Kirlian Image Compression Using the Wavelet Transform and Fuzzy c-means Clustering on Regions of Interest

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ABSTRACT

This paper suggests a novel image compression scheme, using the discrete wavelet transformation (DWT) and the fuzzy c-means clustering technique. The goal is to achieve higher compression rates by applying different compression thresholds for the wavelet coefficients of each DWT band, in terms of how they are clustered according to their absolute values. This methodology is compared to another one based on preserving texturally important image characteristics, by dividing images into regions of textural significance, employing textural descriptors as criteria and fuzzy clustering methodologies. These descriptors include co occurrence matrices based measures. While rival image compression methodologies utilizing the DWT apply it to the whole original image, the herein presented novel approaches involve a more sophisticated scheme. That is, different compression ratios are applied to the wavelet coefficients belonging in the different regions of interest, in which either each wavelet domain band of the transformed image or the image itself is clustered, respectively. Regarding the first method, its reconstruction process involves using the inverse DWT on the remaining wavelet coefficients. Concerning the second method, its reconstruction process involves linear combination of the reconstructed regions of interest. An experimental study is conducted to qualitatively assessing both approaches in comparison with the original DWT compression technique, when applied to a set of Kirlian images. We focus on Kirlian images, which is due to their high complexity, comprise of features appearing in many biomedical images.

Keywords: *Computer science, Image Processing.*

1. INTRODUCTION

Image compression plays a critical role in telemetric applications and especially in telemedicine. It is desired hat either single images or sequences of images be transmitted over computer networks at large distances so as that they could be used in a multitude of purposes. For instance, it is necessary that Kirlian images be transmitted so as that reliable, improved and fast Kirlian diagnosis performed by many centers could be facilitated. To this end, image compression is an important research issue. The difficulty, however, in several applications lies on the fact that, while high compression rates are desired, the applicability of the reconstructed images depends on whether some significant characteristics of the original images are preserved after the compression process has been finished.

For instance, in Kirlian image compression applications, diagnosis is effective only when compression techniques preserve all the relevant and important image information needed. This is the case with lossless compression techniques. Lossy compression techniques, on the other hand, are more efficient in terms of storage and transmission needs but there is no warranty that they can preserve the characteristics needed in Kirlian image processing and diagnosis. In this latter case, of lossy compression, image characteristics are usually preserved in the coefficients of the domain space in which the original image is transformed. That is, for instance, in the DWT based Kirlian image compression, the wavelet coefficients keep all the information needed for reconstructing the Kirlian image. The goal of such a compression methodology that aims at maximization of the compression ratio should be to discard only the irrelevant wavelet coefficients according to a criterion, like the magnitude of their values. This can be done either by applying the same constant threshold to the whole transform domain or by applying different thresholds to uniquely defined regions of the transform domain, depending on the significance of these regions in the preservation of image characteristics. The former case is the basis of the original DWT compression approach, while the latter is the basis of the first proposed methodology in this paper.

Another approach for lossy compression is, instead of transforming the whole image, to separately apply the same transformation to the regions of interest in which the image could be divided according to a predetermined characteristic. One important such characteristic of Kirlian images is texture. More specifically, texture analysis of these images can lead to very significant results concerning real tissue motion [1] and thus, can result in improved diagnosis. The goal of such a lossy compression methodology that aims at maximization of the overall compression ratio is to compress each region separately with its own compression ratio, depending on its textural significance, so as to preserve textural characteristics. This is the basis for the second compression methodology presented here. Concerning texture analysis in this approach, it is based on the texture identification analysis adopted by Haralick [3].

This paper aims at investigating two novel compression schemes of Kirlian images, with principles as discussed above, based on the discrete 2-D wavelet transform, both having as goal the preservation of important image characteristics. The first, however, attempts to cluster the bands of wavelet coefficients in regions of importance in terms of their absolute value levels and compress differently the corresponding regions. On the other hand, the second attempts to cluster the original image in terms of Haralick textural measures and compress differently the corresponding regions, by applying the DWT separately to these regions.

