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Genetic Algorithm to Predict Wavelet Coefficients Sign

Ricardo García and Otoniel López and Pablo Piñol and Miguel Martínez and Manuel P. Malumbres [1] and Antonio Martí [2]

Abstract

Most wavelet based encoders, do not compress the wavelet coefficients sign because it has been assumed to be inefficient for a long time. However, in the last years several image encoders like JPEG 2000 include sign coding capabilities. In this paper, we present a new sign coding approximation which uses a genetic algorithm to efficiently predict the sign of wavelet coefficients. Preliminary results show that, by including sign coding capabilities to a non-embedded encoder, the compression gain is up to 17.35%, being the Rate-Distortion (R/D) performance improvement up to 0.25 dB.

Keywords

sign coding, wavelets, image coding, genetic algorithms.

I. Introduction

Wavelet transforms have proved to be very powerful tools for image compression. Many state-of-the-art image codecs, including the JPEG2000 standard [1], employ a wavelet transform in their algorithms. One advantage is the provision of both frequency and spatial localization of image energy. The image energy is compacted into a small fraction of the transform coefficients and compression can be achieved by coding these coefficients. The energy of a wavelet transform coefficient is restricted to non-negative real numbers, but the coefficients themselves are not, and they are defined by both a magnitude and a sign. Shapiro stated in [2] that a transform coefficient is equally likely to be positive or negative and thus one bit should be used to encode the sign. In recent years, several authors have begun to use context modeling for sign coding [3][4][5].

For example, in [5], A. Deever and S. Hemami examines sign coding in detail in the context of an embedded wavelet image coder. The paper shows that a Peak Signal to Noise Ratio (PSNR) improvement up to 0.7 dB is possible when sign entropy coding and a new extrapolation technique based on the mutual information that biorthogonal basis vectors provide to improve the estimation of insignificant coefficients are combined. However, the contribution of sign coding by itself to the PSNR improvement is only up to 0.4 dB.

In [4] the Embedded Block Coding with Optimized Truncation of the embedded bit-streams (EBCOT), core coding tool of the JPEG 2000 standard, encodes the sign of wavelet coefficients using context information from the sign of horizontal and vertical neighbor coefficients (North, South, East, West directions). Five context are used to model the sign coding stage.

In [3], X. Wu presents a high order context modeling encoder. In this coder, the sign and the textures share the same context modeling. This model is based on a different neighborhood for the HL, LH and HH wavelet subbands. For the HL subband, the information of North, North-West, North-East, North-North and South sign is used to predict the current coefficient sign. The neighbors sign information used for the LH subband are North, North-West, North-East, West-West and East. Finally, for the HH subband, an inter-band prediction is used besides the intra-band prediction used by the HL and LH subbands.

Genetic algorithms were first introduced by Holland in [6] and they are nowadays well known techniques for finding nearly optimal solutions of very large problems and also, they have been used in image processing [7][8].

In a genetic algorithm, the evolution usually starts from a population of randomly generated individuals and happens in generations. In each generation, the fitness of every individual in the population is evaluated by means of a cost function that determines the optimal degree we are looking for (i.e compression rate). Multiple individuals are stochastically selected from the current population (based on their fitness), and modified (recombined and possibly randomly mutated) to form a new population. The new population is then used in the next iteration of the algorithm. Commonly, the algorithm terminates when either a maximum number of generations has been produced, or a satisfactory fitness level has been reached for the population.

In this paper, we will design a genetic algorithm to efficiently predict the wavelet coefficient signs. If the sign prediction is really good, a binary entropy encoder will be able to get significant compression rates. So, our goal is to define a genetic algorithm that finds out the paremeters of our sign predictor that achieve the best prediction performance. As studied in the literature, the parameters to be found by our genetic algorithm will be a) the neighbor set that defines the prediction context, and b) the sign values (sign patterns) of wavelet coefficient neighbor set with the correspondent sign prediction for current wavelet coefficient.

[1]Universidad Miguel Hernández, e-mail: `r.garcia, otoniel, pablop, mmrach, mels@umh.es`
[2]Universidad Politécnica de Valencia, e-mail: `amarti@disca.upv.es`

After running the genetic algorithm and configured the sign predictor, we will evaluate the impact of the sign coding module in the overall performance of an image wavelet encoder. In particular, we will use the LTW wavelet encoder [9] to determine the bit-rate savings for several test images.

The remainder of the paper is organized as follows: Section II describes our sign coding approximation and also the genetic algorithm structure. In Section III, we show the results of the global encoder system (with sign coding stage) and compare it with SPIHT and JPEG 2000. Finally, in Section IV some conclusions are drawn.

