CHAPTER 5

ROI-BASED MEDICAL IMAGE COMPRESSION

5.1 INTRODUCTION

In this chapter, the third algorithm for medical image compression is presented. The compression efficiency is improved by extending the work for ROI-based medical image compression with the basis of segmentation. For medical images, the diagnostically useful information termed ROI is localized in a small area. A compression algorithm to preserve high quality in diagnostically significant regions and allowing degradation in other regions providing higher compression is necessary. In this proposed work, ROI is processed using MMICTE compression algorithm and MMICT compression elsewhere in the image.

5.2 NEED FOR ROI CODING FOR IMAGE COMPRESSION

All regions of medical images do not have equal significance. In medical images, the portion of the image that encloses the lesion or tumor is considered to be important. Medical applications cannot tolerate deficiency in that diagnostically useful region, a small part of the image termed ROI. When compressing the image, ROI will be coded with high spatial resolution to preserve the significant regions than the background (Yang et al. 2005, Doukas and Maglogiannis 2007 and Ansari and Anand 2008a).
ROI coding suggested by Hu et al. (2008) uses JPEG2000 to ROIs and SPIHT to background (non-ROI). But in this, ROIs are selected manually by hand. ROI coding for image compression can greatly improve the compression efficiency providing better compromise between image quality and CR (Babu and Alamelu 2009). As ROI can have arbitrary forms, selecting ROI directly on the image by the user results in degraded image. So nowadays, automatic extraction of ROIs is the main research area.

5.3 ROI SEGMENTATION

The initial step of an ROI-based compression is segmentation of ROI. Segmentation partitions the image into homogeneous regions based on some characteristic such as intensity or texture (Gonzalez and Woods 2008). Common approaches on medical image segmentation are thresholding, region growing, classifiers, clustering, atlas-guided approaches and deformable approaches. Segmentation algorithms for grey scale images are based on either discontinuity or similarity of image intensity values. Segmentation approach based on discontinuity of image intensity, partitions the image based on abrupt changes in the intensity of the image, such as edges. Segmentation approach based on similarity of image intensity, partitions the image into regions that are similar according to a set of predefined criteria.

ROIs can be selected manually or automated segmentation can be used to extract ROIs. Automated extraction of exact ROIs is desired for diagnostic purposes. Ping and Shanan (2006) introduced a method considering grey features of the image to extract ROIs of medical images.

In this chapter, level set active contour method based on the similarity approach is used for segmentation. Level sets to capture shapes are
first described by Osher and Sethian (1988). Level set method represents a contour as zero level set called a level set function (LSF). Level set method formulates the motion of the contour as the evolution of the level set function. In standard level set methods, the level set function develops irregularities during its evolution destroying the stability of the level set evolution. To overcome this problem, reinitialization has been introduced to restore the regularity of level set function and provide stable level set evolution (Osher and Fedkiv 2002). Even though reinitialization maintains the regularity of level set function, it may incorrectly move the zero level set away from the expected position (Sethian 1999 and Osher and Fedkiv 2002). Active contour method, developed by Liu et al. (2007), proposes an automatic feature extraction using variational level sets, as it incorporates shape and region information into the level set energy functions.

Li et al. (2010) proposed the variational level set formulation with a distance regularization term and an external energy that drives the motion of the zero level contour toward desired locations. The distance regularization eliminates the need for reinitialization. The distance regularized term is defined with a potential function $p(s)$ given by Equation (5.1)

$$p(s) = \frac{1}{(2\pi)^2} \left(1 - \cos(2\pi s)\right)$$  \hspace{1cm} (5.1)

which maintains the desired shape for the level set function. In the Equation (5.1), $s$ is the spatial parameter. If the initial contour is placed outside the object, the zero level contour can shrink in the level set evolution process. If the initial contour is placed inside the object, the contour will expand.
5.4 ROI-BASED COMPRESSION

In this third proposed algorithm, the gross ROI is initially defined by radiologist. The automatic extraction of exact ROI is determined from this gross ROI using variational level set method. Variational level sets incorporate shape and region information into the level set energy functions (Li et al. 2010).

The energy functional is defined by (Li et al. 2010)

\[
\varepsilon(\phi) = \mu R_p(\phi) + \lambda L_g(\phi) + \alpha A_g(\phi)
\]

(5.1)

where \( R_p(\phi) \) is the distance regularization term, \( \lambda = 5, \mu = 0.04 \) and \( \alpha = 1 \) are the coefficients of the energy functionals \( L_g(\phi) \) and \( A_g(\phi) \) (Li et al. 2010). \( A_g(\phi) \) is introduced to speed up the motion of the zero level contour in the level set evolution process. When the zero level contour is far away from object boundaries, \( A_g(\phi) \) speed up the motion of the contour and \( A_g(\phi) \) slow down the motion of the contour when it reaches the object boundaries.

