A Perceptually Optimized Wavelet Embedded ZeroTree Image Coder

A. Bajit, M. Nahid, A. Tamtaoui, and E. H. Bouyakhf

***Abstract*—**In this paper, we propose a *Perceptually Optimized Embedded ZeroTree Image Coder* (POEZIC) that introduces a perceptual weighting to wavelet transform coefficients prior to control SPIHT encoding algorithm in order to reach a targeted bit rate with a perceptual quality improvement with respect to the coding quality obtained using the SPIHT algorithm only.

The paper also, introduces a new objective quality metric based on a Psychovisual model that integrates the properties of the HVS that plays an important role in our POEZIC quality assessment.

Our POEZIC coder is based on a vision model that incorporates various masking effects of human visual system HVS perception. Thus, our coder weights the wavelet coefficients based on that model and attempts to increase the perceptual quality for a given bit rate and observation distance. The perceptual weights for all wavelet subbands are computed based on 1) luminance masking and Contrast masking, 2) the contrast sensitivity function CSF to achieve the perceptual decomposition weighting, 3) the Wavelet Error Sensitivity WES used to reduce the perceptual quantization errors.

The new perceptually optimized codec has the same complexity as the original SPIHT techniques. However, the experiments results show that our coder demonstrates very good performance in terms of quality measurement.

***Keywords*—**DWT, linear-phase 9/7 filter, 9/7 Wavelets Error Sensitivity WES, CSF implementation approaches, JND Just Noticeable Difference, Luminance masking, Contrast masking, standard SPIHT, Objective Quality Measure, Probability Score PS.

I. Introduction

THE last years have seen increasing efforts within the embedded wavelet coding algorithms [1] which not only provides very good compression performance, but also has the property that the bitstream can be truncated at any point and still be decoded to recreate a reasonably good quality image. *Embedded ZeroTree Wavelet coding* (EZW) introduced by J. M. Shapiro [2] and recently by A. Said and W. A. Pearlman [3] using an algorithm based on Set Partitioning In Hierarchical Trees (SPIHT) has proven to be a very effective image compression method based on the PSNR measure.

Minimizing such distortion measures does not necessarily guarantee preservation of good perceptual quality of the reconstructed images and may result in visually annoying artifacts despite the potential for a good PSNR. This is especially true in low bit rate image coding applications where the goal is to remove as much perceptual redundancy as possible while introducing minimal perceptual distortion. Infact knowing these constraints have urged us to develop a new perceptual quality measure named QWI based upon psychometric function used to calculate the probability detection of errors and yields a probability score PS serving for quality evaluation.

In digital image processing, great success has been obtained recently by a class of perceptually based embedded wavelet image coding algorithms, such as PEZ, EZW, and SPIHT algorithms. Some scheme didn’t incorporate the optimal quantization model proposed by Watson. This model is based on a psychovisual experiments of the 9/7 wavelets [4] which determinate an optimal quantization matrix that yields a perceptually lossless compression quality. In other scheme the integration of interesting HVS features are not considered, like Contrast Masking or threshold elevation [6]-[16] and contrast sensitivity function CSF [17], whose particular feature is to filter spatially all imperceptible frequencies by the human visual cortex. Exploiting this fact, we can adapt image contrast (contrast masking), and remove considerable invisible frequencies (CSF) and still quantize efficiently with a perceptually improved quality of the reconstructed image.

In addition, these techniques exhibit very desirable characteristics including very fast execution and embedded bitstream transmission. Although SPIHT based image coders are effective at minimizing MSE, they are not explicitly designed to minimize perceptual-based distortions that are matched to the capacities of the human visual system.

