Evolving Better Satellite Image Compression and Reconstruction Transforms

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ABSTRACT
This paper summarizes the results of a continuing investigation into the evolution of transforms that minimize the error present in satellite images compressed and subsequently reconstructed under conditions subject to quantization error. Using coefficients describing the Daubechies-4 (D4) discrete wavelet transform (DWT) as a starting point, our genetic algorithm (GA) evolves real-valued coefficients describing matched forward and inverse transform pairs that reduce mean squared error (MSE) by 17.9% (0.86 dB) on satellite images used for training, and by an average of more than 11.0% (0.5 dB) on a large test set of satellite images. This result improves upon previous work on satellite images, which evolved only the reconstruction transform, and establishes evolutionary computation as a viable methodology for identifying state-of-the-art solutions to this difficult class of problems.

Categories and Subject Descriptors
G.1.2 [**Numerical Analysis**]: Approximation – *Wavelets and Fractals;* I.4.2 [**Computing Methodologies**]: Image Processing and Computer Vision – *Compression (Coding)*; I.2.8 [**Computing Methodologies**]: Artificial Intelligence – *Problem Solving, Control Methods, and Search*; G.1.6 [**Numerical Analysis**]; Optimization - *Global Optimization.*

General Terms
Algorithms, Experimentation, Performance

Keywords
Evolved Transforms, Wavelets, Genetic Algorithms, Quantization Error, Satellite Images, Image Compression, Image Reconstruction.

1. INTRODUCTION
Wavelets [5] are used as the basis for a wide variety of signal and image processing applications, including the JPEG-2000 image compression standard [23] and the FBI's fingerprint compression standard [3]. Wavelets may be described by four sets of coefficients:

h1 is the set of wavelet numbers for the (forward) DWT.
g1 is the set of scaling numbers for the DWT.
h2 is the set of wavelet numbers for the inverse transform (DWT^{-1}).
g2 is the set of scaling numbers for the DWT^{-1}.

For the Daubechies-4 (D4) wavelet, these sets consist of the following floating-point coefficients:

$h1$ = {-0.1294, 0.2241, 0.8365, 0.4830}
$g1$ = {-0.4830, 0.8365, -0.2241, -0.1294}
$h2$ = {0.4830, 0.8365, 0.2241, -0.1294}
$g2$ = {-0.1294, -0.2241, 0.8365, -0.4830}

Quantization (the process of approximating a given signal using a relatively small number of bits) allows digital images to be more easily compressed; unfortunately, quantization is often the most significant source of distortion in digital images. Dequantization step $Q^{-1}(q)$ produces an image γ' that differs from the original image γ according to a distortion measure ρ, which may be computed as the MSE measured in the reconstructed image γ'. The ability of wavelet-based transforms to produce high-quality reconstructed images significantly degrades at higher quantization levels, ultimately resulting in reconstructed images with unacceptably high MSE.

A series of recent advances ([7], [8], [1], [11], [12], [13]) has demonstrated how a GA [6] can evolve optimized transforms that outperform wavelets for a variety of signal and image compression and reconstruction tasks under conditions subject to quantization. The availability of supercomputing and cluster computing environments, such as those provided by the Arctic Regional Supercomputer Center (ARSC), has made it possible for evolutionary computing to achieve "routine human-competitive intelligence" [10]. Simultaneously, rigorous analysis of algorithms, operators, training sets, and fitness landscapes ([16], [17], [18], [19], [20], [21]) has dramatically increased the power of our GA to evolve optimized solutions in this domain. In 2006 [14], we developed a GA that evolved matched forward and inverse transform pairs that reduced average MSE in reconstructed photographs (such as the famous “lenna”, “baboon”, and “airplane” images) by more than 22% (1.126 dB). Next, we extended this approach [15] to evolve multi-resolution analysis (MRA) transforms [9], reducing MSE by more than 10% (0.50 dB) at three levels of decomposition.

In 2007, we applied our approach to the fingerprint compression and reconstruction problem [2], whose famous state-of-the art solution incorporates the biorthogonal 9/7 discrete wavelet transform (DWT) filter pair of Cohen, Daubechies, and Feauveau [4]. Under conditions subject to 16:1 quantization (i.e., retaining the largest 6.25% of the coefficients and setting the rest to 0), the best four-level MRA transform evolved by our GA reduced MSE by an average of 24.03% (1.20 dB) on the four fingerprint images used for training, in comparison to the 9/7 wavelet, and averaged 16.01% (0.76 dB) MSE reduction for a test population of 80 fingerprint images. This result improved upon the best previously reported result [8], which produced new wavelet transforms by combining a GA with the lifting scheme [22], and thus established a new state-of-the-art for fingerprint compression and reconstruction under conditions subject to quantization error.