II. Wavelet sign prediction

Most wavelet image codecs do not consider the use of sign coding tools since the wavelet coefficients located at the high frequency subbands form a zero-mean process, and therefore equally likely positive as negative.

Schwartz, Zandi and Boliek were the first authors to consider sign coding, using one neighboring pixel in their context modeling algorithm [10]. The main idea behind this approach is to find correlations along and across edges.

The HL subbands of a multi-scale 2-D wavelet decomposition are formed from low-pass vertical filtering and high-pass horizontal filtering. The high-pass filtering detects vertical edges, thus the HL subbands contain mainly vertical edge information. Oppositely defined are the LH subbands that contain primarily horizontal edge information.

As Deever explained in [5], given a vertical edge in an HL subband, it is reasonable to expect that neighboring coefficients along the edge have the same sign as the coefficient being coded. This is because vertical correlation often remains very high along vertical edges in images. When a low-pass filter is applied along the image columns, it results in a series of similar rows, as elements in a row tend to be very similar to elements directly above or below due to the high vertical correlation. Subsequent high-pass filtering along similar rows is expected to yield vertically correlated transform coefficients.

It is also important to consider correlation across edges, being the nature of the correlation directly affected by the structure of the high pass filter. For Daubechies' 9/7 filters, wavelet coefficient signs are strongly negatively correlated across edges because this filter is very similar to a second derivative of a Gaussian, so, it is expected that wavelet coefficients will change sign as the edge is crossed. Although the discrete wavelet transform involves sub sampling, the sub sampled coefficients remain strongly negatively correlated across edges. In this manner, when a wavelet coefficient is optimally predicted as a function of its across-edge neighbors (e.g. left and right neighbors in HL subbands), the optimal prediction coefficients are negative, indicating an expected sign change. This conclusion is general for any wavelet with a shape similar to a second derivative of a Gaussian.

To estimate sign correlation in a practical way, we have applied a 6-level Dyadic Wavelet Transform decomposition of the source image and then a low quantization level to the resulting wavelet coefficients. As a first approach and taking into account that the sign neighborhood correlation depends on the subband type (HL,LH,HH) as Deever assesses in [5], we have used three different neighbors depending on the subband type. So, for HL subband, the neighbors used are N, NN and W. Taking into account symmetry, for the LH subband, those neighbors are W, WW, and N. For the HH subband they are N, W, and NW, exploiting the correlation along and across the diagonal edges. This lead us to a maximum of 3^3 Neighbor Sign Patterns (NSP) for each subband type.

TABLE I

Probability distribution of neighbor sign patterns (NSPs) of HL_6 subband ($8x8$ coefficients) in Lena image

C	N	NN	W	Occurrences	%Probability
+	+	+	+	13	20.31
+	+	+	-	8	12.50
-	-	-	+	8	12.50
-	+	+	+	6	9.38
-	-	+	+	6	9.38
Others				23	35.93

In Table I we show the NSP probability distribution for HL_6 subband (from the sixth decomposition level) of Lena test image. As shown, the probability that the current coefficient (C) is positive when its N, NN and W neighbors are also positive is around 20%. Besides, if the N and NN neighbors have the same sign and the W neighbor has the opposite sign, the current coefficient (C) has the opposite sign of its W neighbor with a probability of 25% as shown in rows two and three in Table I. The visible sign neighborhood correlation suggest that the sign bits of wavelet coefficients are compressible. Using the previously mentioned neighborhood for each subband type, we have developed a genetic algorithm (GA) in order to find an accurate sign estimation.

A. Genetic algorithm for wavelet sign prediction

The goal of the desired genetic algorithm would be to find a table where for each Sign Neigborhood Pattern (V_k) we have a sign prediction ($S_{i,j}$) for coefficient $C_{i,j}$. There is no an univocal relationship between a neighbor sign combination, i.e not always for a same V_k pattern, $S_{i,j}$ is always positive or negative. However, it is possible that for a V_k pattern, $S_{i,j}$ is more probably to be positive or negative. But, the problem is still more complex, because a sign prediction for a neighbor sign pattern could fit well for an image and not for others. Therefore, the idea is to find suboptimal neighbor sign pattern predictions that better fit for a representative set of images.

The use of genetic algorithms to compress the sign of wavelet coefficients is twofold. First, when the number of neighbors used to analyze the sign correlation grows or when there is a great number of images to be used in the analysis, the search space is excessively wide. Second, it is not intuitive to find a way of combining the predictions obtained for several images.

