Region of Interest Extraction for Lossless Compression of Bone X-Ray Images

S. Kazeminia, N. Karimi, S.M.R. Soroushmehr, S. Samavi, H. Derksen and K. Najarian

***Abstract*—For few decades digital X-ray imaging has been one of the most important tools for medical diagnosis. With the advent of distance medicine and the use of big data in this respect, the need for efficient storage and online transmission of these images is becoming an essential feature. Limited storage space and limited transmission bandwidth are the main challenges. Efficient image compression methods are lossy while the information of medical images should be preserved with no change. Hence, lossless compression methods are necessary for this purpose. In this paper, a novel method has been proposed to eliminate the non-ROI data from bone X-ray images. Background pixels do not contain any valuable medical information. The proposed method is based on the histogram dispersion method. ROI is separated from the background and it is compressed with a lossless compression method to preserve medical information of the image. Compression ratios of the implemented results show that the proposed algorithm is capable of effective reduction of the statistical and spatial redundancies.**

I. Introduction

New medical technologies are equipped with more productive sensors which can generate higher image qualities with different modalities. One of the most popular medical image modality is X-ray imaging that is utilized in many medical applications such as diagnosing of bone fractures and degeneration, infections, and tumors. Due to its popularity, the number of images produces and hence the required storage and bandwidth for transmission are increasing. In order to decrease the amount of required storage, these images need to be compressed. To do so, the features of the images must be explored. One of these features is the existence of redundancy in the images which can be classified into two main categories: (1) statistical, (2) psycho-visual. Statistical redundancy refers to the non-uniform probability distribution of symbols that represent an image or a video. As an example, we can refer to inter-pixel or spatial correlation that is the similarity among neighboring pixels. Psycho-visual redundancy is the lack of sensitivity of human visual system toward certain intensity changes in an image.

Compression algorithms are classified as lossy, near lossless and lossless techniques. Lossy compression encoding methods use approximations for representing the content and produce high compression ratios. Near lossless compression methods could also achieve high compression ratios. However, they have a specific limitation on the amount of data elimination. In lossless compression method, images are encoded in full quality and low compression ratio. In medical images as details are very important and any modification on the region of interest (ROI) of these images leads to incorrect diagnosis, lossless compression is crucial in many medical applications [1].

Segmentation of ROI and its lossless compression could be a solution which could produce good compression ratio and preserve the vital information. However, ROI extraction from bone X-ray images is a complicated process. There are various challenges such as non-uniform intensity in tissue and bone areas and low contrast of these images. For ROI extraction, these challenges cause poor performance of standard segmentation methods like watershed, Otsu [2] and region growing [3]. In some cases, these methods mistakenly consider some parts of ROI as non-ROI and they eliminate a part of a bone from the ROI. For the original image of Fig. 1(a) we see poor performance of standard segmentation methods, presented in Fig. 1(b)-(d). Other edge-based segmentation methods such as Canny and Sobel [2] have poor performance on bone X-ray images. Fig. 1(e) shows results of applying Canny method. In both of them the results do not represent exact boundaries. If we consider the largest boundary of the detected edges, instead of the ROI boundary, we lose parts of the tissue and parts of the bones. Several lossy, near lossless and lossless compression methods are proposed for CT and MRI medical images compression [4-6]. Also, in [1] and [7] two methods were proposed for ROI extraction of CT images and angiograms with good performances. However, there is no reliable ROI extraction method proposed for bone X-ray images.

In this paper, we propose a novel method for ROI extraction of bone X-ray images which is based on analysis of the background region intensity distribution. We find the intensity of the boundary between the ROI and non-ROI regions. The background region pixels intensities are assigned the same value. This would increase both the statistical and spatial redundancies. This generated image would contain all the essential medical information and will be losslessly compressed. A suitable prediction method is

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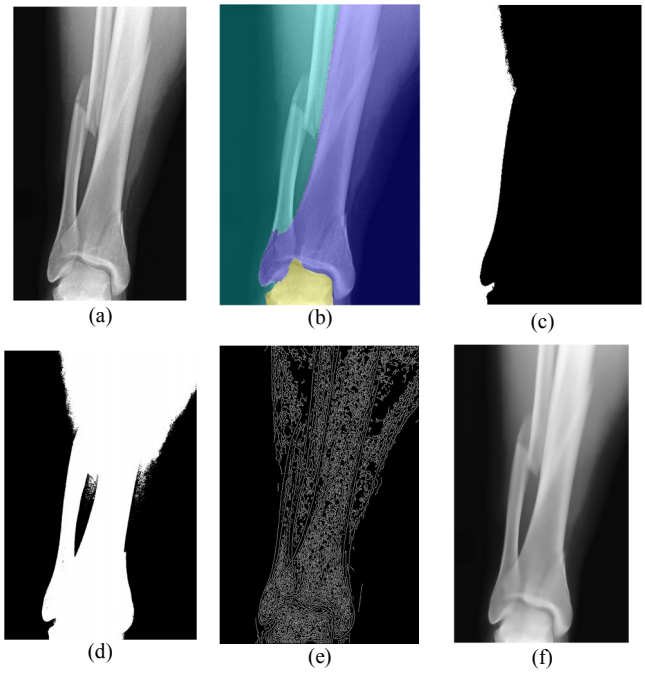

