Performance of Wavelet Based Compression in TI TMS320C6201 DSP

V. Kustov, P. Srinivasan, S. Mitra, D Mehrl, Department of Electrical Engineering, Texas Tech University, Lubbock, TX, 79409, MS-3102

1. ABSTRACT

Image/signal compression with high fidelity reconstruction at very low bit rates (compression ratios around 100:1) is a necessity in many applications in multimedia, digital libraries, and telemedicine. The advantage of using transform coding is that the signals are expressed in terms of orthogonal basis functions and thus have decorrelated components. Wavelet based compression algorithms are used as wavelets have localization in both time and frequency domains. One wavelet based compression algorithm has been implemented in the TI TMS320C6201 fixed point DSP with a 50% increase in speed at the Computer Vision and Image Analysis Laboratory (CVIAL) at Texas Tech University. Wavelet compression algorithms can be improved by designing image specific filters for an application. The algorithm described here creates wavelet filters adaptively at a time when the image becomes available to it. The best wavelet decomposition for a given image is found, creating the "most convenient space" for the follow up algorithm (e.g. EZW [3,9] or AFLC-VQ [7,8] developed at CVIAL). This results in a better overall algorithm's performance. One of the optimization criteria used during the algorithm's trial was a maximization of the scaling function energy (the low-resolution domain). Daub 4[4] filters were used for comparison. The algorithm found a 4-coefficient wavelet filter that concentrated 3 times more energy in the low-resolution domain than the Daub 4 filter. This resulted in a lower distortion rate when the EZW algorithm was used to compress the image.

2. INTRODUCTION

In image signal processing it is very useful to map the original image onto some other space prior to applying an image compression algorithm. Some of the orthogonal transforms used for this purpose are the Discrete Cosine Transform (DCT), Discrete Fourier Transform (DFT), and the Karunen Loewe transform (KLT). The DCT and DFT localize energy in the frequency domain, but not in the time domain. For example, JPEG [5] divides the original image into blocks of pixels and then the Discrete Cosine Transform (DCT) is performed on each of the blocks. Different spatial information is contained across different blocks, while the frequency content of the image shows up within each individual block. Such an algorithm creates blocking artifacts at higher compression ratios due to the original division of the image into the blocks (specifically, the blocking artifact is caused by short basis functions, e.g. truncated DCT functions). The wavelet transform gives a time frequency localization of the signal, and both the spatial and frequency contents of the image are preserved without any prior division of the image into blocks. This, in general, results in a better performance of wavelet based compression algorithms compared to non-wavelet ones, even if the wavelet basis functions are of the same length as truncated wave functions like DCT in JPEG, since well designed compactly supported wavelet and scaling functions do not have any discontinuities at the boundaries. Fourier analysis is suited for stationary signals, but wavelets are applicable to non-stationary signals as well. There are many types of wavelet filters used for various applications. The properties of the system are mathematically characterized, and the filters are derived. The use of a particular filter depends on the application, and the "best" filter that is optimal for most applications does not exist. For example the family of Daubechies' maxflat filters are the "best" in decomposing polynomials with a maximum power of p, using the minimum possible number of filter taps. Other types of wavelets are good at handling discontinuities. The question of which wavelet filter is the "best" for a particular signal being processed by a particular algorithm remains open.

3. METHODOLOGY

The solution presented here is not a global one, instead, the algorithm has been designed to create wavelet filters adaptively for an image belonging to a class of signals/images fitting a particular model. Given particular optimization criteria our algorithm finds the “best” wavelet decomposition for a given image. This algorithm creates the ”most convenient space” for the follow-up algorithm (whether it is wavelet based JPEG, MPEG, EZW or AFLC-VQ) to work with, resulting in a better overall algorithmic performance. One of the criteria we used during the algorithm’s trial was a maximization of the energy in the scaling function (low resolution domain). The Daub 4 wavelet filters were used for comparison.

Equations 1 through 10 are well known equations in the wavelet theory [2 ,4] and are introduced here to help understand our novel wavelet design method.

Any signal in an L^2 space can be represented using the scaling basis as

$$x(t) = \sum c(0,n)\phi(t-n). \quad (1)$$

$$c(0,n) = \langle x(t),\phi(t-n)\rangle. \quad (2)$$

The signal representation using the discrete wavelet transform is

$$X(t) = \sum_m \sum_n d(m,n)\psi_{mn}(t), \quad (3)$$

where $\phi(t)$ and $\psi(t)$ are the scaling and wavelet functions respectively, and c and d are the scaling and wavelet coefficients respectively.