2. EVOLVED TRANSFORMS FOR SATELLITE IMAGE COMPRESSION AND RECONSTRUCTION

Another important application of wavelets that is subject to quantization error is the compression and reconstruction of satellite images subject to bandwidth restrictions [19]. State-of-the-art solutions utilizing DWTs introduce unacceptably high MSE, degrading the ability of military planners to observe and react to tactics of grounds-based enemies. Thus the key question addressed by the research described in this paper is:

> Can our GA evolve matched forward and inverse transform pairs that improve upon the performance of wavelets for the difficult task of compressing and reconstructing satellite images subject to quantization error?

Prior research involving satellite images ([19], [20]) focused upon evolving the reconstruction (inverse) transforms only; the forward transform continued to utilize standard wavelet coefficients, without modification. Would the simultaneous evolution of coefficients for both the compression (forward) and reconstruction transform result in further decreases in MSE during this research?

Each of the training runs described in this paper were characterized by the following:

(a) The initial population was seeded with randomly mutated copies of the D4 wavelet. Each individual thus consisted of 16 real-valued coefficients (four for each set).

(b) Training runs utilized satellite photographs of military interest, such the image shown in Fig. 1. MSE of reconstructed images was computed by calculating the difference between gray-scale intensity levels at each pixel of the original and reconstructed image.

3. TEST RESULTS

First, the satellite image from Fig. 1 was compressed, quantized using a 4.4:1 quantization step (keeping the largest 23% of the coefficients), dequantized, and reconstructed using the D4 wavelet producing the distorted image shown in Fig. 2. Next, our best GA-evolved transform was applied in an identical manner to the original image, producing the image shown in Fig. 3. The MSE present in Fig. 3 is 17.9% (0.86 dB) less than that of Fig. 2. Testing these transforms on other satellite images reveals that the evolved transform reduces MSE by an average of 11.0% (0.51 dB).

MSE reductions of less than 30% are difficult to discern with the naked eye. The difference in the quality of these reconstructed images is best revealed by constructing difference images. For this research, difference images created by computing the MSE between the original image and the compressed, quantized, dequantized, and reconstructed images produced by the D4 wavelet and the best evolved transform, and then multiplying this difference by 3.5. These difference images are shown in Fig. 4 and Fig. 5. Clearly, most of the information loss due to quantization occurs at edges, where the energy content of the images is highest. The brighter lines in Fig. 4 are indicative of the greater information loss introduced by the D4 wavelet.

Our GA evolved the following sets of coefficients:

h1 (lowD) = {-0.2272, 0.3825, 1.0423, 0.0777}

g1 (highD) = {-0.3893, 0.8224, -0.3917, -0.0507}

h2 (lowR) = {0.3865, 0.7834, 0.4031, -0.0010}

g2 (highR) = {-0.3524, -0.3128, 0.9859, -0.0654}

These coefficients correspond to the following percentages of the original wavelet coefficients:

h1: {175.58%, 170.68%, 124.60%, 16.9%}

g1: {80.60%, 98.31%, 174.79%, 39.18%}

h2: {80.02%, 93.65%, 179.88%, 0.77%}

g2: {272.33%, 139.58%, 117.86%, 13.54%}

It is interesting to note that the fourth coefficient in each vector has virtually disappeared, while other coefficients have substantially increased in magnitude.

Transforms evolved using satellite images like Fig. 1 were also tested against non-satellite images, including the photographs and fingerprint images used in previous experiments (as described above). For the test set consisting of twelve 256x256-pixel and six 512x512-pixel photographs, our evolved transforms reduced MSE by an average of 8.6% in comparison to the D4 wavelet. For another test set consisting of 80 fingerprint images, our evolved transforms reduced MSE by an average of 9.6% Thus, at a single level of resolution, our GA evolved transforms that effectively generalize when tested against classes of images that are different from the training set. This result is somewhat surprising, and seems to contradict our recent experience with evolved transforms, which in general shows that transforms evolved against one class of images do poorly when subsequently tested against images from different classes. Nevertheless, we expect the performance of transforms trained on satellite images to degrade as additional multi-resolution levels are introduced.

