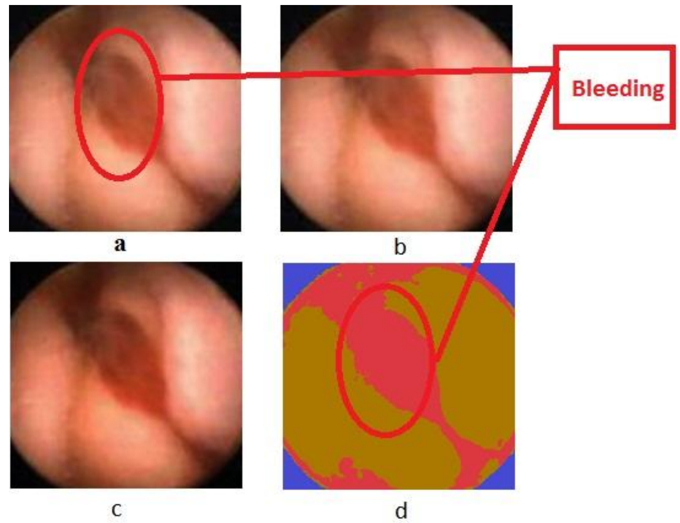

Fig.5 (a) Endoscopy image(b) Filtered image(c) Gamma corrected image(d) Classified image

4.2 Confusion Matrix 2

	Background	**Normal area**	**Bleeding area**	**Accuracy**
Background	**82.5**	9.61	7.87	
Normal area	0	**86.7**	13.2	**88.15%**
Bleeding area	0	4.8	**95.19**	

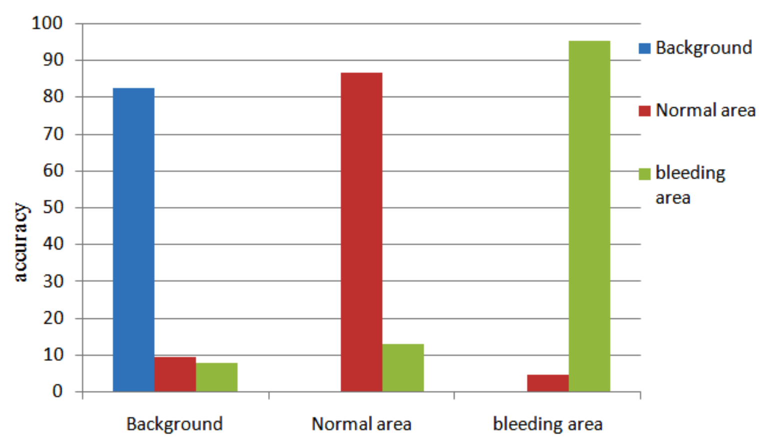

Fig.6. accuracy of each class in classified image

V. CONCLUSION

Above results shows that geometric mean filtering reduce the noise and gamma correction to increase the contrast of image which is used for feature extraction in classification step. Classified results clearly show the disease area like bleeding and ulcerated area in WCE image which can help physicians to review and diagnose rapidly and accurately. Accuracy of classification can be further improved by using wavelet transform or by improving enhancement process.

VI. REFERENCES

[1]Shipra Suman, Fawnizu Azmadi Hussin. *Image Enhancement Using Geometric Mean Filter and Gamma Correction for WCE Images*. 21st international conference, Malaysia,2014.

[2] S. P Banks. *Signal Processing, Image Processing and Pattern Recognition*. Prentice Hall, New York, 1990.

[3] Iddan, G., et al.Wireless capsule endoscopy. Nature 405, 417 (2000).

[4] Liu, C,et al. Gaussian fitting for carotid and radial artery pressure waveforms*: comparison between normal subjects and heart failure patients. Bio-medical Materials and Engineering* 24(1), 271–277,2014

[5] A. P. Dempster, N. M. Laird, and D. B. Rubin. *Maximum likelihood estimation from incomplete data via the em algorithm*. 1977.

[6]Sunayana domadia, Mayank ardeshana .*Wavelet-Transform based K-means Algorithm*, CiiT journal, ICAET 2012, Nagapattinam, 2012.