At this point it is necessary to briefly discuss about image compression and the wavelet transform. The general idea behind image compression is to remove the redundancy in an image so as to find a more compact representation. A popular method for image compression is the so-called transform coding, which represents the image in a different than the original space, such that the coefficients of the analysis in the basis of the new space are decorrelated. It has been shown that the multiresolution wavelet decomposition involves projections onto subspaces spanned by the scaling function basis and the wavelet basis. These projections on the scaling functions basis yield approximations of the signal and the projections on the wavelet basis yield the differences between the approximations of two adjacent levels of resolution. Therefore, the wavelet detail images are decorrelated and can be used for image compression. Indeed, the detail images obtained from the wavelet transform consist of edges in the image. Since there is little correlation among the values on pixels in the edge images, it is easily understood why the wavelet transform is useful in image compression applications. Indeed, image compression is one of the most popular applications of the wavelet transform [4]. However, the most widely accepted contemporary approach for dealing with image compression employing the wavelet transform, is to apply it to the whole image and then, keep its corresponding coefficients which are larger than a predefined threshold. Both the two more sophisticated compression schemes involving the DWT, utilized here in order to achieve preservation of significant image characteristics, extend this original approach by using fuzzy c-means clustering either of the wavelet bands or of the original image and subsequently compressing the corresponding regions with different predefined thresholds. These thresholds depend on the significance of the regions in terms of the clustering criterion involved.

Both these methodologies have been successfully applied, in terms of the trade-off between the preservation of important image features and achievement of high compression ratios, to two kirlian images, in comparison with the simple DWT compression approach.

2. THE TWO WAVELET COMPRESSION SCHEMES USING WAVELET BANDS CLUSTERING AND ORIGINAL IMAGE TEXTURAL CLUSTERING.

The goal of this paper is to achieve higher compression ratio in images using the two-dimensional DWT more effectively by exploiting wavelet domain structure characteristics and image structure characteristics, which are usually unemployed in image compression. More specifically, we aim at exploiting the correlation characteristics of the wavelet coefficients as well as the second order characteristics of images in the design of improved lossy compression systems for Kirlian images.

The first compression scheme outlined here exploits correlation characteristics of the DWT coefficients in order to assign different compression thresholds to the different distributions of correlated coefficients. Therefore, the most significant areas of correlated coefficients in terms of preservation of important image characteristics could be compressed with lower ratios than the others, which might be compressed with higher ratios. Thus, better overall compression ratios would be achieved. The implementation of this principle in the herein presented scheme involves clustering of the DWT obtained wavelet bands. The main result of such a clustering method is to find out how wavelet coefficients are correlated in terms of the magnitude of their absolute values. It is reasonable to assume that, the larger these absolute values the larger the significance of the associated distribution of correlated wavelet coefficients in the preservation of image characteristics. The previous discussion leads to the following implementation. First, the original image is transformed via the 2-D DWT into bands of wavelet coefficients. For a 1-level such transform 4 bands are obtained. Then, the fuzzy c-means clustering technique is applied to each such band, dividing it into two classes. The result is that we obtain two distributions of correlated coefficients for each band. The one with the larger wavelet coefficients, in terms of the magnitude of their absolute values, is considered as the important region while the other as the non-important one. Then, for each important such region of a wavelet band a lower compression ratio is applied, the same for all important regions of the wavelet domain (and equal to r1), than the one applied for the corresponding non-important regions (equal to r2). Therefore, $r1<r2$. Afterwards, in the reconstruction process, the inverse 2-D DWT is applied to all the remaining wavelet coefficients, while the ones removed during the compression process are considered equal to zero.

Concerning the second suggested compression scheme, a good measure related to second order image structure is texture [3]. The rationale underlying the proposed compression methodology is that the significance of image regions varies in space. That is, not all image areas are important in describing the spatial probability distribution of its pixel intensities and subsequently in contributing to the visual effects of the image under consideration. A measure of such image region significance can be derived by exploiting textural information. When the textural characteristics in an image region assume high values then, it is reasonable to suppose that the textural information content of this area is very important. Therefore, the image spatial probability distribution can be more precisely derived if a larger number of features describing it is extracted for such an area than for other ones. Thus, if a compression methodology keeps a larger number of coefficients in texturally significant regions than in the other regions then, a much better decompressed image can be finally obtained since its probability distribution can be more accurately restored. In the sequel, the steps involved in the suggested compression scheme are illustrated.

1. The goal of the first stage of this second methodology is, therefore, to cluster the image into two classes, namely, in significant and non significant textural regions. To this end, first, the

image is raster scanned with sliding windows of M x M dimensions. We have experimented with 256 x 256 images and we have found that M=8 is a good size for the sliding window.