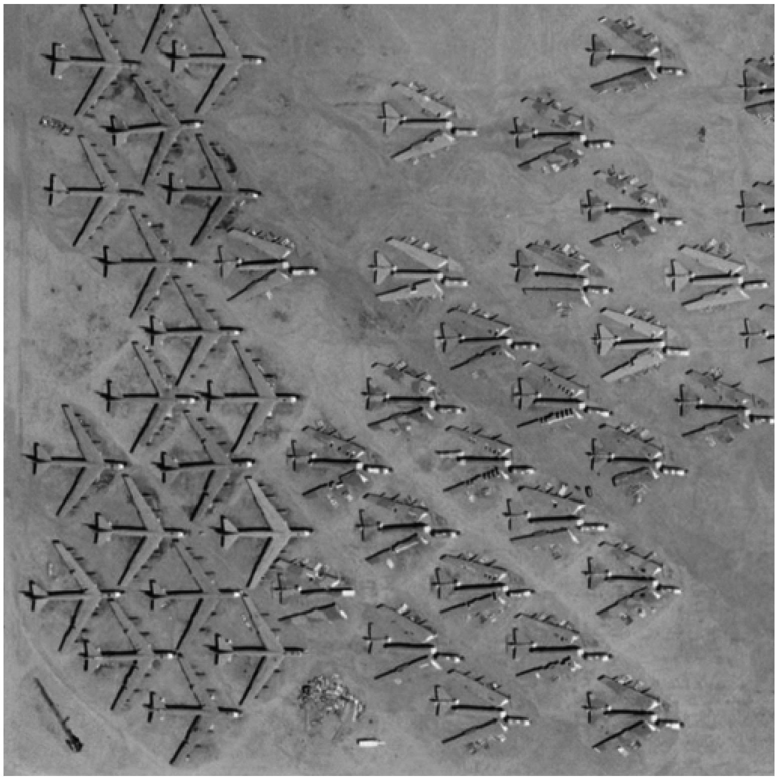

Fig. 1. A Typical Satellite Image Used for Training.

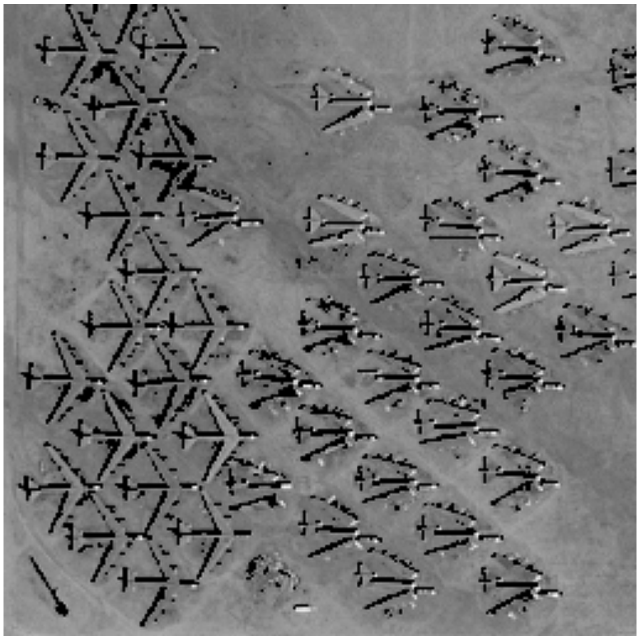

Fig. 2. Wavelet Compressed and Reconstructed Image.

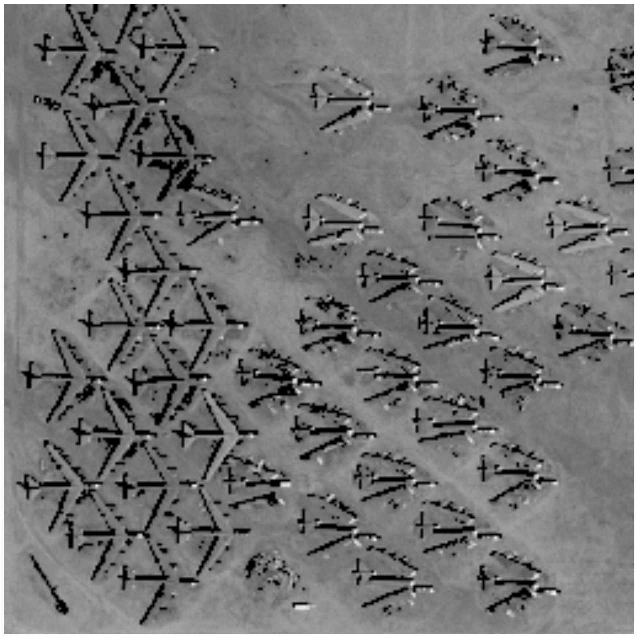

Fig. 3. The Image Compressed and Reconstructed via an Evolved Transform.

