Evolved Transforms Beat the FBI Wavelet for Improved Fingerprint Compression and Reconstruction

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Abstract: - This paper describes the evolution of new wavelet and scaling numbers for optimized transforms that consistently outperform the 9/7 discrete wavelet transform (DWT) for fingerprint compression and reconstruction.

Key-Words: - compression, reconstruction, wavelets, genetic algorithms, fingerprints

1 Introduction

As stated on the US Federal Bureau of Investigation (FBI) web site, "criminal identification by means of fingerprints is one of the most potent factors in apprehending fugitives who might otherwise escape arrest and continue their criminal activities indefinitely." The FBI's Criminal Justice Information Services (CJIS) Division maintains the National Repository of Criminal History Records and Criminal History Data, which includes ten fingerprint records for over 81 million criminals, government employees, and civil service applicants. Records for approximately 7,000 individuals are added to this repository every day. Law enforcement officials can use the Integrated Automated Fingerprint Identification System (IAFIS) to find a match in less than two hours for criminal fingerprints, and less than 24 hours for civilian fingerprints.

The FBI fingerprint compression standard [2] is based upon the biorthogonal 9/7 wavelet filter pair developed in 1992 by Cohen, Daubechies, and Feauveau [3]. DWTs [4] may be described by four sets of floating-point coefficients: *h1* (Lo_D) and *g1* (Hi_D) are the wavelet and scaling numbers for the (forward) discrete wavelet (decomposition) transform (DWT), while *h2* (Lo_R) and *g2* (Hi_R) define the wavelet and scaling numbers for the inverse (reconstruction) transform (DWT^{-1}). Fig. 1 lists these coefficients for the 9/7 DWT.

The 9/7 wavelet was subsequently adopted for Part 1 of the Joint Photographic Experts Group's JPEG2000 still image compression standard [17]. JPEG2000 was developed as a successor to the original JPEG standard; it delivers superior compression performance while offering features useful for such diverse applications as the Internet, digital cameras, and medical image processing.

h1 =	[0.03783, -0.02385, -0.11062, 0.37740, 0.85270, 0.37740, -0.11062, -0.02385, 0.03783]
g1 =	[0.06454, -0.04069, -0.41809, 0.78849, -0.41809, -0.04069, 0.06454]
h2 =	[-0.06454, -0.04069, 0.41809, 0.78849, 0.41809, -0.04069, -0.06454]
g2 =	[0.03783, 0.02385, -0.11062, -0.37740, 0.85270, -0.37740, -0.11062, 0.02385, 0.03783]

Fig. 1. 9/7 (CDF) Wavelet Transform Wavelet and Scaling Coefficients.

2 Previous Results

Quantization (the process of approximating a given signal using a relatively small number of bits) allows digital images to be more easily compressed. Quantization is often the most significant source of distortion in digital images. Dequantization step $\mathbf{Q}^{-1}(\boldsymbol{q})$ produces an image $\boldsymbol{\gamma}'$ that differs from the original image $\boldsymbol{\gamma}$ according to a distortion measure $\boldsymbol{\rho}$, which in general may be computed as a linear combination of the MSE for each pixel.

Since 2004, researchers at the University of Alaska Anchorage, in cooperation with researchers at the Air Force Institute of Technology, Wright State University, and Wright-Patterson Air Force Base (USA), have been interested in evolving coefficients describing transforms that outperform wavelets for signal and image processing applications subject to quantization error. These projects ([1], [10], [11], [12], [13], [14], [15]) have succeeded at each of the following tasks:

