An Improved Technique for Evolving Wavelet Coefficients for Fingerprint Image Compression

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***Abstract*—In this paper, an improved technique for evolving wavelet coefficients refined for compression and reconstruction of fingerprint images is presented. The FBI fingerprint compression standard [1, 2] uses the cdf 9/7 wavelet filter coefficients. Lifting scheme is an efficient way to represent classical wavelets with fewer filter coefficients [3, 4]. Here Genetic algorithm (GA) is used to evolve better lifting filter coefficients for cdf 9/7 wavelet to compress and reconstruct fingerprint images with better quality. Since the lifting filter coefficients are few in numbers compared to the corresponding classical wavelet filter coefficients, they are evolved at a faster rate using GA. A better reconstructed image quality in terms of Peak-Signal-to-Noise-Ratio (PSNR) is achieved with the best lifting filter coefficients evolved for a compression ratio 16:1. These evolved coefficients perform well for other compression ratios also.**

Keywords-*Wavelets, Lifting Scheme, Evolved transforms, Genetic algorithms, Thresholding, Image compression*

I. INTRODUCTION

Digital image compression is essential for applications such as storage and transmission. Image compression refers to the process of reducing the amount of data required to represent a digital image for efficient storage and transmission. Wavelet-based image coders are the state of art in image compression. It is a transform coding technique where the wavelet transform of the image is modified. A reversible, linear transform such as wavelet transform is used to map the image into a set of transform coefficients, which are then quantized and coded. Fig. 1 shows a typical wavelet coding system. The computed transform converts a large portion of the original image to horizontal, vertical and diagonal decomposition coefficients. These coefficients are quantized and coded to minimize inter-coefficient and coding redundancy. Decoding is done by inverting the encoding operation, except quantization, which cannot be reversed exactly. Peak-Signal-to-Noise-Ratio (PSNR) and Root Mean Squared Error (RMSE) are the two measures of compression performance. RMSE is given by (1).

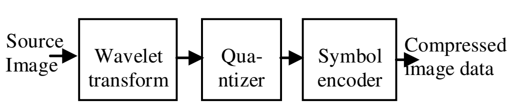


Figure 1. Wavelet transform encoder block diagram.

$$RMSE = \sqrt{\frac{1}{N\,x\,M}\sum_{x=0}^{N-1}\sum_{y=0}^{M-1}[f(x,y)-\tilde{f}(x,y)]^2} \quad (1)$$

where $f(x,y)$ and $\tilde{f}(x,y)$ are the original and reconstructed image respectively with size MxN. For a Peak gray level of 255, the corresponding PSNR in dB is,

$$PSNR = 20 \log_{10} \frac{255}{RMSE} dB \quad (2)$$

The FBI fingerprint compression standard [1, 2] uses the cdf 9/7 classical wavelet filters introduced in 1992 by Cohen, Daubechies, and Feauveau [5]. The cdf 9/7 classical wavelet is comprised of 16 filter coefficients. Brendan Babb [1] in his work evolved classical wavelet filter coefficients with four level MRA transforms. For the four levels of the MRA he evolved 128 separate coefficients, 16 coefficients for forward and 16 for inverse transforms in each level. His work involved a huge amount of computational complexity and hence he used supercomputers for evolution. He used a population size of 240-280 and the number of generations exceeded 15000. The evolved transform averaged 0.76dB of picture quality in terms of PSNR over 80 fingerprint images. Uli Grasemann and Risto Mikkulainen [6] described a method based on the co-evolutionary algorithm to evolve specialized wavelets for fingerprint image compression. They considered the properties of lifting by which any random sequence of lifting steps will encode a valid wavelet and any wavelet can be represented using the genetic code. Random values from a Gaussian distribution are assumed as initial coefficients for GA evolution. Each of the 80 runs of the algorithm took 45 minutes on a 3GHz Xeon Processor. On a population of 80 fingerprint image an average of 0.75dB improvement in PSNR has been reported. The lifting scheme introduced by W. Sweldens [3, 4] is an efficient way to represent classical wavelets with fewer coefficients. I. Daubechies and W. Sweldens [7] showed that any orthogonal and biorthogonal wavelet analysis process can be made into lifting steps by employing factorization of polyphase matrix. By this, only 4 lifting filter coefficients are needed to represent the cdf 9/7 wavelet system. By refining these general purposes lifting filter coefficients using GA, optimum filter coefficients adapted to fingerprint compression application can be obtained.