This paper presents a Perceptually Optimized Embedded ZeroTree Image Coder based on a vision model that incorporates various masking effects of human visual system HVS perception which prior to encoding, weights the wavelet coefficients according to their perceptual importance and, therefore minimizes a perceptually more relevant distortion measure than PSNR and reaches the targeted bit rate with an increasing perceptual quality with respect to that obtained by the SPIHT algorithm only. Adopted HVS models been used in our algorithm are wavelet JND thresholds, Luminance Masking, Contrast Masking: section II, Contrast Sensitivity Function detailed in section IV and Quantization Error Sensitivity Function used to reduce the detect ability by the human observer of quantization errors discussed in section V. Finally a large discussion of the POEZIC results will be done in section VII including an introduction of a new Objective Quality Measure QWI that yields a Probability Score PS used to measure the coding quality.

II. Discrete Wavelet Pyramid Decomposition

Our coder is a combination of 5 function stages respectively Wavelet transformation, Perceptual Model SetUp, Perceptual Mask Weighting (Luminance Making on Contrast Masking based on Wavelet JND Thresholds), CSF weighting, Wavelet Quantization Error Sensitivity Weighting WES, and finally SPIHT Embedded coding.

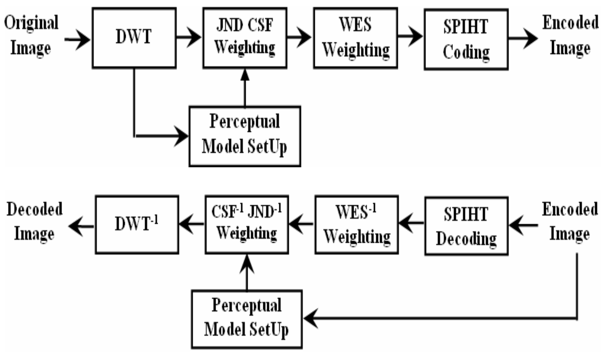

Fig. 1 A Perceptually Optimized Embedded ZeroTree Image Coding & Decoding Algorithm

A brief introduction of our scheme can be described as follow. First we decompose the original image with a discrete wavelet to perform a spatial-frequency representation [20] using a 9/7 linear-phase wavelets filter [4]. This wavelet is characterized with special mathematics features [21] which ensure a perfect reconstruction. It is recommended by the image standard compression JPEG2000 and is the most useful wavelet filter in image vision [15].

In the second step we compute the perceptual model SetUp which is based on the following algorithm: first we compute the luminance masking and wavelet JND thresholds required for the contrast masking calculation (Section III).

In the third step we adopt the contrast sensitivity function [6] used to weight, in the spatio-frequency field, the image spectrum in order to keep only the frequencies that are visible by the human visual cortex.

Then perceptual mask is used to weight subband wavelet coefficients which removes all imperceptible frequencies with respect to the human visual system HVS perception.

In order to improve the quality of the embedded SPIHT quantization and coding we compute the wavelet quantization error sensitivity mask employed to weight the processed wavelet coefficients with respect to the wavelet thresholds obtained from the Watson model. Using this model the quantization errors are under the visibility of threshold errors and then as target the perceptually lossless compression is achieved (section V) for a given observation distance.

The final step is embedded coding of the modified wavelet coefficients for a given target rate. Here we adopt the standard SPIHT [3] coding algorithm which belongs to the family of embedded ZeroTree [2] coding started first Val by Shapiro's EZW algorithm and improved next by Pearlman.

III. Luminance and Contrast Masking

In this work, three visual phenomena are modeled to compute the perceptual Weighting Model SetUp matrix: the JND thresholds or Just Noticeable Difference [5], Luminance Masking [15] (also known as *light adaptation*), Contrast Masking [15] and the Contrast Sensitivity Function CSF (detailed in section IV). This model correlates well with the famous cortical decomposition (*Human Visual Cortex field*).

The JND thresholds are thus computed from the base detection threshold for a subband. The mathematical model for the JND threshold is obtained from the psychophysical experiments adopted by Watson corresponding to the 9/7 biorthogonale wavelet basis [4-5].