Figure 1. (a) Original bone X-ray image, (b) ROI extraction using watershed, (c) ROI extraction using region growing segmentation method, (d) ROI extraction using Otsu thresholding method, (e) detected edges using Canny method, (f) smoothed image using Guided Filter.

employed for this purpose. The binary mask that identifies ROI pixels is efficiently compressed and is accompanied with the compressed ROI image pixels. The proposed method is compared with standard and efficient lossless compression methods. Experimental results show effectiveness and

efficiency of the proposed method. The remainder of this paper is organized as follows. The proposed method is explained in details in Section II. In Section III we apply our algorithm to several bone X-ray images and compare the results with other lossless compression methods. Afterward, conclusion and future works are presented in Section IV.

II. Proposed Method

A. Noise Reduction and Smoothing

X-ray images contain inevitable noise which makes any type of segmentation cumbersome. Hence, preprocessing step to remove the noise is needed before ROI detection step. Simple blurring of the image using Gaussian filter will weaken the important edges in the image. A guided image filtering has been recently introduced in [8] that computes the output image considering the contents of a guidance image. The algorithm is fast and accurate and also preserves edges and gradients. Fig. 5 shows a noisy bone X-ray image. The output of filtering using guided filter on the original image of Fig.1(a) is shown in Fig.1(f). This step is very important for the consequent step. The noisy image has high fluctuations in the background region that demands the next step which finds inappropriate boundary intensities.

B. ROI Boundary Detection

For finding the intensity of boundary pixels that could be used for separation of the dark background of an image, difficulties such as intensity overlaps on tissue and bone segments do not exist. Background pixel intensities are in a lower range of the spectrum. Bone segment intensities are normally in the higher range and the tissue pixels densities are in between. In some cases, we see some tissue pixels and some bone pixels having intensity overlaps. But in background, this overlap does not exist. Hence, the distribution of background intensities is relatively concentrated. In other words, pixels of the same segment have similar intensity values. Hence, these pixels belong to a dense part of the histogram. According to this observation, negative concavities on histogram can be an initial simple metric to separate segments of the image. In bone X-ray images, background contains a large area and its structure is uniformly dark. ROI, including tissues and bones, is non-uniform and it is lighter than the background. According to background's features we can use negative concavity to separate it from ROI. In order to find boundaries of the background, the intensity of the first negative concavity of the smoothed image histogram is considered. The red arrow on the histogram of Fig 2 shows the mentioned intensity. By knowing this intensity, a binary mask of the size of the original image can be formed. In this mask, all positions corresponding to pixels with intensities lower than the estimated boundary value are set to zero.

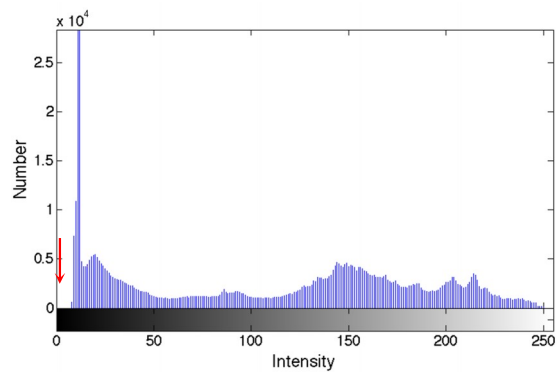

Figure 2. Histogram of the smoothed bone X-ray image.

Conversely, all pixels that are above the boundary value are represented as 1 in the mask. In Fig. 3(a) the image is altered in the non-ROI regions by changing the background intensity values to zero. In this image the information content of the ROI is unaltered and no loss is exerted on the pixels of ROI. The corresponding mask is shown in Fig. 3(b). All the white pixels in this mask correspond to the ROI pixels and the black pixels indicate the background of the X-ray image.