In this paper a faster method for evolving the lifting filter coefficients using GA for fingerprint image compression is proposed. In particular, the method for evolving the cdf 9/7 wavelet lifting filter coefficients using GA at a faster rate compared to the corresponding classical wavelet is presented.

The rest of the paper is structured as follows. Section II gives a brief overview of lifting scheme and its implementation. The proposed work of evolving lifting filter coefficients using GA is described in Section III. Section IV provides results and discussions and Section V concludes the paper.

II. LIFTING SCHEME

The lifting scheme is an approach to construct the so-called second-generation wavelets, i.e., wavelets which are not necessarily translations and dilations of one function. Space-frequency localization of non-stationary signals can be done in spatial domain through lifting. It has an advantage that all computations can be done in-place. Thus the lifting scheme makes the computational time optimal. I. Daubechies and W. Sweldens [7] showed that any wavelet-analysis-process can be made into lifting steps by employing factorization of polyphase matrix. There are too many factorizations exist; the one chosen here is the symmetric lifting scheme with only 4 coefficients.

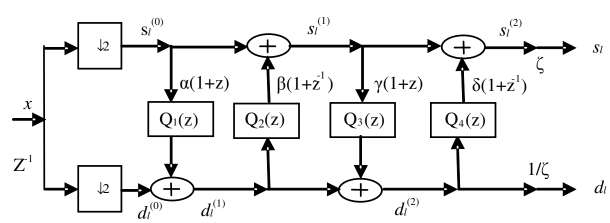
The lifting scheme starts with a set of well-known filters and lifting steps are used to improve (lift) the properties of a corresponding wavelet decomposition. Lifting consists of three steps: *Split, Predict and Update*. *Split* stage splits the signal into two disjoint sets of odd and even samples. Since the two sets are correlated, given one set, we can *predict* the other using a predictor. The update operator maintains the same average value of the approximate signal as the original signal. A number of such lifting steps can be used to obtain desired properties of a wavelet transform. The inverse transform is found by just reversing the order of the operations and flipping the signs. Fig. 2 shows the lifting implementation of the cdf 9/7 (Cohen-Daubechies-Fauvaue 4.4) transform (decomposition only) [8]. Here $x=\{x_l \mid l\in Z\}$ is the input sequence. $s_l^{(0)}$ and $d_l^{(0)}$ are the even and odd subsequence obtained by splitting x. $s_l^{(i)}$ and $d_l^{(i)}$ are the intermediate values computed during lifting. The superscript i is used to identify the lifting steps. $s_{l+1}^{(i)}, s_{l-1}^{(i)}$ and $d_{l+1}^{(i)}, d_{l-1}^{(i)}$ are the right shifted and left shifted even and odd subsequences resp. Q_1, Q_2, Q_3, Q_4 are the lifting filters. The lifting coefficients of cdf 9/7 wavelet filter are given by [7, 8] as

$\alpha = -1.586134342060$, $\beta = -0.052980118573$, $\gamma = 0.882911075531$, $\delta = 0.443506852044$.
$\zeta = 1.149604398860$ is the scaling factor.

III. EVOLUTION OF LIFTING FILTER COEFFICIENTS

Genetic algorithms [9] are search algorithms based on the mechanics of natural selection and natural genetics. They combine survival of the fittest among candidates with a structured yet randomized information exchange to form a search algorithm. In every generation, a new set of children (new generation) is created using bits and pieces of the fittest of the parents (current generation) and the process is repeated in search of a better candidate. GA, in general, is comprised of three operators: *Reproduction, crossover and Mutation*. Reproduction is a process in which individual candidates are copied according to their objective function values. Crossover yields new candidates as part of the new generation. Mutation is an operation that helps to avoid premature convergence of GA.