In image coding, the detection thresholds will depend on the mean luminance of the local image region and, therefore, a luminance masking correction factor must be derived and applied to the contrast sensitivity profile to account for this variation. In this work, the luminance masking adjustment is approximated using a power function [15], here we adopt the model used in JPEG200 with a factor exponent of 0.649 [15].

Another factor that will affect the detection threshold is the contrast masking also known as threshold elevation, which takes into account the fact that the visibility of one image component (the target) changes with the presence of other image components (the masker) [6-16]. Contrast masking measures the variation of the detection threshold of a target signal as a function of the contrast of the masker. The resulting masking sensitivity profiles are referred to as target threshold versus masker contrast functions. In our case, the masker signal is represented by the wavelet coefficients of the input image to be coded while the target signal is represented by the quantization distortion.

The final perceptual model is shown in Fig. 2, where the computation algorithm corresponding to JND thresholds, Luminance Masking, Contrast Masking & CSF are well done for just a short 3D illustration especially with Lena wavelet coefficients with respect to a given observation distance of 4.

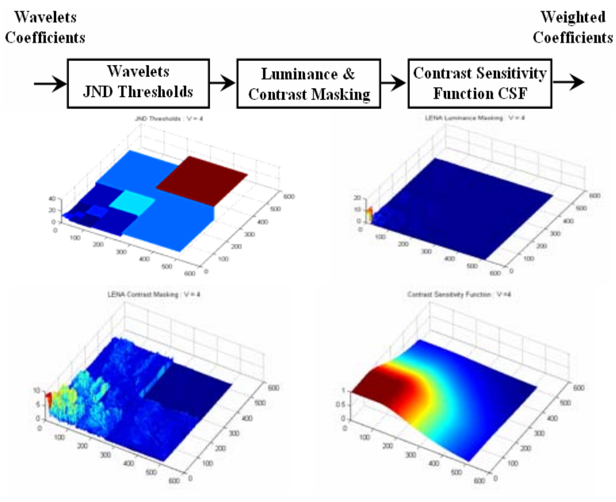

Fig. 2 Perceptual masking model SetUp

IV. CSF Weighting Implementation Approaches

To optimize wavelets coefficients weighting and improve the visual quality of the reconstructed image we take benefits of the contrast sensitivity function CSF [17]. The CSF function describes in quantitative terms how good the human visual system HVS perceives a signal at a given spatial frequency. It sets the contrast perception in relation with the spatial frequency usually measured in cycles per optical degree, which gives the CSF a shape that is independent of the viewing distance. A typical CSF shape is shown in Fig. 3.

Common to all compression techniques is the fact that they focus on an improved coding efficiency, which is not necessarily equivalent to an improved visual quality. The CSF function transforms the wavelet decomposed image on an image which is perceptible and remove all imperceptible frequencies that are invisible by the human visual cortex.

The viewing conditions (*r: spatial resolution* and *v: observation distance*) were assumed as being fixed. This may not be realistic, as an observer can look at the images from any distance. Nevertheless, fixing *r* and *v* is necessary to apply a frequency weighting. Therefore it is shown, that with a slight modification of the CSF shape and the assumption of "worst case viewing conditions" a CSF weighting that works properly for all different viewing distances and typical display media resolutions is the JPEG2000 model of Fig. 3 (*right*).

In the compression applications, the CSF can basically be exploited to modify the wavelet-coefficients before and after quantization, it shapes directly the spectrum of the quantization noise. This strategy is opposed to the direct algorithm that classically codes the detectable frequencies plus some redundant ones, which will additional coding bits.