Once the ROI is segmented using variational level set method, compression is to be performed. Different encoding schemes with varying quality levels can be used for ROI and background. The MMICTE algorithm is used for ROI to preserve the diagnostic information with full resolution. The background of the image is highly compressed using MMICT with PSNR equal to or greater than 30 dB (Mastriani 2009 and Kafri and Sulieman 2009). This PSNR of 30 dB is chosen since it is the minimum value for better image quality. The background need not be exemplified with full resolution, as it helps the viewer just to identify the position of the ROI within the original image.
5.4.1 Algorithm of the proposed method

1. Extraction of ROI

1.1 Radiologist defines the approximate ROI.

1.2 Initialize the contour as zero level set called LSF.

1.3 LSF ($\phi$) is defined with the energy function

$$\mathcal{E}(\phi) = \mu R_p(\phi) + \gamma L_g(\phi) + \alpha A_g(\phi)$$

1.4 The energy term $L_g(\phi)$ is minimized in the process of level set evolution when the zero level contour is located at the object boundaries.

1.5 The energy term $A_g(\phi)$ controls the motion of zero level contour in level set evolution process.

1.6 If recommended number of iterations is reached, then stop the contour evolution and extract the segmented region ROI.

2. ROI is processed using MMICTE.

3. Non-ROI is highly compressed using MMICT with PSNR $\geq 30$ dB.

4. Merge reconstructed ROI image and reconstructed Non-ROI image to reconstruct the image.
5.5 RESULTS AND DISCUSSION

The proposed ROI coding method has been discussed for MRI, CT, X-ray and US images. Figure 5.1 shows the results of MRI image. Figures 5.2 and 5.3 show the results of US image. Figure 5.1 (a), 5.2 (a) and 5.3 (a) show the original images and Figure 5.1 (b), 5.2 (b) and 5.3 (b) show the segmented ROI regions in the original images. Figures 5.1 (c), 5.2 (c) and 5.3 (c) show only the segmented ROIs that contain the abnormality. The reconstructed ROIs in Figures 5.1 (d), 5.2 (d) and 5.3 (d) show that the ROIs are perfectly recovered without any loss. Figures 5.1 (e), 5.2 (e) and 5.3 (e) display the Non ROI regions of the images after removal of the segmented ROIs. Figures 5.1 (f), 5.2 (f) and 5.3 (f) present the Non ROIs reconstructed at visually acceptable quality. In Figures 5.1 (g), 5.2 (g) and 5.3 (g), the fully reconstructed images are shown. The experimental results reveal that the images can be reconstructed by using MMICTE algorithm to preserve the diagnostic information with full resolution in ROI and MMICT algorithm with loss in background region. MMICTE reconstructed images are shown in Figures 5.1 (h), 5.2 (h) and 5.3 (h) for comparison.

The results are shown in tabular form which compares the results of compression methods in terms of quantitative measures: compression ratio and PSNR. The comparison table of the proposed method for ROI and background can be seen in Table 5.1 for MRI, CT, X-ray and US images. The compressed sizes of ROI and Non-ROI are shown. The tabular results shown in Table 5.2 compare CR obtained for full reconstructed image using ROI-based compression and also for the same input image processed and reconstructed using MMICTE. Table 5.2 also compares the compression ratio of the compressed images shown in Figure 5.1, 5.2 and 5.3 for ROI based compression with MMICTE been applied to the whole image. The work is for
medical images and minimum PSNR of 30 dB is chosen outside the ROI to produce compression, as it is the minimum value for better image quality.

