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A Perceptually Optimized Foveation Based Wavelet Embedded ZeroTree Image Coding

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Abstract**—**In this paper, we propose a *Perceptually Optimized Foveation based Embedded ZeroTree Image Coder* (POEFIC) that introduces a perceptual weighting to wavelet coefficients prior to control SPIHT encoding algorithm in order to reach a targeted bit rate with a perceptual quality improvement with respect to a given bit rate a fixation point which determines the region of interest ROI.

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 POEFIC quality assessment.

Our POEFIC 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) foveation masking to remove or reduce considerable high frequencies from peripheral regions 2) luminance and Contrast masking, 3) the contrast sensitivity function CSF to achieve the perceptual decomposition weighting.

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, Foveation Filtering, CSF implementation approaches, 9/7 Wavelet JND Thresholds and Wavelet Error Sensitivity WES, Luminance and Contrast masking, standard SPIHT, Objective Quality Measure, Probability Score PS.

I. Introduction

THE psychovisual experiments demonstrates that spatially, the resolution, or sampling density, has the highest value at the point of the fovea and drops rapidly away from that point as a function of eccentricity. As a result, when a human observer gazes at a point in a real-world image, the region around the point of fixation is projected into the fovea, sampled with the highest density and perceived with the highest contrast sensitivity. In conclusion the sampling density and contrast sensitivity decrease dramatically with increasing the viewing angle namely called eccentricity with respect of that point of fixation.

The motivation behind *foveation image compression scheme* is that there exists considerable high-frequency information redundancy in the peripheral regions, so much more efficient representation of images can be obtained by removing or reducing such information redundancy, based on the foveation point(s) and the viewing distances [1]-[3]. The first aim of that scheme is *foveation filtering*, which foveate a uniform resolution image, such that when the human eyes gaze at the point of fixation, they cannot distinguish between the original and the foveated versions of that image. In Fig. 7 we show an illustrated example of the original “Lena” image and its foveated version. If attention is focussed at the central foveation point, both images will have the same appearance.

In practice, different methods approximate perfect foveation filter. In [4], a pyramid structure is suggested to foveate images. In [5]–[6] foveation filter consists of a bank of low-pass filters having variable cutoff frequencies. In [7], the structure of foveation filter is based on Laplacian pyramid architecture. In [8]–[10], the proposed wavelet based foveation method applies a nonuniform weighting model.

Great success has been obtained recently by a class of wavelet image coding algorithms oriented region of interest (ROI), such as the standard JPEG2000 [11] and the Embedded Foveation Image Coding (EFIC) algorithms [12]. The former scheme didn’t incorporate the optimal quantization model proposed by Watson. This model is based on a psychovisual experiments of the 9/7 wavelets [19] to measure the visibility [20] of wavelet coefficients noise threshold, and determinate an optimal quantization matrix which yields a perceptually lossless compression quality. In the latter scheme the integration of interesting HVS features are not considered, like Luminance and Contrast Masking or threshold elevation [15]-[17] and Contrast Sensitivity Function CSF [18] 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: see *section IV*), and remove considerable invisible frequencies (CSF: see *section V*) and still quantize efficiently with a perceptually improved quality in the region of interest.

In this paper, we propose an optimized foveation based image coding quality (POEFIC) algorithm, which exploit various Psychovisual quality models exploiting the human visual system quality criteria (HVS), to optimize foveated image wavelets coefficients weighting and improve the visual quality of its coded version. This point will be detailed in *section III* with illustrative figures. An objective metric for foveation based image namely, quality wavelet index metric FWQI, plays an important role in our system, which yields a quality scale called Foveated probability scale FPS: *section VII,* whose experiment results demonstrates very good performance in terms of quality measurement.

II. Discrete Wavelet Pyramid Decomposition

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

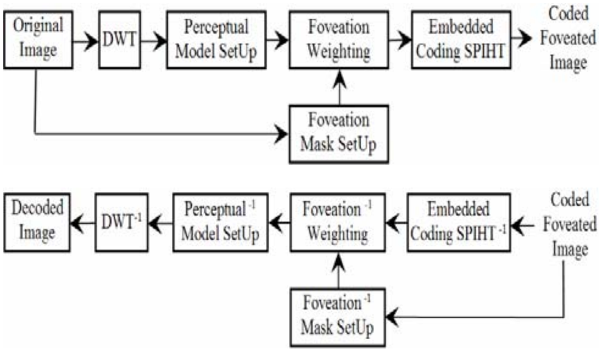

Fig. 1 POEFIC: A Perceptually Optimized Embedded ZeroTree Image Coding & Decoding Algorithm

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 [14] using a 9/7 linear-phase wavelets filter [19]. 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 [11].