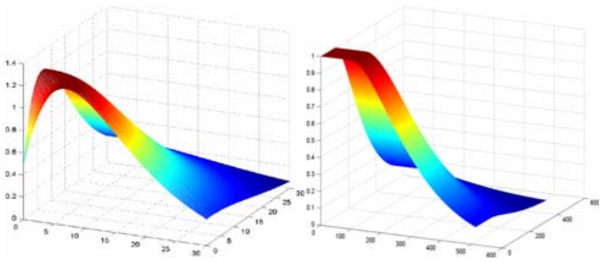

Fig. 3 CSF function models: Mannos (left), Daly (right)

Conventional CSF-implementations into wavelet-based codec are based on a single invariant weighting factor per subband [17]. The first one called Invariant Single Factor weighting (ISF). The basic idea of the ISF-weighting is to assign a single frequency weighting factor per wavelet subband. This approach is simple and stills an efficient perceptual weighting. The second approach weighting represents the DWT filtering which matches exactly the shape of the CSF. It keeps the possibility of an orientation dependent weighting *inside* the subband and is adapted to the local signal properties. The third approach is the mixed strategy which combines the fixed and filtering algorithm, the former is compatible with low frequencies and the latter is ideal for higher frequencies.

V. Quantization Error Sensitivity Function

The third and final step the perceptual quantization operation used to quantize the wavelets Foveated coefficients in order to reduce the entropy manifested by the required bits budget to transmit the compressed image. Compression is achieved by quantization and entropy coding of the DWT coefficients. Typically, a uniform quantize is used, implemented by division by a factor Q and rounding to the nearest integer. The factor Q may differ for different bands.

Quantization of a single DWT coefficient in band will generate an artifact in the reconstructed image. A particular quantization factor in one band will result in coefficient errors in that band that are approximately uniformly distributed over the interval. The error image will be the sum of a lattice of basis functions with amplitudes proportional to the corresponding coefficient errors [5].

Thus, to predict the visibility of the error due to a particular quantization step, we must measure the visibility thresholds for individual basis function and error ensembles. The wavelet coefficients at different subbands and locations supply information of variable perceptual importance to the HVS. In order to develop a good wavelet-based image coding algorithm that considers HVS features, we need to measure the visual importance of the wavelet coefficients.

Psychovisual experiments were conducted to measure the visual sensitivity in wavelet decompositions. Noise was added to the wavelet coefficients of a blank image with uniform mid-gray level. After the inverse wavelet transform, the noise threshold in the spatial domain was tested. A model that provided a reasonable fit to the experimental data is [5].

TABLE I
Error Contrast Sensitivity in the DWT Domain for V = 3.58

Level	Orientation A	H	D	V
1	0.0922	0.1195	0.1358	0.1195
2	0.1753	0.2012	0.1901	0.2012
3	0.2717	0.2723	0.2111	0.2723
4	0.3377	0.2862	0.1763	0.2862
5	0.3242	0.2216	0.1035	0.2216

As shown in Fig. 4 (for a viewing distance of 4) error sensitivity increase rapidly with wavelet spatial frequency, and with orientation from lowpass frequencies to horizontal/vertical to diagonal orientations. Its reverse form yields the wavelet JND thresholds matrix.

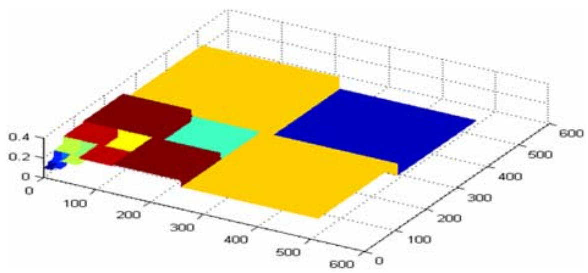

Fig. 4 Watson Error Sensitivity Function WES V = 4

VI. Embedded ZeroTree Wavelet Coding

Embedded ZeroTree wavelet coding is a very effective and computationally inexpensive technique for image compression. Its principles of computation algorithm are (1) wavelet pyramid decomposition of the image, (2) partial ordering of the transform coefficients by the highest bit plane of the magnitude, with the ordering information encoded by means of a set partitioning algorithm that is reproduced at the decoder, (3) ordered bit plane transmission of refinement bits, and (4) exploitation of the self-similarity of the image wavelet pyramid decomposition across different scales.