For fast evolution of wavelet coefficients as well as for fast compression of fingerprint images, symmetrical lifting coefficients of cdf 9/7 [7, 8] were evolved using GA. Symmetrical lifting scheme consist only 4 coefficients whereas classical cdf 9/7 consists 16 coefficients for each level. Binary GA has been used for the evolution. Each chromosome is represented by a 17 bit binary number. The first bit is used as sign bit and the remaining 16 bits are used for the magnitude of the coefficients. Fig. 3 shows the structure of the evolutionary algorithm (GA) for optimizing cdf 9/7 lifting coefficients.



$$s_l^{(0)} = x_{2l}, \qquad d_l^{(0)} = x_{2l+1}$$
$$s_l^{(1)} = s_l^{(0)} + \beta\,(d_l^{(1)} + d_{l-1}^{(1)})$$
$$d_l^{(1)} = d_l^{(0)} + \alpha\,(s_l^{(0)} + s_{l+1}^{(0)})$$
$$s_l^{(2)} = s_l^{(1)} + \delta\,(d_l^{(2)} + d_{l-1}^{(2)})$$
$$d_l^{(2)} = d_l^{(1)} + \gamma\,(s_l^{(1)} + s_{l+1}^{(1)})$$
$$s_l = \zeta\, s_l^{(2)}, \qquad d_l = d_l^{(2)} / \zeta$$

Figure 2. Lifting Implementation of the cdf9/7 transform (decomposition only).

As in [1] the initial population of GA is created by using randomly mutated copies of the symmetrical lifting coefficients of cdf 9/7 and also four representative fingerprint images are taken to feed the training image data set. More number of images in the training data set will cause longer time to evolve the coefficients, whereas if training data set consist a single image only, it will degrade

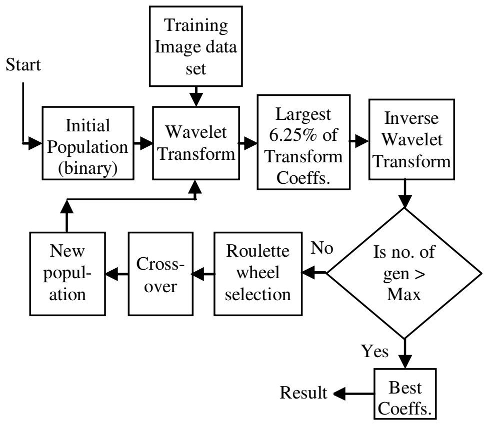


Figure 3. Structure of the Evolutionary algorithm (GA) for optimizing cdf 9/7 lifting coefficients.

the PSNR for many of the other test images. The best evolved wavelet obtained using the training set of four representative images are used to calculate the average improvement in PSNR over 80 fingerprint images.

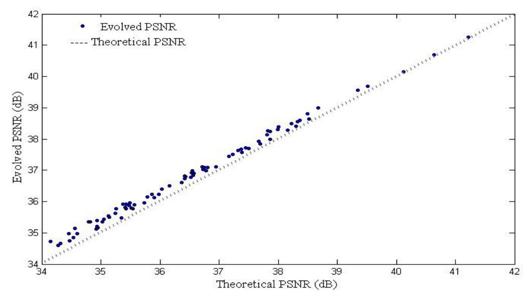
IV. RESULTS AND DISCUSSIONS

The proposed work of evolving wavelet lifting coefficients for cdf 9/7 used binary GA with 4 representative gray scale fingerprint images as training image data set. These images are taken from FVC2000 fingerprint database . Image set B of DB1 database in FVC2000 contains 80 fingerprint images, each of size 300x300 pixels with a resolution of 500 dpi. As a common approach a 4 level MRA is used. Also, as a common technique in image compression, the largest 6.25% of the transformed image coefficients are retained and the remaining values are set to zero, so as to have a compression ratio 16:1. Number of generations is taken as 1000 and 250 is the population size. Roulette wheel selection and single point crossover with $P_c = 0.7$ and mutation rate $P_m = 0.0075$ are used. The algorithm took 33 hours on an AMD Athlon 2.39GHz Processor with 750 MB memory, giving reasonable improvement in PSNR. The best wavelet lifting coefficients (4 coefficients) evolved for the compression ratio 16:1 was used for compressing the fingerprint images. Compared to the classical cdf 9/7 wavelet, the evolved coefficients showed an average improvement of 0.93063 dB in PSNR when tested over the 80 fingerprint images. The evolved coefficients also showed an average improvement of 0.318882 dB in PSNR over the theoretical lifting wavelet coefficients when tested on the 80 fingerprint images. The same evolved wavelet coefficients exhibits improvement in PSNR for other compression ratios also.