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). Second, we weight, in the DWT domain using the contrast sensitivity function [18], 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.

As the human visual system (HVS) is highly space-variant in sampling, coding, processing, and understanding, and because the spatial resolution of the HVS is highest around the point of fixation, and decreases rapidly with increasing eccentricity (viewing angle), we compute in the third step the foveation filter mask. By exploiting advantage of this fact, it is possible to reduce or remove considerable high frequency information redundancy from the peripheral regions and still reconstruct a perceptually good quality image coding.

The final step is embedded coding of the modified wavelet coefficients for a given target rate. Here we adopt the standard SPIHT [22] coding algorithm which belongs to the family of embedded ZeroTree [23] coding started first Val by Shapiro's EZW algorithm and improved next by Pearlman.

III. Foveation Mask Weighting SetUp

In this operation we have to locate the foveation point to determine the foveation mask to weight the decomposed image; as a result all frequencies around the region of interest will be either reduced or removed from the image spectrum [8]-[10]. The foveation filter mask is shown in Fig. 2.

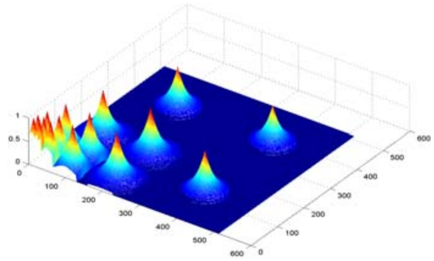

Fig. 2 Foveation filter mask in the DWT domain

The border's foveation filtering shape determinates the region of interest in the DWT domain. This region with respect to DWT decomposition level and orientations limits the frequencies located around the fixation point that will be weighted by the filter mask. In first levels, a great amount of frequencies are removed, but approximately the whole low frequencies are kept and taken into account in coding. The best parameters can be obtained in [30]-[31].

This foveation filter mask depends on many essential parameters like the display Nyquist and cut-off Frequencies. The first one express the visible frequencies towards the fixation region of interest, the second one show the limits of visible frequencies without a display aliasing in the human visual cortex. The minimum of them determinates the final visible frequency spectrum in the area of interest. Other feature of the foveation filter is it's modification of the spectrum occupation depending on the viewing observation distance. This shape eliminates progressively higher frequencies with observation distance increase Fig. 3. As a result, observer is progressively unable to detect high frequencies in image when distance increases [8]-[10].

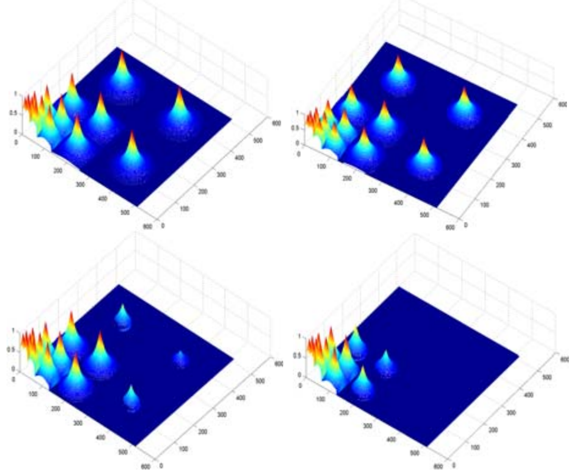

Fig. 3 Foveation Filter error sensitivity mask in the DWT domain. The top-left, top-right, bottom-left, & bottom-right figures: viewing distance V = 1, 3, 6 & 10

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IV. 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 [11] (also known as *light adaptation*), Contrast Masking [15-17] 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 [19-21].

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 [11], here we adopt the model used in JPEG200 with a factor exponent of 0.649 [11].

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) [15-17]. 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. 4, 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.