The wavelet tree rooted at a coefficient in a subband. The resulting code is fully embedded. This means the reception of code bits can be stopped at any point, and the image can be decompressed and reconstructed. Although the SPIHT [2-3] coding does not minimize the MSE for a given rate, it is known to have excellent performance at all rates.

VII. Quality Measure and Experimental Results Discuss

In order to evaluate or compare image compression techniques we need to reliably measure the quality of compressed images by taking into account the famous observer mean opinion score (MOS). Many mathematical measures are often used such as mean squared error (MSE) and peak signal to noise ratio (PSNR). However, these measures often have a poor correlation with MOS and functions, that take advantage of properties of the human visual system (HVS), are often incorporated to improve their performance. Recently, techniques based on multiple channel models of the HVS have been shown to improve correlation to MOS. From these HVS models it is possible to predict, on a pixel by pixel basis, if the noise introduced in the compressed image will be visible to a human observer [20-25]. The VDP [24] map inspired on HVS criteria provides an indication of the degree of visual error as a function of image location. The wavelet transform is one of the most powerful techniques for image compression, because of its similarities to the multiple channel models of the HVS. The DWT decomposes the image into a limited number of spatial frequency channels, with respect to the cortical decomposition. Despite this limitation the quality measure still a goal of the wavelet visible difference predictor WVDP [25] to visually optimize image compression scheme.

A wavelet based image quality metric, namely, wavelet Quality Index QWI predict visible differences between the original and degraded image, which yields a quality measure scale called the Probability Scale PS, plays an important role in our CODEC in terms of image Quality Measurement. This factor means the abilility of detecting a distortion in a subband (λ,θ) at location (i,j) in the DWT field. This probability as well known can be expressed as follow:

$$p(\lambda,\theta,i,j) = 1 - exp\left(-\left|WES(\lambda,\theta,i,j).D(\lambda,\theta,i,j)\right|^{\beta}\right)$$

Where $D(\lambda,\theta,i,j)$ denotes the quantization distortion detection at location (λ,θ,i,j) , $WES(\lambda,\theta,i,j)$ denotes the Watson Error Sensitivity, and β is a parameter chosen to maximize the correspondence of $p(\lambda,\theta,i,j)$ and the probability summation [18-19]. Finally we calculate the probability score by summing, as the Minkowski summation does, all probabilities within all wavelet subbands [18-25]. As a result the probability score PS is expressed as follow:

$$PS = \exp\left(-\sum_{(\lambda,\theta,i,j)}\left|p(\lambda,\theta,i,j)\right|\right)$$

The greater this factor is the best the decoded image quality is compared to the original or full reference image. We test the POEZIC algorithm using 8 bits per pixel gray scale images and compare it with the SPIHT algorithm.

Figs. 5 and 6 show the 512 x 512 “Lena” and “Boat” image encoded with both SPIHT and POEZIC algorithms, both first with respect to a varying targeted bit rate in bpp for a given and fixed viewing distance. At a very low bit-rate of 0.0625 bpp, the mouth, nose, and eye regions are hardly recognizable in the SPIHT coded image, whereas those regions in the POEZIC, coded image exhibit detailed visual information.

At a low bit-rate of 0.125 bpp, SPIHT still decodes a very blurred image, while POEZIC begins to give acceptable quality over the face region. Increasing the bit-rate to 0.25 bpp and 0.5 bpp, the visual quality of the POEZIC coded images is still superior to the SPIHT coded images. When the bit-rate of 0.5 bpp is reached, the POEZIC coded image approaches uniform resolution and the decoded SPIHT and POEZIC images are almost indistinguishable.

Figs. 7 and 8 show the WQI comparisons of the POEZIC and SPIHT compressed “Lena” and “Boat” images with respect to a varying observation distance V for a given and fixed targeted bit rate such 0.0625 bpp, 0.125 bpp and 0.5 bpp. The probability score PS is given as a function of the viewing distance, instead of just one fixed value. In comparison with SPIHT, significant quality gain is achieved by POEZIC through the entire range of viewing distances. This is consistent with the subjective quality.