In Figure 1 we show the genetic algorithm pseudocode for sign prediction. First of all we define each individual, containing a sign prediction for each 3^3 NSP, then each NSP sign prediction of each individual of the universe is randomly initialized as a positive or negative sign.

During evolution, sequences mate and mutate to generate new sequences in the population and best sequences are selected for survival on the basis of their fitness function. The mating of sequences is performed through crossover operator, where parents are randomly selected and its gens (NSPs) are mixed. The best two individuals, the ones that exhibit best prediction performance, are selected for survival. Individuals can also undergo mutation, where a sequence prediction is randomly modified.

Finally, after performing the maximum iterations, the algorithm finishes, obtaining an optimal/suboptimal sign prediction for each NSP. We have performed the fitness evaluation over Lena and Barbara test images, because these images are representative for both low and high textured images respectively.

```
Individual Structure{
//Prediction array for each neighbor sign pattern combination
  sign[NSP];
//indicates the goodness of the individual
  fitness;
  }Individual universe[NUM-POPULATION];

function SignPrediction (SubbandType, ImageFiles,
mutation Probability)
  //Initialization phase:
sign[NSPs]= random(POSITIVE/NEGATIVE)
  Initialize(universe, NUM-POPULATION, NSP);
  //we evaluate each individual of the universe.
For each image in ImageFiles
  EvaluateFitness(SubbandType, ImageFiles, universe);
  for i=0 to NUM-ITERATIONS
  //Select the best two individuals from universe for survival.
       best = SelectBestIndividuals(2);
       //Crossover
       crossPoint=random(NSP);
       //randomly selects a father and a mother to mix gens
       SelectFatherAndMother(random(NUM-POLUTATION));
       universe = MergeFatherAndMother(crossPoint);
       Mutation(universe, mutation Probability);
       universe = universe + best;
       EvaluateFitness(SubbandType, ImageFiles, universe);
  end
  //Finally get the best individual.
  best = SelectBestIndividuals(1);
end of function
```

Fig. 1. Genetic algorithm for sign prediction

Several parameters should be taken into account when training a genetic algorithm: The population size, the individuals initialization, the number of iterations performed, the mutation probability, the crossover point, the crossover method, the selection criteria of the best sequences to be selected for survival, etc. We have performed lots of tests varying these parameters to tune the genetic algorithm. The parameters used to obtain the sign prediction are: population size (100), individuals initialization (ramdomly), number of iterations (1000), mutation probability (0.001), crossover point (ramdomly) and crossover method (best two fitness individuals over four randomly selected parents).

After running the genetic algorithm for each subband type, we obtain an individual containing the prediction of the current coefficient sign ($\hat{SC}_{i,j}[k]$), for each NSP (k) of each subband type. So, what we are going to encode is the correctness of this prediction, i.e., a binary valued symbol from $\hat{SC}_{i,j}[k]\cdot SC_{i,j}$ (see Table II). In order to compress this binary valued symbol, we use two contexts in the arithmetic encoder for each subband type, distributing all sign coding predictions from NSPs between them so as to minimize the zero order entropy of both contexts. The selection criterion is to isolate in one context those NSPs with the highest correctness prediction probability and highest number of occurrences derived from the probability distribution found in the previous analysis. The rest of them are grouped into the other context. However, there are certain NSPs with low correctness probability but with a great amount of occurrences, so we have to heuristically determine the convenience of including them in the first context or not.

TABLE II
SIGN PREDICTION FOR HL SUBBAND IN LENA IMAGE FOR SOME NSPS

NSP(k)	N	NN	W	Prediction ($\hat{SC}_{i,j}[k]$)
0	*	*	*	-
...				
13	+	+	+	+
14	+	+	-	+
...				
26	-	-	-	+

III. Performance Evaluation

In this section we analyze the behavior of the sign coding when implemented on LTW image encoder [9]. This new encoder implementation is called S-LTW. We will also compare the S-LTW encoder versus JPEG2000 (Jasper 1.701.0) and SPIHT (Spiht 8.01) in terms of R/D and coding delay. All encoders have been tested on an Intel PentiumM Dual Core 3.0 GHz with 2 Gbyte RAM memory.

The test images used in the evaluation are: Barbara (512x512), Bike (2560x2048), Boat (512x512), Cafe (2560x2048), GoldHill (512x512), Lena (512x512), Mandrill (512x512), Woman (2560x2048) and Zelda (512x512).

In Table III we show the relative compression gain with respect to the original LTW due only to the sign coding capability for Barbara and Bike test images. As we can see, the maximum sign compression gain

TABLE III
SIGN COMPRESSION PERFORMANCE AT DIFFERENT BIT-RATES.

