

# Evolving Next Generation Signal Compression and Reconstruction Transforms via Genetic Algorithms

Frank Moore

Dept. of Mathematical Sciences  
CAS 154, 3211 Providence Dr.  
University of Alaska Anchorage  
Anchorage, AK 99508  
1-907-786-4819

[affwm@uaa.alaska.edu](mailto:affwm@uaa.alaska.edu)

Pat Marshall

AFRL/IFTA Bldg. 620  
2241 Avionics Circle  
Room 3CY104  
WPAFB, OH 45433-7334  
1-937-255-6548 x 3586

[pat.marshall@wpafb.af.mil](mailto:pat.marshall@wpafb.af.mil)

## ABSTRACT

Ongoing research has established a new methodology for using genetic algorithms [2] to evolve forward and inverse transforms that significantly reduce quantization error in reconstructed signals and images. The approach promises to revolutionize the signal and image processing field, producing both higher quality images and higher compression ratios than is currently possible with wavelet-based techniques.

## Categories and Subject Descriptors

J.2 [Physical Sciences and Engineering]: Engineering.

## General Terms

Algorithms, Performance, Experimentation.

## Keywords

Genetic algorithms, wavelets, optimization, evolved transforms.

## I. INTRODUCTION

Over the past decade, wavelets [1] have become the standard methodology for signal compression and reconstruction. A discrete wavelet transform (DWT) convolves a given signal against particular wavelet instances at various time scales and positions, producing a highly compressed representation of the original signal. An inverse DWT ( $DWT^{-1}$ ) decompresses the transformed signal to reconstruct an approximation of the original signal. Under lossless conditions, a  $DWT^{-1}$  perfectly describes the original signal  $x(t)$  using a countable set of coefficients. Wavelets, however, are capable of much greater signal compression than can be achieved by lossless methods, and thus provide a powerful technique for efficiently representing large amounts of data.

For many DSP applications, quantization of digitized data is an absolute necessity. *Quantization error* occurs when the number of bits used is insufficient to represent the signal's full dynamic range. In a typical wavelet application, an uncorrupted

signal  $v(k)$  is transformed by a DWT, downsampled ( $\downarrow 2$ ), and quantized (Q) prior to transmission. On the receiving end, the incoming signal is dequantized ( $Q^{-1}$ ), upsampled ( $\uparrow 2$ ), and inverse transformed by a  $DWT^{-1}$ , producing a corrupted signal  $v'(k)$ . Typically, the  $DWT^{-1}$  substitutes zeroes for digit values eliminated from the originally transformed signal. Loss of information due to quantization error may cause the resulting decompressed signal  $g$  to differ measurably from the original signal  $f$ . For many image-processing applications, mean squared error (MSE) is the figure-of-merit of choice for quantifying the quality of reconstructed signals. In this research, we use MSE to quantify quantization noise resulting from a discrete mapping of an arbitrary array of image data points onto a smaller range.

## 2. RESULTS

DWTs and  $DWT^{-1}$ s may be represented by their constituent coefficient sets, typically denoted  $g1$  and  $h1$  for the DWT, and  $g2$  and  $h2$  for the  $DWT^{-1}$ . Here,  $g$  is the wavelet filter, and  $h$  is the scaling filter. The key question addressed by this research is:

*Is it possible to use a genetic algorithm (GA) to evolve optimized sets of  $g$  and  $h$  coefficients describing forward transforms, inverse transforms, or matched transform pairs that significantly reduce the MSE of compressed, downsampled, quantized, dequantized, upsampled, and reconstructed signals, in comparison to the performance of standard wavelet transforms under identical conditions?*

An ongoing program of research conducted at Wright-Patterson Air Force Base and the University of Alaska Anchorage ([3], [4]) has provided considerable evidence suggesting that the search space of non-traditional transforms is indeed rich with such solutions. For selected classes of periodic, one-dimensional signals subjected to quantization, our GAs evolved  $DWT^{-1}$  coefficients that reduced the MSE by more than 90%.

For two-dimensional images, results have been equally dramatic. For example, the "fruits.bmp" image was compressed using a standard Daubechies-4 wavelet transform, subjected to a quantization step of 64, and reconstructed using the standard Daubechies-4 wavelet inverse transform, resulting in the image shown in Fig. 1. Next, a GA used a population of size  $M = 200$  running for  $G = 1700$  generations to evolve the coefficients describing a matched forward and inverse transform pair; this evolved transform was used to compress and subsequently reconstruct "fruits.bmp" under conditions subject to a quantization step of 64, resulting in the image shown in Fig. 2.

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**Fig. 3. “Fruits” reconstructed via the Daubechies-4 wavelet inverse transform (Quantization = 64).**



**Fig. 4. “Fruits” reconstructed by a evolved transform (Quantization = 64).**

The total MSE of Fig. 2 relative to the original image was *89% less* than the MSE produced by the Daubechies-4 wavelet. This significant reduction in MSE is easily detected by the human eye.

Evolving coefficients for forward and inverse transform pairs is computationally intensive. A recent investigation into

the use of sub-images to train the GAs produced two interesting results:

1. If the selected sub-image(s) were sufficiently representative of the original image, then a GA trained against those sub-images achieved MSE reduction performance approximately equal to that of a GA trained on the entire

image. For the same selected M and G values, the run-time efficiency of our GA increased by two orders of magnitude.

2. The GA could also be trained on highly distinctive sub-images containing "needle-in-a-haystack" information. In this case, transforms identified by the GA were highly effective at reconstructing portions of the original image that contained the sub-image, but were less effective at reconstructing the rest of the image. This result suggests that GAs can be used to highlight and ultimately extract sub-images from larger images, thereby providing a new technique for locating specific targets of concern.

### 3. CONCLUSIONS

To date, only still images have been utilized in this effort. However, as this technology matures, we intend to convert the software to execute on digital processing hardware for streaming video applications. The overall goal of this effort is to establish genetic algorithms as the predominant methodology for identifying coefficient sets describing transforms that automatically compensate for such factors as quantization error, producing a consistently high-quality reconstruction of the original signal. The research accomplished to date comprises a first big step towards that goal.

This technology can provide significant benefits to the military. For example, higher data compression translates into decreased bandwidth requirements for digital signal processing of all data, not just images. Consequently, more battlefield data can be transferred, giving commanders a much needed advantage over enemy combatants. In addition, higher quality

images transform into better recognition of targets for pilots, analysts, commanders, etc.

This technology may also greatly simplify the task of semi-autonomous automatic target recognizers (ATRs). By adjusting various transforms for certain targets of concern, the data will be formatted in such a way that the ATR's detection and recognition algorithms will operate with much higher accuracy and fewer false alarms.

### 4. ACKNOWLEDGMENTS

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