Here the wavelet coefficients are the inner product

$$d(m,n) = \langle \psi_{mn}(t),x(t)\rangle. \quad (4)$$

The multiresolution signal decomposition of the signal is based on a sequence of closed subspaces, contained as shown below [2]:

$$\nu_0 \subset \nu_1 \subset \nu_2 \subset \nu_3 \subset \nu_4 \ldots \subset L^2,$$

where ν_0 is the space spun by $\phi(t-n)$.

For orthogonal wavelets (with m = 1), the scaling and wavelet functions can be written as

$$\phi(t) = \sqrt{2} \sum_n h(n)\phi(2t-n), \quad (5)$$

and the wavelet function $\psi(t) = \sqrt{2}\sum_n g(n)\phi(2t-n)$.

Due to orthogonality we have $\langle\phi(t), \phi(t-n)\rangle = \delta(n)$.

This can be written as

$$\int \phi(t)\, \phi(t-k)\, dt = \delta(k). \quad (6)$$

From Equation 5 we have:

$$\sum_n h(n)= \sqrt{2} \quad (7)$$

and

$$\langle h(n), h(n - 2k)\rangle = \delta(k). \quad (8)$$

Since $\phi(t)$ and its integer translates are orthogonal:

$$\Sigma\, h(n)\, h(n - 2k) = \delta(k). \quad (9)$$

The coefficients c(0,n) and d(m,n) can be found either by taking the inner product of Equations 2 and 4, or by convolving signal x(t) with the low and high pass filters h[n] and g[n]. The latter method is less computationally expensive.
It can be shown that the high pass filter coefficients g[n] and the low pass filter coefficients h[n] for the orthogonal wavelet transform are related as:

$$g(n) = (-1)^n h(N-n+1). \qquad (10)$$

Thus, in the orthogonal wavelet design we can look for only h[n] and the rest of the functions (g[n], $\phi(t)$ and $\psi(t)$) can be expressed through h[n].
The filter coefficient design involves solution of a system of bilinear equations. To find N filter taps h[n] we have to solve the system of N/2+1 equations (Equations 7 and 9) which leaves N/2-1 degrees of freedom to be used for filter design.

Our algorithm uses these N/2-1 degrees of freedom to find the optimum filter taps for a given application, by creating the lagrangian function F(**h,l**). Here **h** are the N variables corresponding to our filter taps and **l** are the Lagrangian multipliers.

$$F(\mathbf{h},\mathbf{l}) = f(\mathbf{h}) + \sum_{i=1}^{m} l_i w(\mathbf{h}) \qquad (11)$$

In Equation (11) w(**h**) is the constraint function (e.g. N/2+1 equations that guarantee h[n] to be orthogonal wavelet filter taps), f(**h**) is an optimization function. This is an image dependent function created according to the optimization criteria. In feature enhancement, for example, this function is the reciprocal of the energy of the convolution result of h[n] with the image feature we are trying to enhance. In energy packing applications f(**h**) is the mean square error resulting from the approximation of the eigenvectors of the covariance matrix of the image by the wavelet filters h[n].

By minimizing F(**h**,**l**) we find the optimum wavelet filters h[n] for a given image-optimization criteria combination. This is done by solving the system of equations (12) [6]:

$$\frac{\partial F}{\partial h_n} = 0 \qquad n=1..N$$

$$(12)$$

$$\frac{\partial F}{\partial li} = 0 \qquad i=1..N/2+1$$

4. RESULTS

After applying the algorithm a 4-coefficient wavelet filter that put three times more energy in the low resolution domain than the Daub 4 filter was found. This, in turn, resulted in a lower distortion rate when the EZW algorithm (scalar quantization) was used to compress the image, since the wavelet decomposition coefficients (high resolution domain), that were truncated, were smaller (contained less information). Figure 1 shows same scale pictures of the scaling function (low resolution approximation) of the 1 level decompositions of the standard Lena image using Daub4 filters (1a) and the adaptive 4 coefficient filter (1b). As can be seen the Daub4 approximation contains fewer details. The reconstruction of the original image using only the low resolution band in the Duab4 decomposition results in a larger loss of the details compared to our same length filter (the details that do not show in the low resolution band are obviously lost if only this band is transmitted). This type of the wavelet decomposition is very valuable for progressive transmission where a small area containing most of the information (the low resolution band) is transmitted first, allowing for a fast preview of the image before the rest of the details will arrive.

Figures 2,3,and 4 show same scale pictures of the diagonal, horizontal, and vertical decompositions of the standard Lena image using Daub4 filters and our 4-coefficient filter. As it can be seen Daub4 decomposition contains more texture than ours. Consequently when these coefficient are approximated using the same method, more information on texture will be lost in Daub 4 case compared to the adaptive wavelets. Although looking at these four figures one might get the impression that the Daubechies family of maxflat filters is inferior to the adaptive wavelets, this conclusion is wrong. Our filters were created adaptively for a particular (Lena) image, while the Daubechies filters are designed for a general very broad class of signals. In most other cases the Daubechies filters will outperform these, if they were to be used non-adaptively (that is created for one particular image/class of images and then used on others).