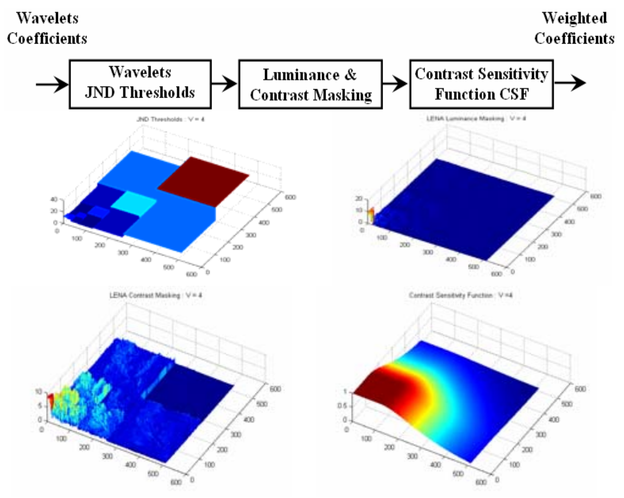

Fig. 4 Perceptual masking model SetUp

V. 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 [18]. 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. 5.

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. 5 (*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.

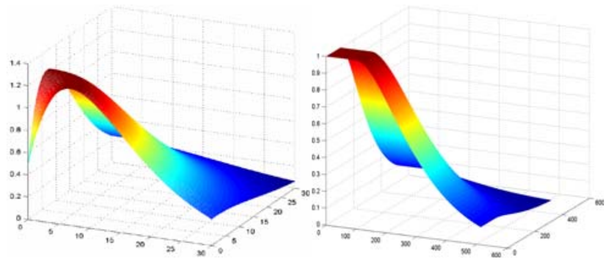

Fig. 5 CSF function models: Mannos (left), Daly (right)

Conventional CSF-implementations into wavelet-based codec are based on a single invariant weighting factor per subband [18]. 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 corresponding to the fixation point. 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.

VI. Embedded ZeroTree Wavelet Coding

Embedded ZeroTree wavelet coding [22] 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 [23] 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 coded 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 the human visual system (HVS) properties, are often incorporated to improve their performance. Recently, techniques based on multiple channel models of the HVS have been shown to improve correlation with the 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 [24-25]. The VDP [26] 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 [27] to visually optimize image coding scheme.

A wavelet based image quality metric, namely, foveation wavelet Quality Index FQWI 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 ability 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: $p(\lambda,\theta,i,j) = 1-\exp\left(-\left|ROI.WES(\lambda,\theta,i,j).D(\lambda,\theta,i,j)\right|^{\beta}\right)$

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, ROI denotes the DWT region of interest, and β is a parameter chosen to maximize the correspondence of $p(\lambda,\theta,i,j)$ and the probability summation [28-29]. Finally we calculate the probability score by summing, as the Minkowski summation does, all probabilities within all wavelet subbands [30-31]. As a result the probability score PS is expressed as follow:

$$PS = \exp\left(-\left(\sum_{(\lambda,\theta,i,j)}\left|p(\lambda,\theta,i,j)\right|\right)^{1/\beta}\right)$$

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

Figs. 6-7 show the 512 x 512 “Boat” and “Mandrill” images encoded with both SPIHT and POEFIC 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 main region of fixation is hardly recognizable in the SPIHT coded image, whereas that gazed region in the POEFIC coded image exhibit detailed visual information.

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

Figs. 8-9 shows the FWQI comparisons of the POEFIC and SPIHT compressed “Boat” and “Mandrill” images with respect to a varying observation distance V for a given and fixed targeted bit rate such 0.015625 bpp, 0.06125 bpp and 0.25 bpp. The foveation probability score FPS 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 POEFIC through the entire range of viewing distances. This is consistent with the subjective quality.

In Fig. 10, we show how the FPS value increases with the bit-rate. It shows the POEFIC compression of the “Zelda” image with multiple targeted bit rate for viewing distance of V=4. At low bit-rates such as 0.03125 bpp and 0.0625 bpp, POEFIC maintains acceptable and good quality at the gazed point in the 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 of 0.25 bpp. The wavelet quality measure results values (FPS) of both compressed “Zelda” images (Visually Optimized Version POEFIC “Right” and Standard SPIHT “Left”) are well mentioned above each coded image.

The performances obtained by our coder are resumed in Tables I-II which show the quality gain with both varying viewing condition and targeted bit rate for the test images “Goldhill”, “Barbara”, “Mandrill” and “Boat”.

