AN ENDOMETRIAL CANCER IMAGE COMPRESSION WITH LOSSLESS REGION OF INTEREST

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Abstract— Medical Imaging is an important keystone of modern healthcare and will continue to play a role of ever increasing importance at all levels of the healthcare system due to advances in imaging technology (US,CT, MR and Molecular Imaging). Due to this big data of medical images compression is required to achieve efficient transmission and storage. The proposed procedure is applied to diverse ultrasound cancerous images (endometrial cancer). Hence diagnosis of this type of uterus cancer in the premier stage is crucial, certain segmentation algorithms are applied and these will separate the infected region from the background which will be easy for the medical practitioners to decide the cancer and steer medication. The US image which is developed from an organ is applied to SRAD filter for preprocessing and the filtered image is given to level set segmentation and finally the contextual part of the image is encoded selectively on the high priority basis with a very low compression rate using wavelet decomposition.

Index Terms— Endometrial cancer segmentation; Lossless compression; Speckle noise; Ultrasound image.

I. INTRODUCTION

Over the past decade, medical imaging data has experienced exponential growth, creating a huge demand for data storage. Medical image archives are increasing by 30-50 % annually .Images are usually being archived longer by health providers than regulatory requirements Digital medical images like X-Ray, Magnetic Resonance Imaging (MRI), Ultrasound(US), Computed Tomography(CT) are extensively used in diagnosis. The ease of storing and transmission of digital medical images is a boon to patients and medical professionals. So for that numerous and diverse image compression methods have been proposed to compress medical images (see 21-22). Image storage is required most commonly for educational, business documents and medical images [20].

Image data compression techniques are concerned with reduction of the number of bits required to store or transmit images without any appreciable loss of information. Compression techniques used are very important while compressing digital medical images as the region of interest for diagnosis is generally small when compared to the whole image captured [15].

Image compression can be classified as lossy and lossless. Lossless compression techniques compress with no data loss but have low compression rate such as LOCO-I [24], CALIC [25], JPEG-LS [26],and JPEG 2K (5/3) [27] and lossy compression techniques can compress at high compression ratio but with a slight loss of data such as JPEG 28[], JPEG2K(9/7) [29][18]. Using lossless techniques in medical image does not give enough advantage in transmission and storage and lossy techniques may lose crucial data required for diagnosis. An efficient block based lossless compression of medical images is proposed using LHT and Huffman coding [17] To maximize compression, multiple compression techniques is proposed which is based on Region of Interest (ROI) [19]. Also Feature extraction [4] and classification [5] can be performed from the segmented ROI for easy detection of masses in patients. The marked area of ROI is compressed using lossless compression.

Endometrial cancers are the most common gynaecologic cancers with over 35,000 women diagnosed each year. Endometrial cancer refers to several types of malignancies that arise from the endometrial, or lining, of the uterus. Endometrial carcinoma is the third most common cause of gynaecologic cancer death (behind ovarian and cervical cancer). Most case of endometrial cancer occur between the ages of 60 and 70 years, but a few cases may occur before age 40. So early detection of this type of cancer can play an important role in reducing the associated morbidity and mortality rates.

Ultrasound imaging is a widely used technology for diagnosing and treatment of cancer. Non invasive methods used to diagnose cancer still have limitations. Detection techniques are currently based on physical examination. Various approaches have been used to automatically detect regions of interest in Ultrasound (US) images [see 13-14]. Geometric active contour models are the most flexible methods used [8] based upon a stopping function. For efficient edge detection an improved stopping term based on coefficient of variation is also proposed [9].

US image segmentation is an important problem in medical image analysis. The main disadvantage of ultrasound images is their poor quality, which are also affected by Speckle Noise [3][7]. Speckle is caused by interference effects of echoes from unresolvable random scatterers due to the coherent nature of ultrasound scanners. The US image which is developed from an organ is applied to SRAD filter which is then correlated with various speckle noise reducing filters, on the basis certain quality metrics measurements [1]. Therefore, in general, many of the image segmentation methods may not be suitable in case of US images. So for that some pre-processing methods are followed. Segmentation is performed after pre-processing to distinguish one or more regions of interest (ROI) from the selected image.