From Table 5.1, for MRI (liver mass) shown in Figure 5.1, ROI is represented with compressed size of 5638 bits with PSNR of 55.38 dB and Non-ROI is represented with compressed size of 50902 bits with PSNR of 33.93 dB. The full image is represented with 56540 bits which yields CR of 9.3. But if the same image is compressed with MMICTE algorithm which is given in Table 5.2, total of 121927 bits (CR = 4.3) are needed. The results reveal that ROI-based compression makes it possible to achieve high compression ratios with good visual quality, especially in the ROI. The PSNR values obtained by ROI-based method reveal that the PSNR of full image is around 36 dB which is within the acceptable limit for medical images. Moreover Figures 5.2 and 5.3 illustrate and also confirm that the proposed ROI compression yields images with high quality in diagnostically significant regions and also provide higher compression for the full image.
Figure 5.1  (a) Original MRI image (liver mass)  (b) Segmented image  
(c) Segmented ROI (d) Reconstructed ROI output 
(Compressed size = 5638 bits, PSNR = 55.58 dB)
Figure 5.1  (e) Non-ROI of the input image (f) Reconstructed Non-ROI output (Compressed size = 50902 bits, PSNR = 33.93 dB) 
(g) Reconstructed image combining ROI output with Non-ROI output (CR = 9.3, PSNR = 36.23 dB) 
(h) Reconstructed image with MMICTE (CR = 4.3, PSNR = 40.76)
Figure 5.2  (a) Original US image (renal cyst)  (b) Segmented image  
(c) Segmented ROI  (d) Reconstructed ROI output  
(Compressed size = 8066 bits, PSNR = 57.89 dB)
Figure 5.2  
(e) Non-ROI of the input image  
(f) Reconstructed Non-ROI output (Compressed size = 31451 bits, PSNR = 36.91 dB)  
(g) Reconstructed image combining ROI output with Non-ROI output (CR = 13.3, PSNR = 36.99 dB)  
(h) Reconstructed image with MMICTE (CR = 4.3, PSNR = 41.99)
Figure 5.3  (a) Original US image (liver cyst) (b) Segmented image (c) Segmented ROI (d) Reconstructed ROI output
(Compressed size = 54051 bits, PSNR = 56.22 dB)

(Figure 5.3 Continued)
Figure 5.3  (e) Non-ROI of the input image (f) Reconstructed Non-ROI output (Compressed size = 42323 bits, PSNR = 34.86 dB) (g) Reconstructed image combining ROI output with Non-ROI output (CR = 11.5, PSNR = 37.76 dB)  
(h) Reconstructed image with MMICTE (CR = 3.9, PSNR = 41.5)
Table 5.1  Numerical results of ROI-based medical image compression for medical images of size 524288 bits (256 × 256 × 8 bits)

<table>
<thead>
<tr>
<th>Image</th>
<th>ROI Compressed size (bits)</th>
<th>ROI PSNR (dB)</th>
<th>Non-ROI Compressed size (bits)</th>
<th>Non-ROI PSNR (dB)</th>
<th>Full image CR</th>
<th>Full image PSNR (dB)</th>
</tr>
</thead>
<tbody>
<tr>
<td>MRI image (liver mass)</td>
<td>5638</td>
<td>55.58</td>
<td>50902</td>
<td>33.93</td>
<td>9.3</td>
<td>36.23</td>
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<tr>
<td>MRI image (brain tumor)</td>
<td>38270</td>
<td>47.28</td>
<td>26750</td>
<td>36.4</td>
<td>7.0</td>
<td>37.67</td>
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<tr>
<td>CT image (cyst)</td>
<td>72717</td>
<td>45.14</td>
<td>21926</td>
<td>32.14</td>
<td>5.5</td>
<td>35.81</td>
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<tr>
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<td>56375</td>
<td>48.46</td>
<td>19686</td>
<td>33.45</td>
<td>6.9</td>
<td>35.44</td>
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<td>X-Ray image (bone cyst)</td>
<td>34493</td>
<td>45.77</td>
<td>15287</td>
<td>36.58</td>
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<td>38.27</td>
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<td>8066</td>
<td>57.89</td>
<td>31451</td>
<td>36.91</td>
<td>13.3</td>
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<tr>
<td>US image (liver cyst)</td>
<td>54051</td>
<td>56.22</td>
<td>42323</td>
<td>34.86</td>
<td>11.5</td>
<td>37.76</td>
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<td>US image (thyroid cyst)</td>
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<td>23097</td>
<td>37.34</td>
<td>9.9</td>
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<tr>
<td>Image</td>
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<td>MMICTE</td>
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<tr>
<td>Image</td>
<td>CR</td>
<td>PSNR (dB)</td>
<td>CR</td>
<td>PSNR (dB)</td>
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<td>MRI image (liver mass)</td>
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<td>4.3</td>
<td>40.76</td>
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<tr>
<td>MRI image (brain tumor)</td>
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<td>42.57</td>
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<tr>
<td>CT image (brain space occupying lesion)</td>
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<td>3.2</td>
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<tr>
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<tr>
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<td>4.3</td>
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<tr>
<td>US image (liver cyst)</td>
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<tr>
<td>US image (thyroid cyst)</td>
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</table>
5.6 CONCLUSION

ROI-based medical image compression algorithm is proposed to improve compression efficiency. ROI is segmented using variational level set method of evolution. MMICTE algorithm is used to encode ROI region. The MIMICT with PSNR equal to or greater than 30 dB is used for background to achieve higher compression. The results illustrate that ROI coding provides a high compression ratio, by preserving the pixel values in diagnostically significant regions while background is reconstructed at visually acceptable quality.