Table I shows comparative performances of three different lossy compression algorithms namely JPEG, EZW, and AFLC-VQ in terms of MSE, and PSNR for a range of compression ratios up to around 100:1. AFLC-VQ is a wavelet based compression algorithm using vector quantization but without subsequent entropy coding. AFLC-VQ outperforms EZW without entropy coding at all compression ratios.

Table 1. Comparison among AFLC-VQ, JPEG and EZW(for a Cervical Spine Image) [8]

Compression scheme	CR	MSE	PSNR
AFLC-VQ (without entropy coding)	32.51	17.48	35.71
	78.77	77.10	29.26
	113.78	92.06	28.49
JPEG (with entropy coding)	32	15.56	36.21
	78	57.51	30.53
	102	94.51	28.38
EZW (without arithmetic coding)	32	37.96	32.34
	78	134.25	26.85
	113	204.04	25.03
EZW (with arithmetic coding)	32	13.07	36.97
	78	49.11	31.21
	113	58.76	30.44

Figure 1a

Figure 1b

Scaling function coefficients (low resolution) of the decompositions of the standard Lena image using Daub4 (1a) and our filter (1b).

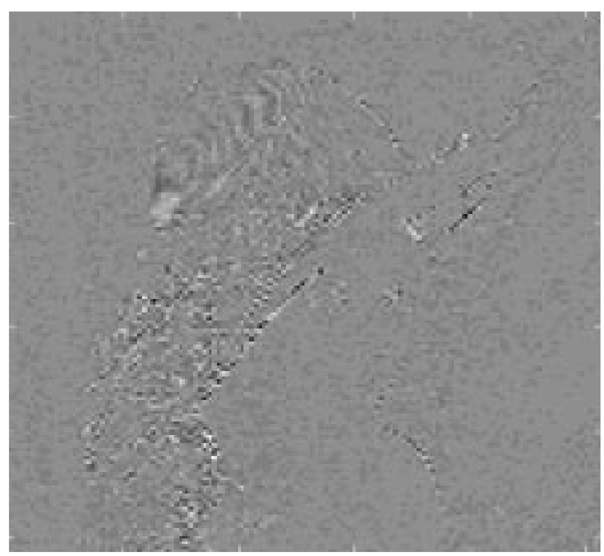

Figure 2a

Figure 2b

Wavelet coefficients of the diagonal components of the decompositions of the standard Lena image using Daub4 (2a) and our filter (2b).

Figure 3a

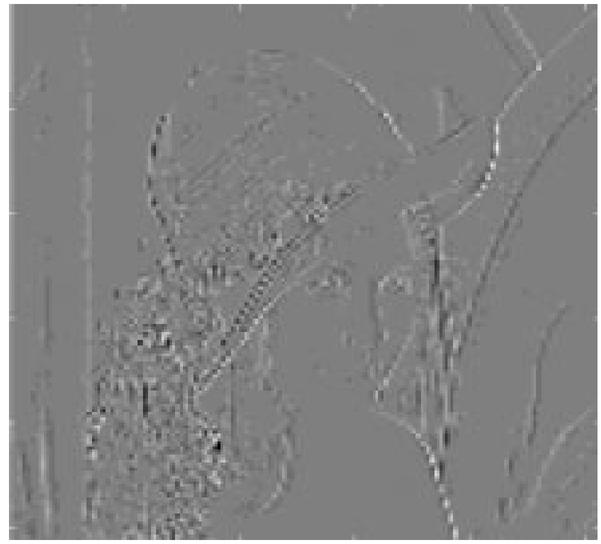

Figure 3b

Wavelet coefficients of the vertical components of the decompositions of the standard Lena image using Daub4 (3a) and our filter (3b).

Figure 4 a

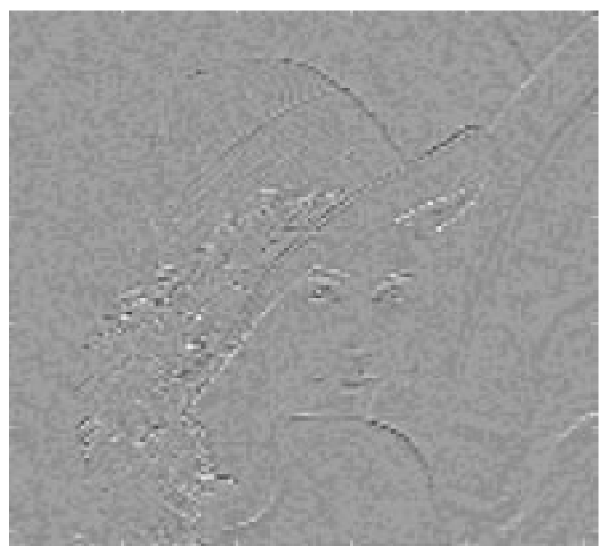

Figure 4b

Wavelet coefficients of the horizontal components of the decompositions of standard Lena image using Daub4 (4a) and our filter (4b).