1. First, we showed that a genetic algorithm (GA) [6] could be used to evolve coefficients describing an inverse transform capable of reducing the mean squared error (MSE) in reconstructed one-dimensional signals previously compressed by a DWT and subjected to quantization error. Results were promising [10], with error reductions consistently exceeding 91% for sinusoidal signals.
2. Next [11], we demonstrated that this approach could be successfully applied to photographic images. Our GA evolved inverse transforms capable of reducing MSE by as much as 10.7% in comparison to the selected wavelet.
3. Next [1], we extended this work by simultaneously evolving coefficients describing matched forward and inverse transform pairs. The resulting transforms were capable of more than 20% MSE reduction in comparison to the Daubechies-4 (D4) transform under conditions subject to a quantization step of 64, while maintaining an average compressed file size (FS) less than or equal to the FS produced by the D4 transform.
4. Next [13], we utilized the massive computational power of supercomputers at the Arctic Regional Supercomputer Center (ARSC) to evolve one-level transforms. For a quantization step of 64, these transforms reduced MSE by nearly 40% (2.203 dB) for the training image, and by an average of nearly 23% (1.126 dB) on test images. In addition, according to an Information Entropy (IE) measure commonly used to accurately estimate FS, the average compressed FS for evolved transforms was less than or equal to that of the D4 wavelet.
5. Next, the GA was used to evolve multiresolution analysis (MRA) transforms [9] described by a single set of coefficients used at every level. The resulting transforms were capable of an average MSE reduction of 7.61% (0.34 dB) under conditions subject to a quantization step of 64, while keeping FS in check.
6. Finally, the GA was expanded to evolve MRA transforms that utilized a different set of coefficients at each MRA level. Each individual consisted of 48 real-valued coefficients (16 for each MRA level). At quantization equal to 64, the evolved MRA transform reduced MSE by as much as 12.92% (0.60 dB), again while keeping average FS less than or equal to the FS produced by the three-level D4 MRA transform.

For the first five tasks, the GA seeded each individual in the initial population with randomly mutated copies of a selected wavelet; the evolved transforms thus had identical structure to the selected wavelet, but different wavelet and scaling numbers. For the final task, the coefficients at each level of the transform were independently initialized to a different randomly mutated copy of the selected wavelet's coefficients.

The published research most closely related to this project combined a coevolutionary GA [7] with the lifting scheme [16] to evolve wavelets specifically for fingerprint images. The best solutions evolved by those researchers "averages 0.75 dB quality improvement over the FBI wavelet" when subsequently tested on a population of 80 fingerprints [8]. These results demonstrated that evolved wavelets could outperform the industry standard, and provided a baseline with which our results could be compared.

3 Evolved 9/7 Transforms

The results of previous investigations were promising. The percentage reductions in MSE (in excess of 20% for one-level transforms) were often large enough to be detected by the naked eye. However, key issues needed to be addressed:

1. Most of the work described above used the D4 wavelet to seed the initial population. Could the GA-based methodology be extended to evolve coefficients for a 9/7-shaped transform that was capable of outperforming the 9/7 wavelet for the fingerprint compression and reconstruction problem?
2. All of the work described above assumed the presence of error due to scalar quantization [5]. Could the GA evolve coefficients for improved transforms under conditions subject to different types of quantization error, or even no quantization error at all?

Positive answers to each of these questions suggest that the technique of using GAs to evolve transform coefficients might indeed be powerful enough to supplant wavelet transforms in future image compression standards.

The following modifications to our GA were necessary to carry out these experiments:

1. First, we revised our GA to accommodate asymmetric transforms. Our GA seeded the initial population with randomly mutated 9/7 wavelet coefficients.
2. Next, we extended our GA to accommodate evolution of four-level MRA transforms. With 16 forward and 16 inverse coefficients for at each level, each four-level transform in the population was now defined by a total of 128 floating-point values.
3. The training population was extended to include three representative fingerprint images. This extension helped reduce the possibility of overtraining which might negatively impact the performance of evolved transforms during subsequent testing on fingerprints not explicitly anticipated by the training population.
4. A common technique in wavelet-based image processing retains the first 1/r transform values, and sets the remaining values to 0. The test results below used r = 16 to maximum comparability with other published results ([2], [8]).

4 Test Results

Several training runs on ARSC supercomputers evolved coefficients for a 9/7-shaped transform. These runs produced the following results:

1. The best transform evolved by the GA reduced MSE by an average of 24.46% (1.22 dB) on the three fingerprint images used for training.
2. The best transform averaged 20.79% (1.01 dB) MSE reduction when tested against a population of 20 high-fidelity fingerprint images.
3. The average size FS compressed by the evolved transform was virtually identical to the FS produced by the 9/7 wavelet.
4. Evolved transforms were subsequently tested on photographs commonly used by the signal processing community, such as “zelda”, “lenna”, and “airplane”. The MSE of the evolved transforms was consistently worse on these images than the original 9/7 wavelet. This result suggests that the GA is capable of automatically discovering and exploiting specific features of fingerprints that do not commonly appear in other photographic images.