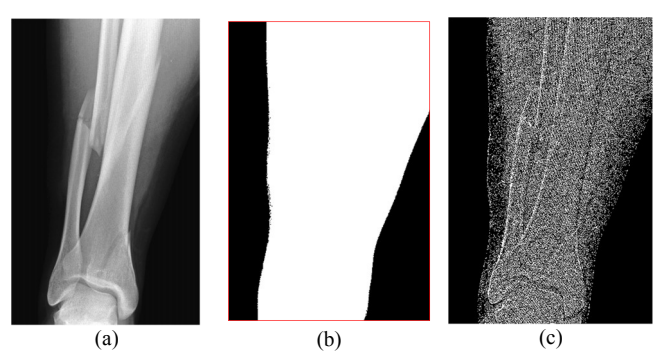

Figure 3. (a) Bone X-ray image with uniform background, (b) binary mask of bone X-ray image, (c) ALCM prediction errors of our processed image.

Since, the background of the bone X-ray images does not have any important data, its pixels are converted to a single value. It should be noted that usually human visual system cannot easily recognize these modifications except for the boundary regions. With this conversion all pixels of the background will have the same intensity and hence the statistical redundancy will be increased. This increased statistical redundancy is exploited in the compression stage of the algorithm.

C. Compression

To compress the binary mask, whose elements could only contain two possible values of zero or one, we used run-length encoding (RLE) [9]. RLE first converts the image to a sequence and then counts the number of consequent similar values until it encounters a different value. For the case of our ROI mask, the efficiency of RLE is high since long sequences of 0's or 1's are present in such a mask.

For ROI pixels, spatial redundancy can provide lossless compression. This is done by noticing that neighboring pixels in a region have similar intensities. This similarity translates into spatial redundancy. The spatial redundancy can be converted to statistical redundancy by using prediction methods. An efficient predictor for this purpose is the activity level classification model (ALCM) [10] which has been used for the compression of medical images such as 3D MRI [11] and mammographic images [12]. The value of the current pixel in ALCM is predicted by a linear combination of some of the neighboring pixels that are already processed. The weights of this linear combination are computed as the encoding proceeds. The same weight is initially assigned to all involved pixels. After prediction is performed, the weights could change in the following manner: If the predicted value were lower than the real value of the pixel then $1/256$ is subtracted from the weight of the largest neighboring pixel and added to the weight of the smallest neighboring pixel. If the predicted value were higher than the actual pixel, then the weight of largest neighbor is increased by $1/256$ and the weight of the smallest neighbor is reduced by the same amount [10].

We used forth order ALCM predictor of which its neighboring pixels are shown in Fig.4. Fig.3 (c) shows absolute values of prediction errors when ALCM is applied to Fig. 3(a) where non-ROI pixels are assigned a single value. As expected, the non-ROI prediction errors are all zeros. The histogram of ROI pixels in Fig. 3(a) as well as the resulted histogram after running ALCM on the ROI pixels (Fig. 3. (c)) are shown in Fig. 5. We can see a sharp increase in the small prediction errors. The histogram of the ALCM errors shows a noticeable increase in the statistical redundancy.

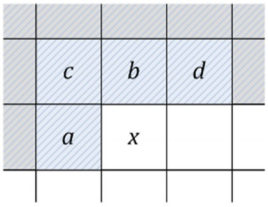

Figure 4. Causal neighboring pixels used in forth order ALCM.

Subsequently, arithmetic encoding [13] is applied to the prediction errors as well as to the output of RLE values of the binary ROI mask. The first bit of the ROI mask is registered. Hence, by knowing the arithmetic code stream, the size of the mask, and the first bit of the mask, the mask could be reconstructed by the decoder. Also, the arithmetic code stream of the ROI pixel errors is delivered to the decoder which can reconstruct the ROI pixels.

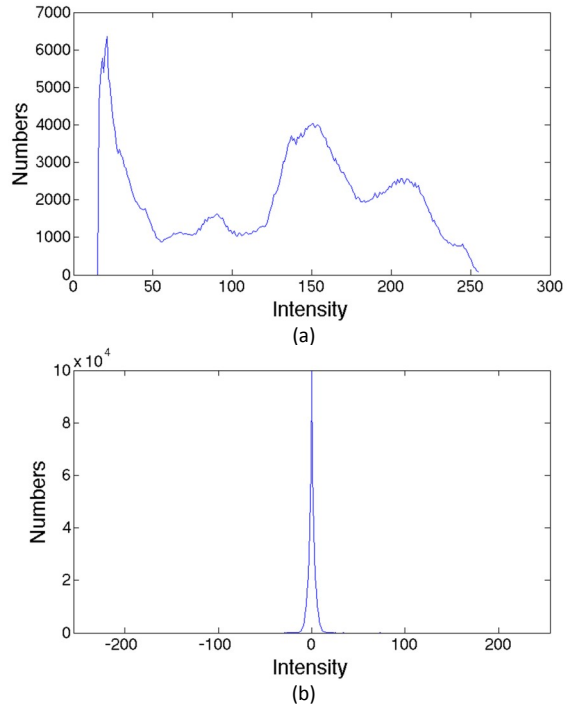

Figure. 5. (a) Histogram of ROI pixels in Fig.3, (b) histogram of prediction errors of ROI pixels.