In Fig. 9, we show how the WQI value increases with the bit-rate. Fig. 9 shows the POEZIC compression of the “Lena” image with multiple targeted bit rate for , as an illustration, a fixed viewing distance of V=4. At low bit-rates such as 0.03125 bpp and 0.0625 bpp, POEZIC maintains acceptable quality at the whole image versus the standard SPIHT coder. Again, a visually high-quality uniform resolution image is obtained from the same bit stream with a sufficient bit-rate (0.5 bpp). The wavelet quality measure results values (PS) of both compressed “Lena” images (Visually Optimized Version POEZIC “Right” and Standard SPIHT “Left”) are well mentioned above each compressed image.

The performance obtained by our coder is resumed in Tables II-III which shows the quality gain with both varying viewing condition and targeted bit rate for the images test “Lena”, “Barbara”, “Mandrill” and “Boat”.

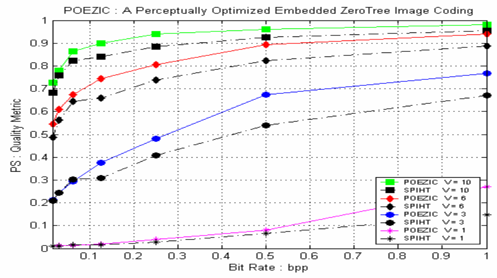

Fig. 5 Wavelet Quality Index QWI of POEZIC vs SPIHT Boat

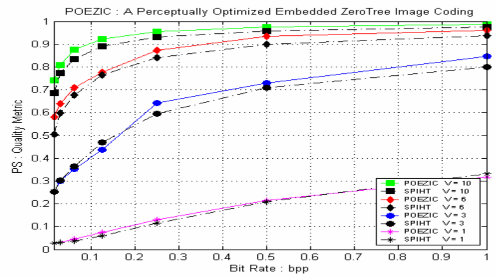

Fig. 6 Wavelet Quality Index QWI of POEZIC vs SPIHT LENA

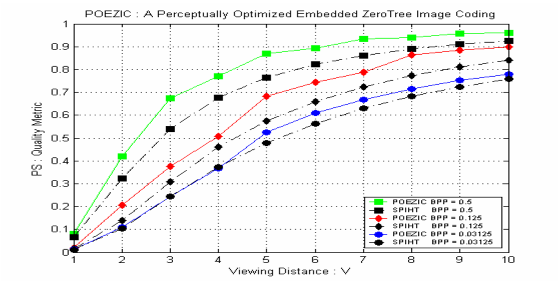

Fig. 7 Wavelet Quality Index QWI of POEZIC vs SPIHT BOAT image at 0.03125 bpp, 0.125 bpp and 0.5 bpp

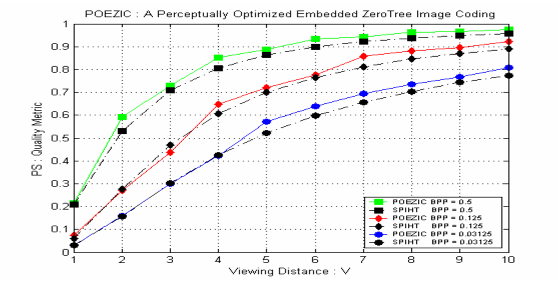

Fig. 8 Wavelet Quality Index QWI of POEZIC vs SPIHT LENA image at 0.03125 bpp, 0.125 bpp and 0.5 bpp

Fig. 9 “Lena” image compression results. The images of the left column that follow are for SPIHT ONLY coded images. The images of the right column that follow are for the visually optimized SPIHT POEZIC coded images. The bit rates from top to bottom are 0.0625 bpp, 0.125 bpp and 0.5 bpp respectively