4. DISCUSSION

The wavelet decomposition research has been conducted at the CVIAL in two basic areas. The first area is feature enhancement in the wavelet domain. These wavelet filters when applied to images create large wavelet coefficients corresponding to a particular pattern, while other patterns are "suppressed". Pattern recognition and noise removal applications will greatly enhance their performance when applied to the above described decomposition.

The second area has a goal of maximizing (packing) the energy in the scaling function coefficients while minimizing the energy contained in the wavelet function domain. The wavelet basis functions approximate the K-L transform either for a given image (the adaptive design), or for a given model/class of images (the image independent design). By achieving the biggest decorrelation efficiency this basis functions (in the two dimensional case also called basis pictures) pack all the energy in a small area in the transform domain. The rest of the transform domain coefficients can be either discarded or coarsely approximated. This method is powerful when used for designing long wavelet filters. Since in image decomposition the image is represented by a superposition of the basis pictures (two dimensional basis functions), it is impossible to represent a high entropy image by a few short basis functions, since the latter has low entropy as a result of the small size. However, if longer basis functions are used, the image can be represented by fewer basis functions; the information in the original image will be contained in a few transform coefficients. When scalar quantization is applied, the ringing artifacts that are associated with the use of long basis function are not significant in this case because of the low information content of the wavelet domain. The problem that arises is that these adaptively designed filter coefficients, corresponding to the longer scaling/wavelet functions should be stored with the encoded image, thus increasing the size of the encoded file. This is the main reason while the K-L transform has not been widely used. It has the best energy packing ability; however it also requires storing a basis matrix that is in general equal to the size of the image itself. The method adopted in this paper seeks to find wavelet basis functions/filters of the size that do not increase the size of the encoded file significantly.

Although these new methods for image compression show superior results compared to the ones most commonly used at present, they require longer coding/decoding times. For example adding adaptive wavelet design to the existing compression algorithm enhances its performance at the expense of a longer total execution time of the application.

Texas Instruments' 'C6000 platform capability to perform 1200-2400 MIPS (300-600 MMACS for 16-bit fixed point data) and 1 GFLOPS (334 MMACS for 32-bit floating point data) makes it possible to execute our image processing algorithms in real time. In our research Texas Instruments' TMS320C6201-160 fixed point DSP (1200 MIPS) was used, primarily because of its availability at the time (fall of 1998). Several software modules were developed for executing image processing applications developed for PC's in the DSP. These modules provide tools for PC program developers to run their codes on TI DSP's without actually developing separate applications for DSP's. These new modules were tested using image processing applications developed at the CVIAL as well as applications developed elsewhere. Some other issues were addressed as well. One of the major problems in using DSP's for large size images is memory management. Most images are characterized by large amounts of data that need to be processed in real time. A typical TV resolution gray scale image requires about 256 Kbytes of memory space, while 3 color plane high resolution medical images range in sizes from 6 to 24 Mbytes, which necessitates placing image data in the external memory. Advanced algorithms for data compression developed both at the CVIAL and at other universities are quite complex requiring large size executable files (.out files for TI DSP'). In most cases the executable code within the .out file could not fit into a 64 Kbytes internal program memory space, which necessitated placing less frequently used functions into the external memory as well. Nonetheless, the use of pipelining involving the four DMA channels allowed us to implement on-chip data processing and large block data transfers between the CPU and the external memory in parallel which resulted in a very good overall system performance; the applications running faster than on PC's with the same CPU frequency Pentium processors.

6. CONCLUSION

Most of the wavelet based algorithms developed at the CVIAL have little date dependency. The wavelet transform, for example, can be viewed as the matrix multiplication operation in which different rows-columns combinations can be processed in parallel. This fact and the fact that most images are represented by large data sets make our applications suitable for taking full advantage of the parallel execution and pipelining embedded in VelociTI™ Advanced Very Long Instruction Word (VLIW) 'C6200 CPU Core consisting of eight independent functional units.

The wavelet based advanced data compression algorithms that have been developed at CVIAL as well as those that are still in the development process allow for a superior data reconstruction compared to other common data compression algorithms, but this superior performance comes at the expense of the increased execution time. The TI 'C6000 platform offsets the increased execution time making it possible to implement coding/decoding in real time.

Due to a growing demand for real time advanced image processing applications further research will be done involving new TI DSP's on the market as well as the ones that should be introduced on the market soon.

7. REFERENCES

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