2. For each such window we perform a texture identification analysis based on cooccurrence matrices [3]. These matrices represent the spatial distribution and the dependence of the gray levels within a local area. Each (i,j) th entry of the matrices, represents the probability of going from one pixel with gray level (i) to another with a gray level (j) under a predefined distance and angle. More matrices are formed for specific spatial distances and predefined angles. From these matrices, sets of statistical measures are computed (called feature vectors) for building different texture models. We have considered four angles, namely 0, 45, 90, 135 as well as a predefined distance of one pixel in the formation of the cooccurrence matrices. Therefore, we have formed four cooccurrence matrices. Due to computational complexity issues regarding cooccurrence matrices analysis a quantization procedure are usually applied to the image under consideration. We have experimented with quantization of 16 and 64 gray levels. Among the 14 statistical measures, originally proposed by Haralick [3], that are derived from each cooccurrence matrix we have considered only four of them. Namely, angular second moment, correlation, inverse difference moment and entropy.

Energy - Angular Second Moment

$$f_1 = \sum_i \sum_j p(i,j)^2$$

Correlation

$$f_2 = \frac{\sum_{i=1}^{N_g} \sum_{j=1}^{N_g} (i*j)p(i,j) - \mu_{xx}\mu_{y\}}}{\sigma_x \sigma_y}$$

Inverse Difference Moment

$$f_3 = \sum_i \sum_j \frac{p(i,j)}{1+(i-j)}$$

Entropy

$$f_4 = \sum_i \sum_j p(i,j) \log(p(i,j))$$

3. When a pattern has been marked as texturally significant, if cooccurrence matrices derived features are used, then, the upper-left point of the corresponding sliding window takes on the label of 255, otherwise the label of zero. Following this labeling procedure, for each original gray level image a new black-white image IMP results illustrating the significant and non significant partitions.
4. The next step in the suggested compression scheme is to decompose the original image into two images. The first one, G1, is obtained by applying the following formula to each pixel (x0,y0) of the original image G0: G1(x0,y0) = MIN(G0(x0,y0), IMPG0(x0,y0)), Where, IMPG0 is the black-white image representing the texturally significant image regions of G0 obtained in the previous step Similarly, the second image, G2, is the outcome of applying the following formula to each pixel (x0,y0) of the original image G0: G2(x0,y0) = MIN(G0(x0,y0), 255-IMPG0(x0,y0))
5. Subsequently, the 2-D DWT is applied to G1 and G2 successively. Let us call DWT_G1, DWT_G2 this wavelet transforms respectively. Then, the compression ratio is determined for each one of the DWT_G1, DWT_G2. In all our experiments we have used compression ratios of 60% for DWT_G1 and 80% for DWT_G2. DWT_G1´ and DWT_G2´ are the compressed DWT_G1, DWT_G2 respectively.
6. The final step is image reconstruction. Let us call G^0 the reconstructed image. This is obtained by the following formula from DWT_G1´, DWT_G2´: G^0 = a*

INV_2D_DWT(DWT_G1´) +b*INV_2D_DWT(DWT_G2´), Where, INV_2D_DWT is the well known inverse transform of the 2-D DWT and a, b are user defined coefficients. In all our experiments we have used a=1 and b=1. The selection of these coefficients, however, is crucial for dealing with the blocking effects which are expected to appear in the boundaries between the texturally important and non-important regions. Although the results shown in the next section are very promising, more sophisticated schemes than the use of a simple linear combination between INV_2D_DWT(DWT_G1´) and INV_2D_DWT(DWT_G2´), however, are necessary to overcome these problems

3. EXPERIMENTAL STUDY AND DISCUSSION OF THE RESULTS

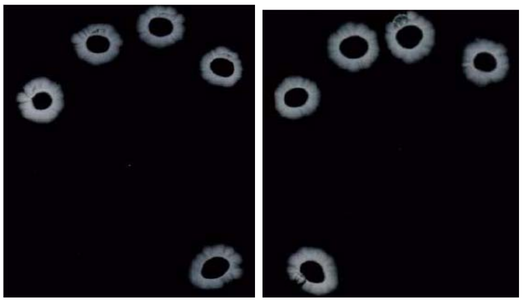

Figure 1. Original images (pol-2, pol-4)

We have tested the two proposed compression approaches along with the original DWT compression technique on two Kirlian images of patients with cancer [8]. The original cancerous Kirlian images pol-2, pol-4 are shown in Fig. 1.