Bit-rate (bpp)	**S-LTW #Significant Coefficients**	**S-LTW #Bits Saved**	**SPIHT #Significant Coefficients**	**SPIHT #Bits Saved**	**%Gain**
Barbara (512x512)					
1	45740	7936	54657	9482	**17.35**
0.5	22331	3648	27535	4499	16.34
0.25	10484	1520	13460	1951	14.50
0.125	4343	304	6016	421	7.00
Bike (2048x2560)					
1	855266	115200	1371280	184711	13.47
0.5	412212	64424	798202	124758	15.63
0.25	198943	30472	366927	56213	15.32
0.125	91767	11992	162990	21302	13.07

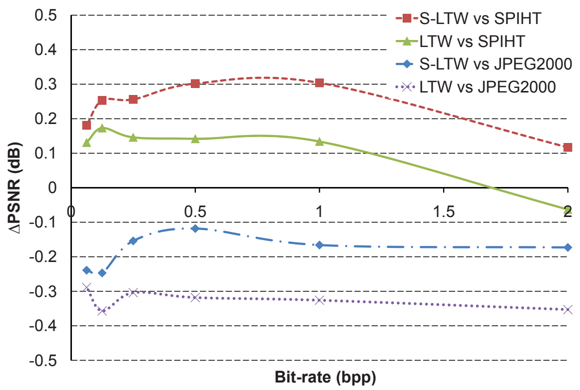

Fig. 2. PSNR-Gain for Bike image

is 17.35%. Furthermore, we show an estimation of the bit savings for SPIHT encoder.

TABLE IV
CODING DELAY (SECONDS).

Bit-rate (bpp)	**JPEG 2000**	**SPIHT**	**LTW Orig.**	**S-LTW**
CODING Barbara (512x512)				
1	0.080	0.042	**0.037**	0.023
0.5	0.076	0.026	**0.022**	0.014
0.25	0.074	0.018	**0.013**	0.009
0.125	0.073	0.014	**0.010**	0.006
CODING Bike (2048x2560)				
1	2.623	0.920	**0.647**	0.430
0.5	2.543	0.521	**0.381**	0.259
0.25	2.507	0.323	**0.224**	0.162
0.125	2.518	0.221	**0.158**	0.117

In Figure 2 we show the R/D improvement when comparing original LTW versus JPEG2000/SPIHT and S-LTW versus JPEG2000/SPIHT. As shown, there is an increase in the PSNR difference between SPIHT and the new S-LTW encoder, and regarding JPEG2000, we can see than now S-LTW has a minor loss in PSNR than original LTW.

Regarding coding delay, the use of a higher context modeling in the arithmetic encoder implies a higher computational cost. In order to compensate the coding speed loss, we have changed the arithmetic encoder stage by a fast arithmetic encoder [11]. As it can be seen in Table IV, S-LTW encoder is 49% faster on average in the coding process than SPIHT encoder and 86% faster on average than JPEG2000. Furthermore, S-LTW encoder is even faster than the original LTW version which does not include the sign coding stage (1.5 times faster on average in the coding process).

IV. CONCLUSIONS

We have presented a genetic algorithm that is able to find a good sign predictor of wavelet coefficient sign. So, by encoding the sign prediction result (success or failure) with an arithmetic encoder, the sign information will be highly compacted in the final bitstream. In order to prove our proposal we have implemented the sign predictor over the non-embedded LTW encoder. The new S-LTW proposed encoder has slightly better R/D performance (up to 0.25 dB), or in terms of bitstream, it is able to reduce the bitstream size up to 17% for the same quality level. Regarding coding delay, the new image encoder is on average 2 times as fast as SPIHT in the coding process and 1.5 times as fast as original LTW due to the inclusion of a fast arithmetic encoder.

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CERTIFICADO DE PARTICIPACIÓN

Francisco Almeida Rodríguez,

Catedrático del área de Lenguajes y Sistemas Informáticos de la Universidad de La Laguna y responsable del Comité Organizador de las XXII Jornadas de Paralelismo, JP2011

Certifica que:

Otoniel López

ha participado en las XXII Jornadas de Paralelismo celebradas en la Escuela Técnica Superior de Ingeniería Informática de la Universidad de La Laguna los días 7, 8 y 9 de septiembre de 2011, en la que ha presentado el trabajo titulado:

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Y para que así conste, y a petición del interesado, se expide el presente certificado en La Laguna a 9 de septiembre de 2011

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