III. EXPERIMENTAL RESULTS

In order to evaluate the performance of the proposed method, we have implemented our algorithm in 64-bit MATLAB ® 2013. We applied our algorithm on 60 bone X-ray images which are available at [14]. For every image, after smoothing and finding the ROI boundary, we constructed a binary mask to separate ROI from non-ROI. Then, we have converted the intensity of the background pixels to a single value.

In Fig. (6), three samples of original input images and their generated ROI masks are presented. The image of Fig. 6(a) is an example of low contrast where the edges of the soft tissue are not very apparent. However, the proposed method has correctly detected its ROI. In Fig. 6(b), in spite of small size of the true background, it did not cause the algorithm to identify soft tissue as the background and we see that ROI is correctly identified. In Fig. 6(c), bone pixels have much higher intensity values than those of the soft tissues but the ROI is still correctly segmented.

To show the performance of our compression method we compared our methods with SPIHT [15], JPEG-LS[16], and APT[17]. SPIHT is a lossless and transform based image coder that decorrelates the image data by using wavelet transform. Also, JPEG-LS is a standard predictive coding based lossless compression method and APT uses non-causal prediction and hierarchical schemes termed binary pyramid.

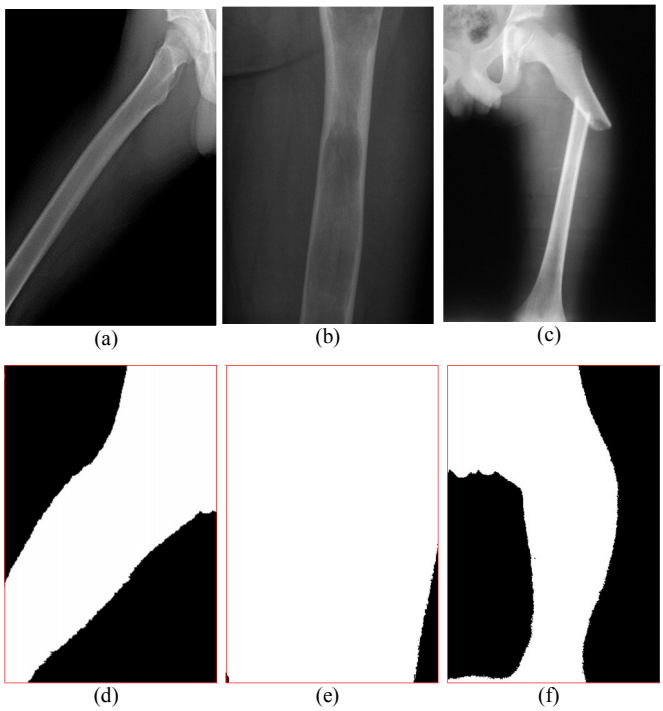

Figure. 6. (a)-(c) Original bone X-ray images, (d)-(e) correspoding ROI's extracted by the proposed method.

Algorithms were run on all 60 images. Then, the average bit rates on each method were calculated.

Table I shows the average bit rate resulted from the compression methods. In the simulation, all the images were first preprocessed by the proposed ROI segmentation and conversion of the non-ROI pixels to zero. Hence, same images are fed to our and other compression methods. Based on these results, our method has the lowest bit rate in both cases that corresponds to the highest compression ratio among these methods.

TABLE I. COMPARISION BETWEEN THREE DIFFERENT METHODS

	Compression Methods				
	SPIHT [15]	**JPEG_LS [16]**	**APT [17]**	***Our Method***	
				Mask	***ROI***
Average Bit Rate	1.877	1.698	1.859	0.035	1.598
				1.633	

IV. CONCLUSION

Employing new devices with sensitive sensors in medical imaging provides high quality images with more useful details and large sizes. To store, retrieve, and transmit these images with vital information, lossless compression methods are used. But these compression methods have low compression ratios. In this paper, we proposed a method to reduce the data of bone X-ray images by separating ROI from non-ROI. We increased both spatial and statistical redundancies in these images. Then, we employed lossless compression methods. We compared our results with those situations where no ROI separation was employed. We also compared our method with standard and well-known lossless compression methods. In average, we achieved the bit rate of 1.633 which was the lowest bit per pixel among the comparison methods.

V. ACKNOWLEDGMENT

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