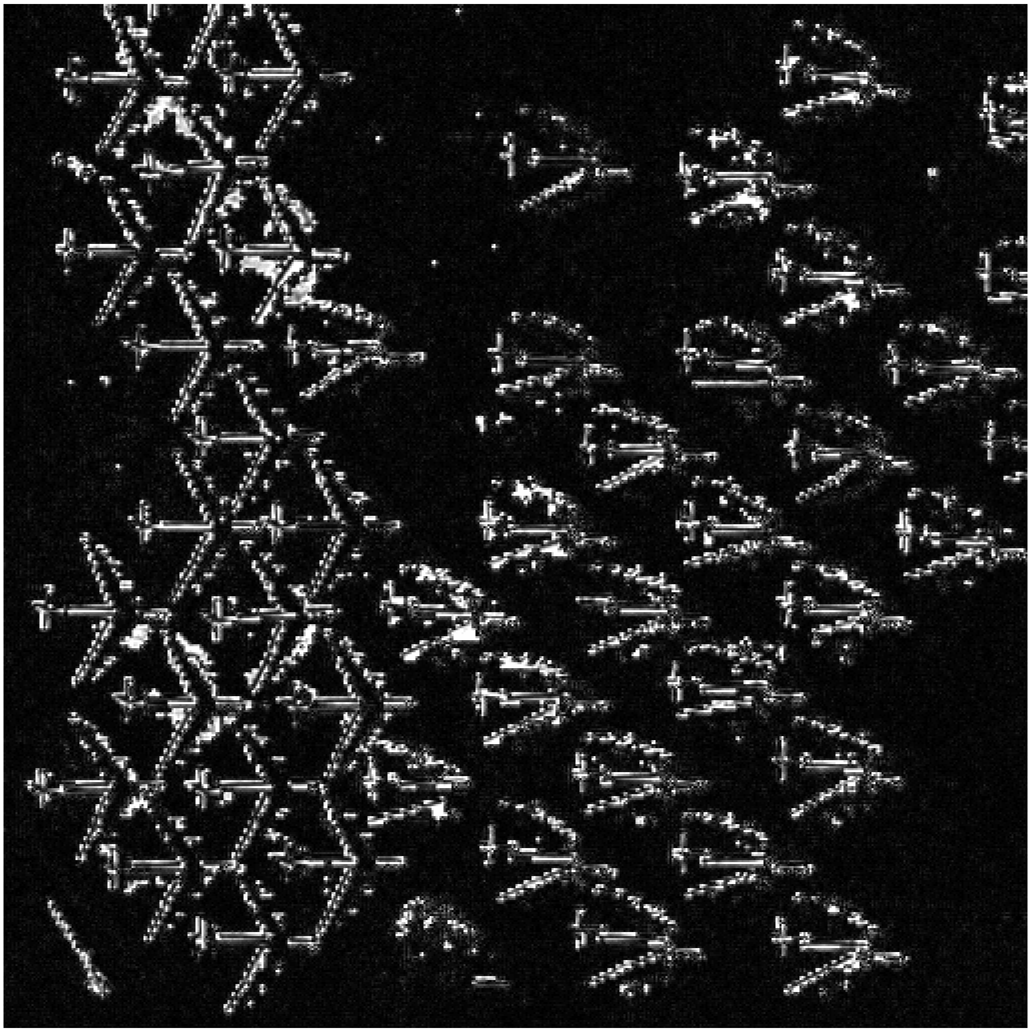

Fig. 4. Difference Image Highlighting Differences Between the Wavelet-compressed Image and the Original Satellite Image.