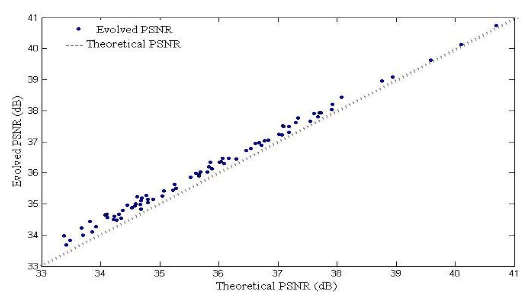
Fig. 4 shows a typical fingerprint image taken from the fingerprint database and the image reconstructed using evolved cdf 9/7 lifting coefficients for compression ratio 16:1. Fig. 5 shows the plot of theoretical vs. evolved PSNR for compression ratios 16:1 and 18:1. The diagonal dotted line corresponds to the theoretical PSNR, where as the thick dots represents the evolved PSNR for the 80 images. For all images, value of the evolved PSNR is above the theoretical PSNR. Fig. 6 shows the comparison of theoretical and evolved PSNR for a degraded image for CR=16:1. Here,

(a) (b)

Figure 4. A typical fingerprint image (a) original (b) reconstructed (CR=16:1).



(a)



(b)

Figure 5. Plot of theoretical PSNR vs. evolved PSNR for: (a) CR=16:1 (b) CR=18:1.

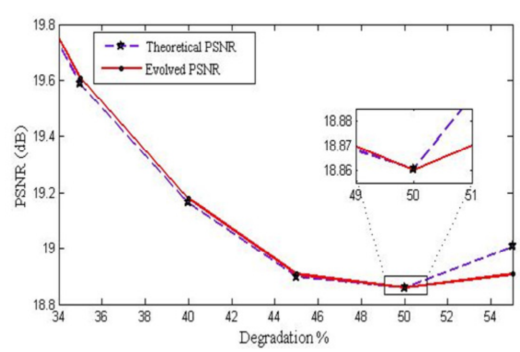


Figure 6. Comparison of theoretical and evolved PSNR for a degraded image for CR=16:1.

quality of the input image 101_1.tif is degraded by various amounts by setting certain percentages of lower pixel values to zero. Percentage degradation is calculated as

$$Degradation = \frac{No. of \ pixels \ set \ to \ zero}{Total \ no. of \ pixels} \times 100 \ \% . \qquad (3)$$

As shown in the figure, the evolved PSNR is better than the theoretical PSNR for lower values of degradation. The theoretical PSNR becomes better beyond 50% of degradation. Similar results are obtained for higher compression ratios also with some improvement in the % of degradation at which the theoretical PSNR becomes better than the evolved one. For example, with compression ratio 20 and 25 the change occurs at 55-60% and 65-70% degradation respectively. For lower compression ratios theoretical coefficients start to outperform the evolved coefficients at lower degradation values. For example, with compression ratios 14 and 12, the theoretical PSNR crosses the evolved PSNR at 6-7% and 3-4% of degradation respectively. Fig. 7 shows the 101_1.tif image with 40 % degradation (i.e., 40 % of lower pixel values are set to zero) and the reconstructed images using theoretical as well as evolved coefficients. Table I gives the average improvement in PSNR using the best evolved lifting coefficients for different runs of the algorithm. Improvement in PSNR for the evolved coefficients over the theoretical coefficients for various compression ratios are given in Table II. Fig. 8 shows the convergence plot of a typical GA evolution of lifting coefficients. As shown, by generation 205 the algorithm converges to the maximum value of the fitness function (PSNR). So the optimum lifting coefficients can be obtained within a lesser number of generations than we used. As per the results the evolved lifting wavelet coefficients give a much better PSNR than the classical wavelet for fingerprint image compression for CR=16:1. It can also be noted that the speed of evolution is higher compared to the other methods in [1, 6], even though they used different platforms. The evolved coefficients also give better PSNR when compared to the theoretical lifting coefficients. They perform well for other compression ratios also.

(a) (b) (c)

Figure 7. 101_1.tif image (a) with 40 % degradation (b) reonstructed image using theoretical coefficients (c) reonstructed image using evolved coefficients.