Fig. 2 shows a typical fingerprint from the test set. Fig. 3 shows the same fingerprint after compression and reconstruction by the 9/7 wavelet, while Fig. 4 shows the difference between Fig. 2 and Fig. 3.

Fig. 2. A Typical Fingerprint Image.

Fig. 3. The Fingerprint Image Compressed and Reconstructed by the 9/7 Wavelet.

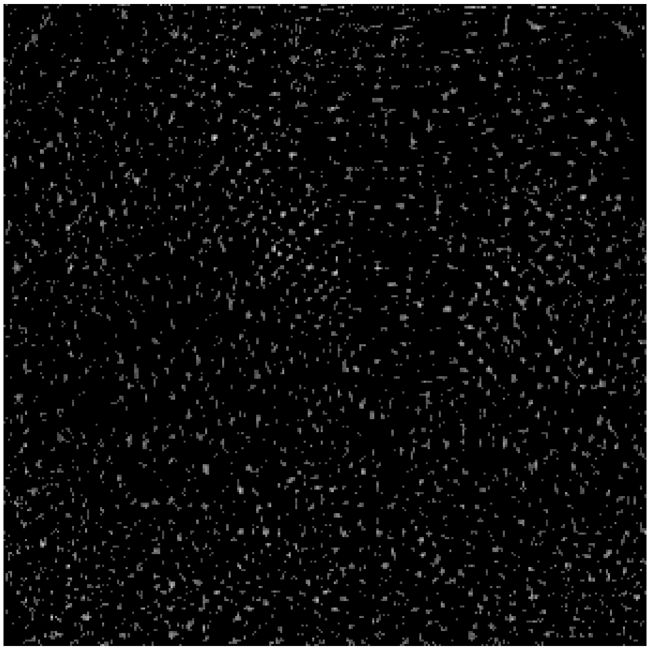

Fig. 4. The Difference Image Illustrating the Significant Differences Between the Original Fingerprint and the Fingerprint Compressed and Reconstructed by the 9/7 Wavelet.

Fig. 5 shows this fingerprint after compression and reconstruction by a best-of-run evolved transform, while Fig. 6 shows the difference between Fig. 2 and Fig. 5.

Fig. 5. The Fingerprint Image Compressed and Reconstructed by a Best-of-Run Evolved Transform.

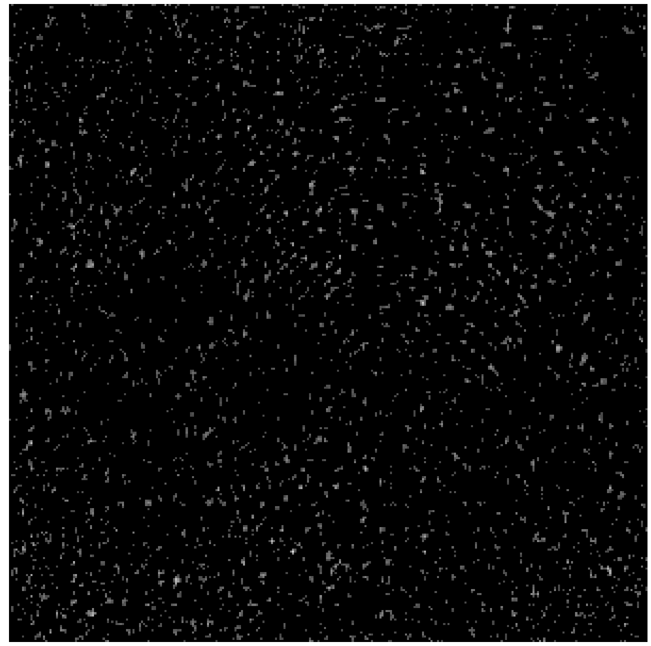

Fig. 6. The Difference Image Illustrating the Significant Differences between the Original Fingerprint and the Fingerprint Compressed and Reconstructed by the Evolved Transform. Improvement over the 9/7 Wavelet is obvious.

Fig. 4 and Fig. 6 were constructed by taking the absolute value of the difference between the grey-scale intensity of each pixel from the original and reconstructed images, setting any values less than 8 to zero, and then multiplying the remaining values by 9 to make the most significant differences easier to see. Comparison between Fig. 6 and Fig. 4 reveals the degree to which evolved transforms outperform the 9/7 wavelet for this application.

Coefficients for the evolved transform used for Fig. 5 and Fig. 6 are shown in Fig. 7. Note that the GA has identified a different set of optimized coefficients at each of four MRA levels.