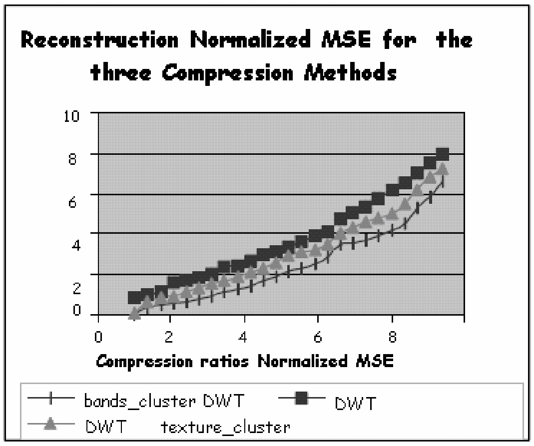

Figure 2. Normalized MSE of reconstructed image versus compression ratios of the three compression methods under comparison for the (pol4) image

In the figures and charts of this section, the first proposed compression scheme is called DWT bands cluster while the second one is called DWT texture cluster. Fig. 2 exhibits the Normalized Mean Square Error (MSE) of reconstructed image versus compression ratios of the three compression methods under comparison for the (pol-4) image. For the third compression method, that is, the original DWT based compression (the image is 2-D DWT transformed and only the wavelet coefficients larger than a predefined threshold are kept in the reconstruction process, while the rest is discarded), axis x in figure 2 shows the predefined unique compression threshold. On the other hand, for the two suggested methodologies axis x represents the average compression ratio between the compression ratio applied to the important regions and the one applied to the onimportant regions, either in the wavelet bands domain or in the image domain.

We should point out that, concerning the application of the DWT texture cluster compression method in Fig. 2, the best reconstruction result is exhibited involving either 16 or 64 intensity levels in the cooccurrence matrices analysis. While measures calculated over the cooccurrence matrices are enriched in accuracy when larger cooccurrence matrices are used, since the more levels result in more extended such matrices, it is too computationally intensive to use more than 64 levels. This is the reason we haven't used in our comparisons 128 and 256 levels.

Figure 2 illustrates that the reconstruction results are best for the DWT bands_cluster compression, while DWT texture_cluster compression gives a little worse results. The original DWT compression has given the worst reconstruction results. Figures 3 and 4 illustrate the reconstruction results for the DWT based bands_cluster compression and the original DWT based compression, for the same average compression ratios, respectively. The images obtained by the former method are clearer than the ones obtained by the latter, which are smoother and more blurred.

At this point it should be reported that the MATLAB fuzzy and wavelet toolboxes have been employed in all these simulations.

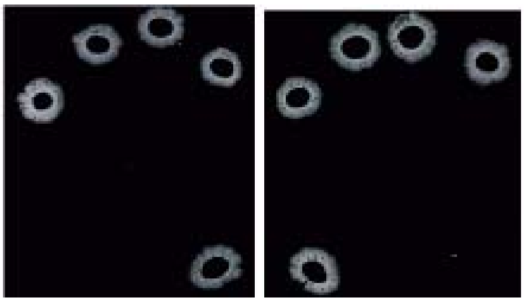

Figure 3. Reconstructed images (pol-2, pol-4) using fuzzy c-means clustering of the wavelet bands. Compression ratios are 0.35 and 0.65 for the significant and the non-significant regions for both images

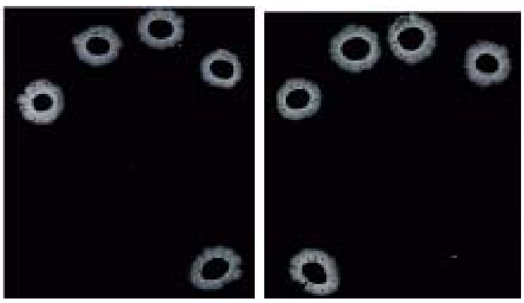

Figure 4. Reconstructed images (pol-2, pol-4) applying the inverse DWT to the whole wavelet space. The Compression ratio is 0.5 for both images.

4. CONCLUSIONS

Two novel image compression schemes for Kirlian images have been presented based on the 2-D DWT and the fuzzy c-means based clustering. The promising results obtained concerning reconstructed images quality as well as preservation of significant image details, while, on the other hand achieving high compression rates, illustrate that the proposed approaches deserve further investigations. The main problem remaining to be dealt with is the elimination of blocking effects in the partitions boundaries that is there is need for smoothing the reconstructed image in these boundaries.

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