V. CONCLUSION

This paper presents an improved technique for evolving wavelet coefficients, refined for compression and reconstruction of fingerprint images. The idea uses lifting scheme combined with GA to evolve better lifting filter coefficients for cdf 9/7 wavelet to compress and reconstruct fingerprint images with better quality. Since the lifting filter coefficients are few in numbers compared to the corresponding classical wavelet filter coefficients, they are evolved at a faster rate using GA. Compared to the classical cdf 9/7 wavelet a better reconstructed image

TABLE I. AVERAGE PSNR OVER 80 FINGERPRINT IMAGES.

RUN (CR=16:1)	Average PSNR (dB)	
	Evolved lifting coeffs.	*Improvement*
1	36.831229	0.296099
2	36.854012	**0.318882**
3	36.842539	0.307409
4	36.822665	0.287535
PSNR for theoretical coefficient = 36.53513		

TABLE II. AVERAGE PSNR FOR THE BEST EVOLVED LIFTING COEFFICIENTS.

CR	Average PSNR (dB)		
	Theoretical Lifting coeffs	*Evolved lifting coeffs.*	*Improve-ment*
5:1	43.08954	43.21995	0.13041
10:1	39.19117	39.46790	0.27673
12:1	38.18787	38.48655	0.29870
14:1	37.31285	37.61974	0.30690
16:1	36.53513	36.85401	0.31888
18:1	35.84354	36.14824	0.30470
20:1	35.22623	35.52591	0.29968
25:1	33.94791	34.23097	0.28310
30:1	32.95175	33.21570	0.26396
Lifting coefficients are evolved for CR=16:1			

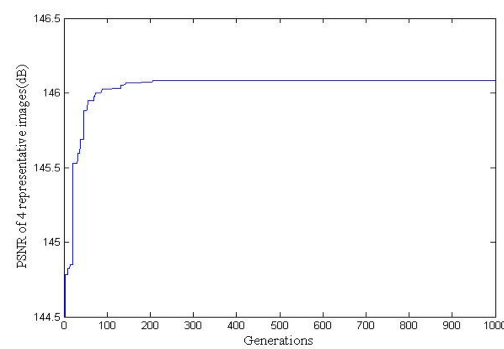


Figure 8. Convergence plot of a typical GA evolution of lifting coefficients

quality in terms of PSNR is achieved with the best lifting filter coefficients evolved for a compression ratio 16:1.The speed of evolution is higher compared to that of classical wavelet. Further the PSNR achieved with the evolved coefficients is better than the corresponding theoretical lifting wavelet filter coefficients. Thus the evolved wavelet performs much better than the classical wavelets and the theoretical lifting wavelet coefficients. These coefficients perform well for other compression ratios also.

REFERENCES

[1] B. Babb, "Evolved transforms surpass the FBI wavelet for improved fingerprint compression and reconstruction," Proc. GECCO conference companion on Genetic and evolutionary computation , London, July 7-11, 2007.

[2] J. Bradley, C. Brislawn, and T. Hopper, "The FBI Wavelet/ Scalar Quantization Standard for Gray-Scale Fingerprint image Compression," SPIE Vol. 1961, Visual Information Processing II (1993): 293-304.

[3] W. Sweldens, "The Lifting Scheme: A custom-design construction of biorthogonal wavelets," Journal of Applied and Computational Harmonic Analysis, vol. 3, issue 2, pp. 186-200, April 1996.

[4] W. Sweldens,"The Lifting Scheme: A construction of second-generation wavelets," SIAM J.Math Anal., 29 (1997) 511-546.

[5] A. Cohen, I. Daubechies, and J.-C. Feauveau "Biorthogonal Bases of Compactly Supported Wavelets," Communications on Pure and Applied Mathematics, 45 (5), 485-560, June 1992.

[6] U. Grasemann, and R. Mikkulainen, "Effective Image Compression using Evolved Wavelets," Proc. of the Seventh Annual Genetic and Evolutionary Computation Conference (GECCO'2005) , 6/25-29, 2005, Washington, DC, 2: 1961-1968, ACM.

[7] I. Daubechies, W. Sweldens, "Factoring wavelet transforms into lifting steps," Journal of Fourier Analysis and Applications, 4 (1998), 245-267.

[8] D. Taubman, and M Marcellin, JPEG2000: Image Compression Fundamentals, Standards and Practice, Kluwer Academic Publishers, Boston/Dordrecht/London, 2002.

[9] D. Goldberg, Genetic Algorithms in Search, Optimization, and Machine, 1st ed., Addison- Wesley, 1989.