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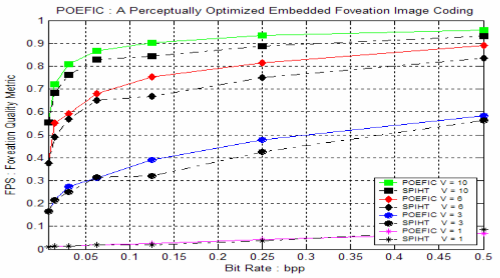

Fig. 6 Foveation Wavelet Quality Index of POEFIC vs SPIHT BOAT

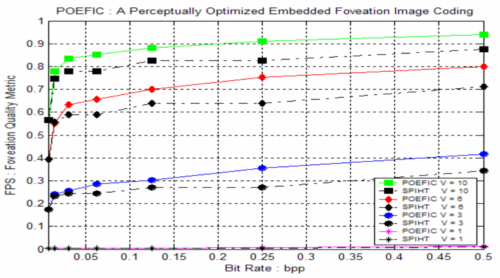

Fig. 7 Foveation Wavelet Quality Index of POEFIC vs SPIHT Mandrill

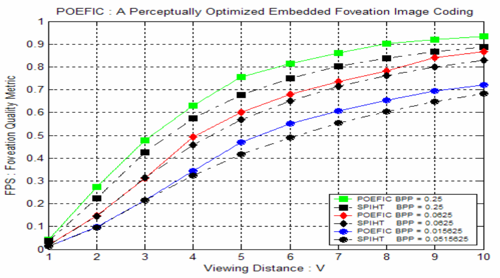

Fig. 8 Foveation Wavelet Quality Index FQWI of POEFIC vs SPIHT BOAT image at 0.015625 bpp, 0.0625 bpp and 0.25 bpp.

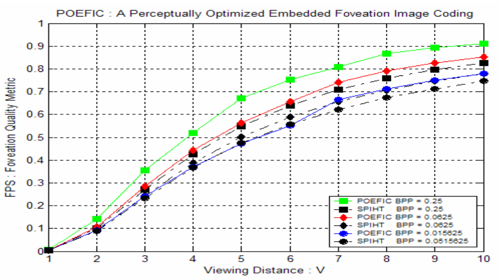

Fig. 9 Foveation Wavelet Quality Index FQWI of POEFIC vs SPIHT Mandrill image at 0.015625 bpp, 0.0625 bpp and 0.25 bpp.

Fig. 10 "Zelda" 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 POEFIC coded images. The bit rates from top to bottom are 0.03125 bpp, 0.0625 bpp and 0.25 bpp respectively, at observation distance of V = 4

TABLE I
FOVEATION WAVELET QUALITY GAIN OF THE POEFIC VS SPIHT FOR VARYING VIEWING CONDITION: V = 1, 3, 6, AND 10

Quality Gain (%) POEFIC vs SPIHT		Test Images			
		Goldhill	Barbara	Mandrill	Boat
Viewing Condition (Observation Distance)	V = 1	7.1936	1.1306	23.7011	7.5911
	V = 3	8.8763	7.5951	14.8419	7.6882
	V = 6	6.8496	7.2226	9.4696	8.0891
	V = 10	4.1526	3.9780	7.6044	5.2402

TABLE II
FOVEATION WAVELET QUALITY GAIN OF THE POEFIC VS SPIHT FOR VARYING BIT RATES: BPP = 0.015625, 0.0625 AND 0.25

Quality Gain (%) POEFIC vs SPIHT		Test Images			
		Goldhill	Barbara	Mandrill	Boat
Targeted Bit Rate (bpp) Bit Per Pixel	Bpp=0.015625	8.3843	4.1297	2.9289	6.6846
	Bpp = 0.0625	5.5059	2.5278	13.0623	4.4034
	Bpp = 0.25	13.5226	4.8666	24.5315	10.5587

VIII. Conclusion

In this paper, we propose a Perceptually Optimized Embedded Foveation based ZeroTree Image Coder algorithm named POEFIC, which exploit a various Human Visual System HVS model to achieve the 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 with an optimal implementation. By exploiting features of the human visual system quality criteria (HVS), we finally optimize the image wavelets coefficients by weighting them using the perceptual model mask, and then we improve the visual quality of the decoded version. A wavelet quality Index FQWI 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 all wavelet subbands. 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 coder, whose experiment results demonstrates very good performance in terms of quality measurement which reach the goal of our aim.

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 POEFIC algorithm can be applied to other embedded coders such *EZW, EBCOT and JPEG2000*. Also, it can be employed to *improve the perceptual quality of the predicted frames* in wavelet based video coding which makes an interest focus in wavelet video coding based on Human Visual System Quality Criteria.

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