5 Discussion and Comparison to Related Work

Fingerprint compression has long been one of the most celebrated applications of wavelets [2]. The research described in this paper has established a methodology for evolving transforms that substantially outperform the 9/7 wavelet. Our evolved transforms exhibited a 1.01 dB average MSE reduction compared to the 9/7 wavelet when tested on 20 representative fingerprints.

In addition, our result improves upon the 0.75 dB reduction reported for Grasemann and Mikkulainen's evolved wavelets [8]. Our GA-based approach thus appears to be more capable of exploiting image qualities that are specific to the class of fingerprints; however, it should be noted that their evolved wavelets were tested using 80 fingerprint images.

Finally, our GA is not constrained to produce transforms having the precise mathematical properties of wavelets [4], such as biorthogonality. Instead, our GA is free to evolve whatever combination of wavelet and scaling coefficients results in the most effective MSE reduction. This additional freedom allows our approach to more effectively search the space of both wavelets and non-wavelet transforms in order to better compensate for quantization error.

Level 1: *h1* = [0.08596, -0.10220, -0.18091, 0.37547, 0.85813, 0.43205, -0.13579, -0.06048, 0.07122]
g1 = [-0.07579, 0.01157, 0.39682, -0.65165, 0.37593, 0.02545, -0.08422]
h2 = [-0.05538, 0.03242, 0.48138, 0.74131, 0.41890, -0.01670, -0.08837]
g2 = [-0.04875, -0.14915, 0.18369, 0.44587, -0.98426, 0.15077, 0.19462, -0.09640, -0.07279]
Level 2: *h1* = [0.08297, -0.10084, -0.17957, 0.37254, 0.83548, 0.42443, -0.13441, -0.06084, 0.07144]
g1 = [-0.074316, 0.01679, 0.41127, -0.68467, 0.38921, 0.02569, -0.08433]
h2 = [-0.06747, 0.03273, 0.47907, 0.72737, 0.42329, -0.01707, -0.09203]
g2 = [-0.09331, -0.12438, 0.24853, 0.32944, -0.81128, 0.37685, 0.22260, -0.09592, -0.08393]
Level 3: *h1* = [0.08574, -0.09858, -0.17908, 0.36978, 0.84210, 0.42101, -0.13371, -0.06497, 0.07067]
g1 = [-0.07640, 0.01488, 0.41305, -0.68569, 0.38896, 0.02611, -0.08186]
h2 = [-0.05803, 0.03236, 0.48665, 0.74446, 0.42063, -0.01733, -0.09087]
g2 = [-0.09965, -0.07280, 0.12577, 0.43528, -0.91393, 0.46213, 0.13136, -0.06202, -0.08072]
Level 4: *h1* = [0.08508, -0.10321, -0.17649, 0.37532, 0.84718, 0.42435, -0.13291, -0.05960, 0.07087]
g1 = [-0.07525, 0.01471, 0.41584, -0.68259, 0.38428, 0.02781, -0.08558]
h2 = [-0.05746, 0.03289, 0.48625, 0.74604, 0.42334, -0.01709, -0.09103]
g2 = [-0.09750, -0.06965, 0.12383, 0.43194, -0.90946, 0.46358, 0.12713, -0.05050, -0.08255]

Fig. 7. Evolved Transform Coefficients, MR = 4 Levels.

6 Future Directions

We are in the process of determining whether evolved transforms having the same structure as the 9/7 wavelet can outperform that wavelet in the broader arena of digital image compression and reconstruction. A positive outcome could have an enormous positive effect upon the way in which digital images are transmitted and stored for such applications as the Internet, digital photography, and medical imaging.

We are also in the process of identifying the advantages of using evolved transforms over the 9/7 wavelet for fingerprint compression applications subject to other types and degrees of quantization. We have previously demonstrated the existence of a Pareto optimal front describing the tradeoff between FS and MSE reduction. For the same FS, our evolved transforms stored higher-quality images than wavelets; alternatively, for equal image quality, our evolved transforms allowed much higher compression. Both advantages would be useful to the digital imaging community.

Other future work includes allowing our GA to simultaneously evolve both the number of coefficients (scaling and wavelet numbers) at each level of a transform, as well as the values of those coefficients. This technique could produce powerful new transforms having structures not currently utilized in the wavelet community.

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