TABLE II
WAVELET QUALITY INDEX GAIN OF THE VISUALLY OPTIMIZED SPIHT POEZIC VS SPIHT WITH RESPECT TO VARYING VIEWING CONDITION V

Quality Gain (%) POEZIC vs SPIHT		Test Images			
		Lena	Barbara	Mandrill	Boat
Viewing Condition (Observation Distance)	V = 1	3.7074	5.0762	7.0793	4.8438
	V = 3	5.4486	7.9890	11.0685	8.6801
	V = 6	0.8617	6.0719	9.5438	11.0888
	V = 10	8.4222	12.1050	18.3714	23.6305

TABLE III
WAVELET QUALITY INDEX GAIN OF THE VISUALLY OPTIMIZED SPIHT POEZIC VS SPIHT WITH RESPECT TO VARYING BIT RATE

Quality Gain (%) POEZIC vs SPIHT		Test Images			
		Lena	Barbara	Mandrill	Boat
Targeted Bit Rate (bpp) Bit Per Pixel	Bpp=0.03125	3.7954	5.3691	3.4714	4.8486
	Bpp=0.125	3.9903	0.4229	8.3578	17.9164
	Bpp=0.5	3.7619	5.4934	22.7728	13.6375

VIII. CONCLUSION

In this paper, we propose an visually or Perceptually Optimized Embedded ZeroTree Image Coder algorithm named POEZIC, which exploit a various Human Visual System HVS model to compute a like cortical decomposition to achieve the final aim of improving the perceptual quality of the reconstructed images versus the quality obtained by the traditional embedded coders especially standard SPIHT in this paper. The proposed perceptual model contains Luminance masking, Contrast masking and Contrast Sensitivity function CSF filter with an optimal implementation. By exploiting features of the human visual system quality criteria (HVS), we finally optimize the original image wavelets coefficients by weighting them using the perceptual model mask, and then we improve the visual quality of the reconstructed or decoded version. A wavelet quality Index QWI yields a quality scale called probability scale PS to measure the quality between the original image and decoded version. The factor computation is based on the Minkowski summation of the psychometric function probabilities within wavelet subband. It predicts the visual differences between the original and degraded image. Note that the greatest this factor the best the coding quality is. This metric plays an important role in our POEZIC coder, whose experiment results demonstrates very good performance in terms of quality measurement. Using the optimized version POEZIC of the standard coder SPIHT, our aim has really been achieved.

To achieve this paper, note that our compression, coding and quality evaluation systems make a great part of a great project concerning the real time video coding and quality assessing in a wireless GSM networks infrastructure. These systems will be incorporated to build the final scheme.

The perceptual model introduced in our POEZIC algorithm can be used in other embedded coders such EZW, EBCOT and JPEG2000. Also, it can be employed to improve the perceptual quality of the reference and the predicted frames in wavelet based video coding which makes an interest focus in wavelet video coding based on Human Visual System Coding Quality Criteria.

REFERENCES

[1] N. Jayant, J. Johnston, and R. Safranek, "Signal compression based on models of human perception," *Proc. IEEE*, vol. 81, no. 10, pp. 1385–1422, Oct. 1993.

[2] J. M. Shapiro, "Embedded image coding using zerotrees of wavelet coefficients", IEEE Trans. Signal Processing, vol. 41, pp. 3445-3462, 1993.

[3] A. Said and W. A. Pearlman, "A new, fast and efficient image codec based on set partitioning in hierarchical trees", IEEE Trans. Circuits and Systems for video Technology, vol. 6, pp. 243-250, June 1996.

[4] A.Cohen, I.Daubechies, and J.C.Feauveau, "Biorthogonal bases of compactly supported wavelets,"Commun. Pure Appl. Math., vol. 45, pp. 485–560, 1992.

[5] A.B Watson, G.Y.Yang, J.A.Solomon, and J.Villasonor,``Visisbility Of Wavelet Quantization Noise,`` IEEE Trans. Image Processing, vol.6 no, 8, pp. 1164-1175 1997.