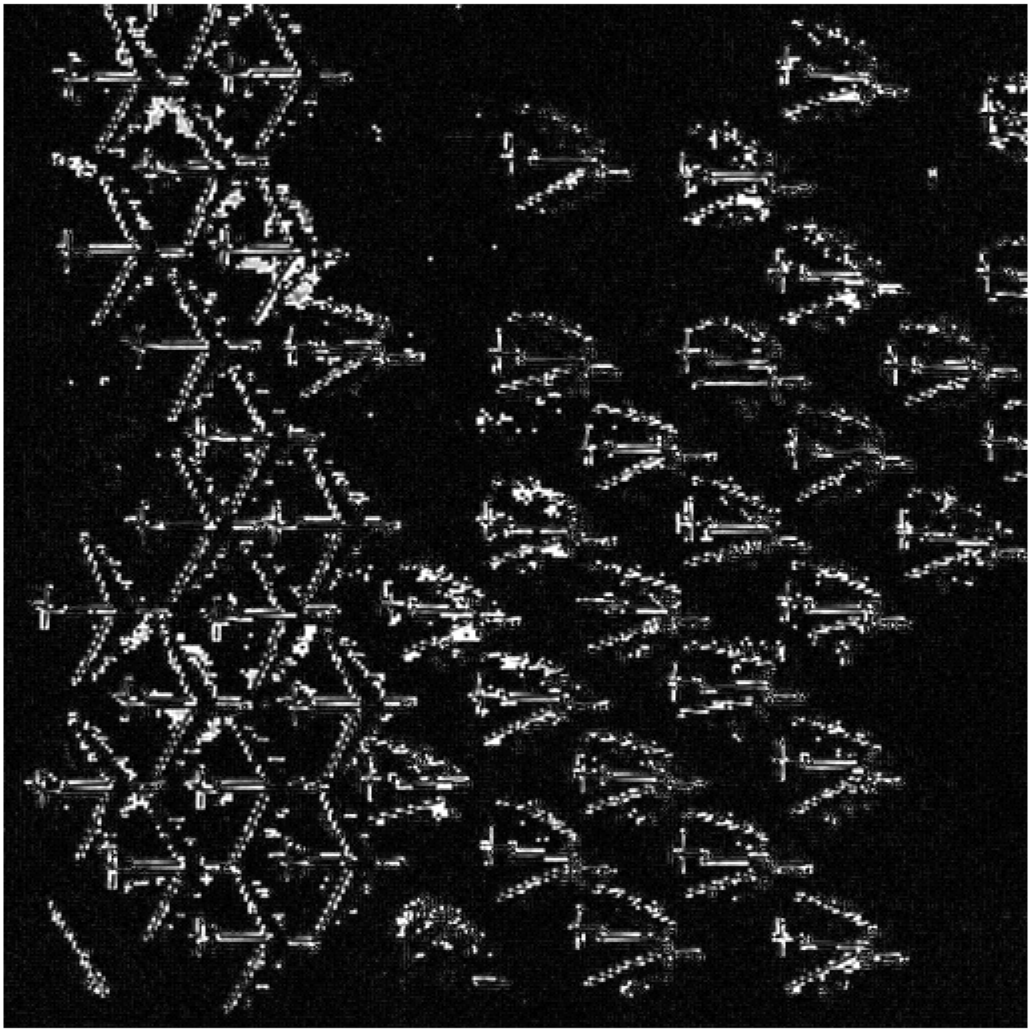

Fig. 5. The Difference Image for the Evolved Transform, Illustrating Significantly Reduced MSE.

4. CONCLUSIONS AND FUTURE DIRECTIONS

This research extends previous work by demonstrating the successful evolution of transforms that outperform wavelets for satellite image compression and reconstruction under conditions subject to quantization error. Simultaneous evolution of both the forward and inverse transform coefficients produced additional MSE reduction not observed when evolving the reconstruction transform only.

The results describe in this paper encourage the application of evolutionary computing-based numerical optimization techniques to difficult real-world problems such as satellite image compression and reconstruction under quantization. Additional tasks to be accomplished by subsequent research include the following:

(a) Expand the current approach by evolving MRA transforms for satellite image compression and reconstruction. The MRA problem is much more complex, since the number of simultaneously evolving parameters increases proportionately to the number of multi-resolution levels used.

(b) Utilize more sophisticated wavelets, such as the 9/7 CDF wavelet [4], as the starting point for evolving both single-level and MRA transforms for satellite image compression and reconstruction.

(c) Investigate the evolution of forward transforms that increase the amount of compression without sacrificing the reconstruction capabilities of the inverse wavelet transform.

(d) Simultaneously evolve both the number of coefficients in each *h* and *g* vector, and the values of those coefficients. This step may potentially evolve powerful new transforms having previously unimagined sizes and shapes, and pave the way for a revolution in signal and image compression and reconstruction.

(e) Establish a theory explaining the success of evolved transforms.

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