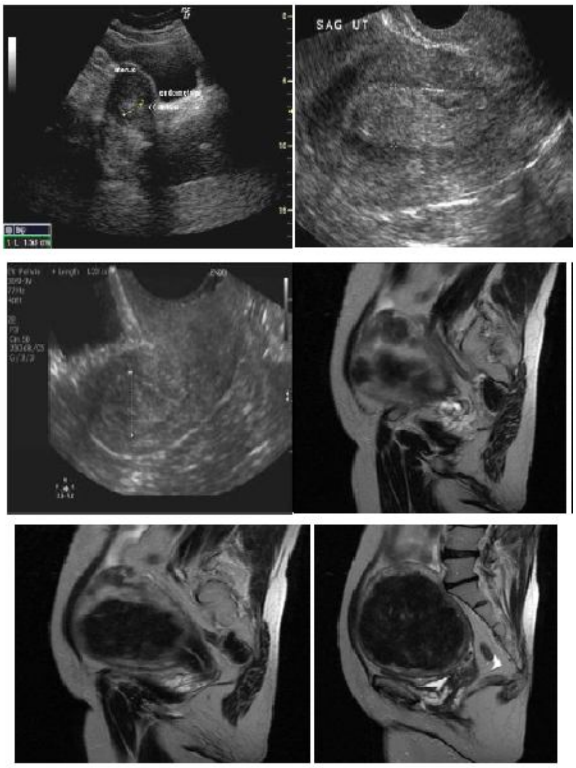

Figure 1: Input medical images

The remaining part of the paper is organized as follows: In Section 2, the technical phenomena related to this work are explained in detail and with necessary representations and equations. Section 3 describes the proposed compression algorithm. Section 4, the performance is evaluated using simulation results and the paper is concluded in Section 5.

II. METHODOLOGY

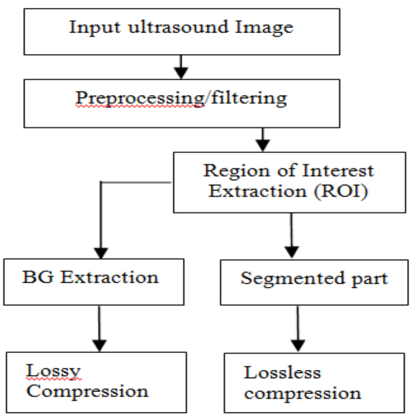

Figure 2: Block diagram of proposed method

A. Preprocessing

The action done before processing by correcting image from different errors is preprocessing. Poor quality of the US images and presence of speckle noise leads to over segmentation [see 11-12]. So in order to get better and meaningful segmentation it is important to improve the quality of the images. This can be done by applying one of the method called SRAD Filtering

The partial differential equation (PDE) based speckle removal approach allows the generation of an image scale space without bias due to filter window size and shape. SRAD not only preserves edges but also magnify edges by inhibiting diffusion across edges and allowing diffusion on either side of the edges. SRAD exploits the instantaneous coefficient of variation, which is shown to be a function of the local gradient magnitude and Laplacian operator to act like an edge detector for speckled imagery. It is given by the equation,

$$q(x,y;t)=\sqrt{\frac{(1/2)(|\nabla I|/I)^2-(1/4^2)(\nabla^2 I/I)^2}{[1+(1/4)(\nabla^2 I/I)]^2}}$$

Where q is the instantaneous coefficient of variation,
∇I is the gradient of the image

$$c(q)=\frac{1}{1+[q^2(x,y;t)-q_o{}^2(t)/[q_o{}^2(t)(1+q_o{}^2(t))]}$$

$$q_0(t)\approx q_0\exp[-\rho t]$$

where ρ is a constant, and q_0 is the speckle coefficient of variation in the observed image. The US image of endometrial cancer and the corresponding filtered output is shown in fig (3) and fig (4)

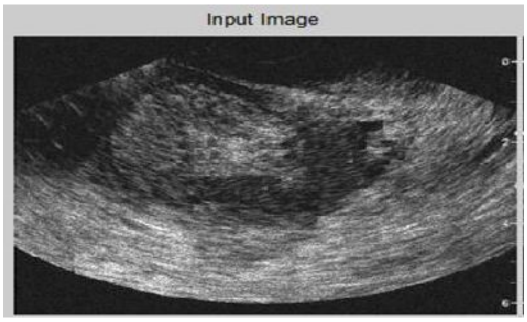

Figure 3: Endometrial cancer US image

Figure 4: SRAD filter output

A.1 Quality Metrics Measurement

Comparison of the filtered images are done using quality metrics measurement. It includes Peak Signal to Noise Ratio (PSNR), Mean Squared Error (MSE), Coefficient of Correlation (CoC), Root Mean Squared Error (RMSE) [7][1].

B. Segmentation

Segmentation is the process of partitioning a digital image into multiple segments (sets of pixels, also known as super pixels).Image segmentation is typically used to discover the objects and boundaries (lines, curves, etc.) present in images. Image segmentation is the process of assigning a label to every pixel in an image. Various segmentation methods are used.

B.1 Morphological Operations

Image morphology is an important tool in image processing. Morphological operations play a key role in automatic object detection. It is used to understand the structure or form of an image. Binary morphological operators such as erosion and dilation combine a local neighbourhood of pixels to achieve the result.