[6] J. Ross and H. D. Speed, "Contrast adaptation and contrast masking in human vision," in *Proc. Roy. Soc. Lond. B*, 1991, pp. 61–69.

[7] G. E. Legge and J. M. Foley, "Contrast masking in human vision," *J. Opt. Soc. Amer. A*, vol. 70, no. 12, pp. 1458–1471, 1980.

[8] D. G. Pelli, "Effects of Visual Noise," Ph.D. dissertation, Cambridge Univ., Cambridge, U.K., 1981.

[9] R. J. Safranek, "A comparison of the coding efficiency of perceptual models," *Proc. SPIE*, vol. 2411, pp. 83–91, 1995.

[10] Watson and J. A. Solomon, "A model of visual contrast gain control and pattern masking," *J. Opt. Soc. Amer.*, vol. 14, pp. 2397–2391, 1997.

[11] T. Pappas, T. Michel, and R. Hinds, "Supra-threshold perceptual image coding," in *IEEE Int. Conf. Image Processing*, 1996, pp. 237–240.

[12] A. B. Watson, "DCT quantization matrices visually optimized for individual images," in *Proc. Hum. Vis., Visual Process., Digital Display IV*, 1993, pp. 202–216.

[13] J. M. Foley and G. M. Boynton, "A new model of human luminance pattern vision mechanisms: analysis of the effects of pattern orientation, spatial phase and temporal frequency," in *Comput. Vis. Based Neurobiol.*, vol. 2054, 1994, pp. 32–42.

[14] J. M. Foley, "Human luminance pattern-vision mechanisms: masking experiments require a new model," *J. Compar. Neurol.*, vol. 11, no. 6, pp. 1710–1719, 1994.

[15] S. Daly, W. Zeng, J. Li, S. Lei, Visual masking in wavelet compression for JPEG 2000, in: Proceedings of IS&T/SPIE Conference on Image and Video Communications and Processing, San Jose, CA, Vol. 3974, January 2000.

[16] I. Honsch and L. J. Karam, "Adaptive image coding with perceptual distortion control," IEEE Trans. Image Process., vol. 11, no. 3, pp. 213-222, Mar. 2002.

[17] Marcus J. Nadenau, Julien Reichel, and Murat Kunt,`` Wavelet-based Color Image Compression: Exploiting the Contrast Sensitivity Function`` 2000.

[18] A. B.Watson, "Probability summation over time," *Vis. Res.*, vol. 19, pp. 515–522, 1979.

[19] J. G. Robson and N. Graham, "Probability summation and regional variation in contrast sensitivity across the visual field," *Vis. Res.*, vol. 21, pp. 409–418, 1981.

[20] P. C. Teo and D. J. Heeger, "Perceptual image distortion," in *Proc. IEEE Int. Conf. Image Processing*, 1994, pp. 982–986.

[21] J. G. Robson and N. Graham, "Probability summation and regional variation in contrast sensitivity across the visual field," *Vis. Res.*, vol. 21, pp. 409–418, 1981.

[22] S. J. P. Westen, R. L. Lagendijk and J. Biemond, "Perceptual Image Quality based on a Multiple Channel HVS Model," Proceedings of ICASSP, pp. 2351-2354, 1995

[23] C. Zetzsche and G. Hauske, "Multiple Channel Model Prediction of Subjective Image Quality," SPIE, Human Vision, Visual Processing, and Display, 1077, pp. 209-215, 1989.

[24] S. Daly, "The visible differences predictor: An algorithm for the assessment of image fidelity," in Digital Images and Human Vision (A. B. Watson, ed.), pp. 179-205, Cambridge, MA: MIT Press, 1993W.-K. Chen, *Linear Networks and Systems* (Book style). Belmont, CA: Wadsworth, 1993, pp. 123–135.

[25] Andrew P. Bradley "A Wavelet Visible Difference Predictor" Member IEEE Transactions on Image Processing Vol. 8. No. 5. May 1999.

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