Erosion can be used to eliminate unwanted white noise pixels from an otherwise black area. Dilation is the opposite of erosion operation. In this paper opening operation is performed. The Opening operation is an erosion operation followed by dilation. Opening is useful for smoothing the edges, breaking the narrow joints and thinning the protrusions that are present in the image. Figure 6 shows morphological operation output

B.2 Level Set Evolution

The level set method was proposed to track moving interfaces [2][10]. It can be used to efficiently address the problem of curve/surface/ propagation in an implicit manner. The main idea of the level set is to minimize the function *φ(x,y)* by solving the corresponding partial differential equation (PDE) using the level set evolution equation as a numerical method. An initial contour is selected, which is then moved by image driven forces to the boundaries of the desired objects. In such models, two types of forces are considered - the internal forces, defined within the curve, are designed to keep the model smooth during the deformation process, while the external forces, which are computed from the underlying image data, are defined to move the model toward an object boundary or other desired features within the image.The general curve evolution PDE in the level set framework is given by

$$\frac{\partial \phi}{\partial t} = | \nabla \phi | F$$

where F is a speed function designed for the boundary detection.

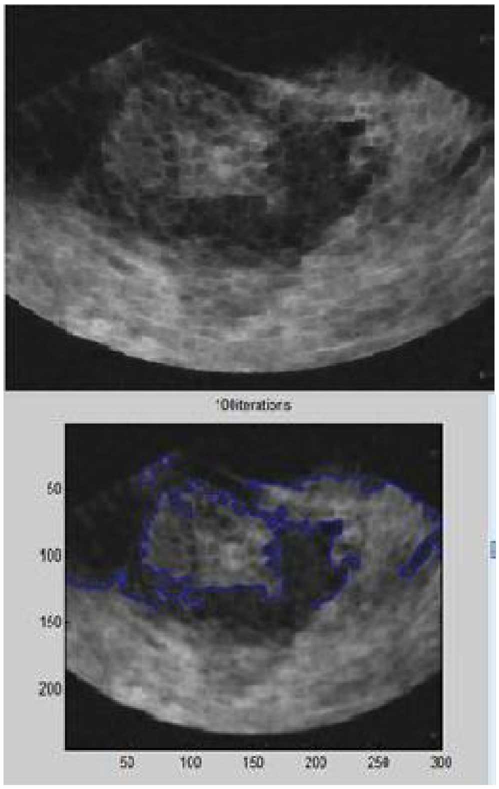

Figure 5: Image output after performing morphological operation and level Set.

III. COMPRESSION ALGORITHM

A typical 12-bit medical image may be 2048 pixels by 2570 pixels in dimension. This translates to a file size of 15,485,760 bytes. A typical 16-bit mammogram image may be 4500 pixels by 4500 pixels in dimension for a file size of 40,500,000 (40 megabytes). This has consequences for disk storage and image transmission time. An image compression scheme based on discrete wavelet transform is proposed in this research which provides sufficient high compression ratios with no appreciable degradation of image quality. The effectiveness and robustness of this approach has been justified using a set of real medical images.

As computational complexity increases, compression ratio also increases. Haar wavelet transform is the simplest transform for image compression, the principle behind this is very simple as calculating averages and differences of adjacent pixels. The Haar DWT is more computationally efficient than the sinusoidal based discrete transforms. Thus the image after level set segmentation is compressed using discrete wavelet transform [16] and a good compression is achieved.

The good performances of the Dwt is shown in Table 1. It is shown that the method has the higher compres-sion result, close to the original image from the image structure aspects. The same image also compressed with Coefficients Thresholding Methods(CTM), cannot yield a better compression ratio.

Table 1

Image	Compression Technique	CR
Fig 5 Level Set output	Global Thresholding of coeff. and fixed encoding	3.13
	Global thresholding of coefficients and huffman encoding	3.34
	Discrete Wavelet Transform	4.01

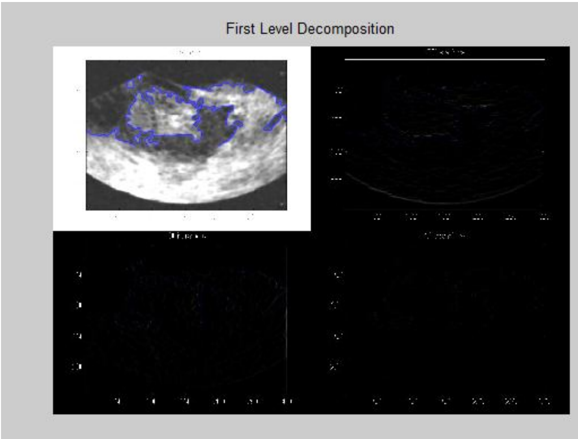

Figure 6: Image output after performing dwt compression

IV. SIMULATION RESULTS

To show the performance of cancerous images several standard images are used. They include endometrial ultrasound and MRI fibroid images (different stages).Figure 5 shows the endometrial cancer image output after performing certain segmentation operations. Given MRI fibroid images are JPEG 464x512 size and US cancer images are JPEG 259x194 size images (figure 1).

CONCLUSION

In this paper Endometrial cancer is segmented using level set evolution [6]. The segmented image is compressed based on wavelet transform. The overall image is compressed by 80% (fig 6). In future work features can be extracted from the segmented region of interest and also classification can be performed which is helpful for the medical experts to identify whether it is an abnormal or normal one [14].

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