The Improvement of an Image Compression Approach Using Weber-Fechner Law

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Abstract. The idea behind image compression is the reduction of the average number of bits per pixel needed for its representation. Indeed, our study of still image compression is based on the non-conservative compression method. This means that the reconstructed image, after a compression/decompression cycle, will be different from the original one. In fact, such a difference brings about a degradation of the original image. In the first part of still image compression, we suggest a chain composed of a discrete wavelet transform followed by neural-networks quantization and a binary encoder. In this paper, we improve the quality of compression by adding a pretreatment phase through the use of the principle of Weber-Fechner law which considers the human-eye sensitivity to luminance as a logarithmic function.

Keywords: Weber-Fechner law · Logarithmic quantization · Discrete wavelet transform · Neural-networks

1 Introduction

The approaches using the artificial neural networks [1, 9] for data intelligent processing seem to be very promising. Essentially, this is due to their structures which provide the opportunities for parallel computations and for the use of the learning process which allows the network to adapt to the data to be processed [2]. Again, the discrete wavelet transform [10, 11] can produce different size sub-images and can identify the relevant information from the details of an image. To improve the compression quality, we use a pretreatment step which employs the principle of Weber-Fechner law [4, 12] for the logarithmic quantization of the original image. In this article, we disclose the extent to which it is important to use the logarithmic quantization in the improvement of the compression quality by taking the wavelet transform and Kohonen's networks [3] as a basis. To show how important the compression law is, we will, first, study the principle of Weber-Fechner law in quantifying the original image. Second, we will detail our approach to the compression of still images. Finally, we will compare the two approaches so as to assess our new method.

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2 The Proposed Image Compression Approach

Our new image compression approach consists of three steps: the quantization of the original image by Weber-Fechner law, the discrete wavelet transform and the quantization by Kohonen's network. Figure 1 elucidates the steps of compression by means of our approach.

Fig. 1. Image compression steps

2.1 Weber-Fechner Law

Sensitivity to contrast [12, 13] is the ability of the human visual system to detect the changes in luminance (achromatic) and the chromatic changes. Any measure of sensitivity to contrast depends on the level of luminance of the stimuli, their spatial frequencies, and their chrominance as well as the human observer adaptation level [5]. Indeed, contrast allows measuring the relative change in luminance with respect to the neighborhood. This property is known as Weber-Fechner law:

$$C^{w} = \frac{\Delta L}{L} \tag{1}$$

Where ΔL is the difference in luminance between the stimulus and its neighborhood and L is the luminance of the neighborhood. The Contrast Sensitivity Functions (CFS) [13] is typically used to quantify these dependencies (Fig. 2).

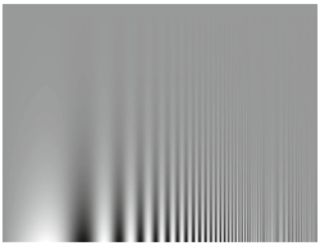

Fig. 2. Contrast sensitivity functions

Weber law regards the sensitivity of the human eye to luminance as a logarithmic function [6, 18]. Weber developed a quantitative description of the relationship between the stimulus intensity and the discrimination which is now known as Weber law.

$$\frac{\Delta S}{S} = K \tag{2}$$

Where ΔS is the perceived intensity difference with respect to a stimulus S and K which is a constant. Fechner-Weber applied the law to the sensory experience. He found that the intensity of sensation is proportional to the logarithm of the stimulus intensity.

$$\Delta S = k * S \Rightarrow \Delta P = k' \tag{3}$$

$$\Delta P = k' = k * \frac{\Delta S}{S} = k * \Delta(\log S) \tag{4}$$

$$\Delta P = P_1 - P_0 = k * \log(\frac{S_1}{S_0}) \tag{5}$$

If the absolute threshold is S0 = 1 and the associated sensation is P0 = 0, Fechner assumes that the amplitude of sensation is proportional to the logarithm of the stimulus. This relationship is called Weber-Fechner law.

$$P = k * \log(S) \tag{6}$$

Thus, according to Weber-Fechner law, the quality measurement must take into account the logarithmic sensitivity of the eye to light and the decreases in the image gray levels are considered imperceptible to the human eye [4]. On the other side of the coin, the logarithmic quantization reduces the entropy of the image which will lead to a higher compression ratio without noticeable degradation of the original image. We use the principle of Weber-Fechner law to quantify the image signal S (Fig. 3) as a pre-treatment phase before the wavelet transform.

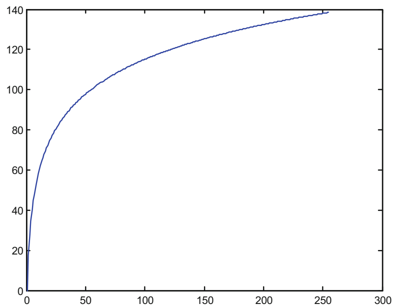

Fig. 3. Logarithmic quantization of the original image

2.2 Discrete Wavelet Transformation

The dimensional discrete wavelet transformation (DWT) [10] is based on the image multi-resolution analysis concept [14]. It is divided into a set of sub bands representing the information carried by the source image at different levels of resolution: the image approximation (LL) and the images of the horizontal details (HL), the vertical details (LH), the diagonal details (HH) [11]. The procurement of those pictures is the result of the following steps (Fig. 4):

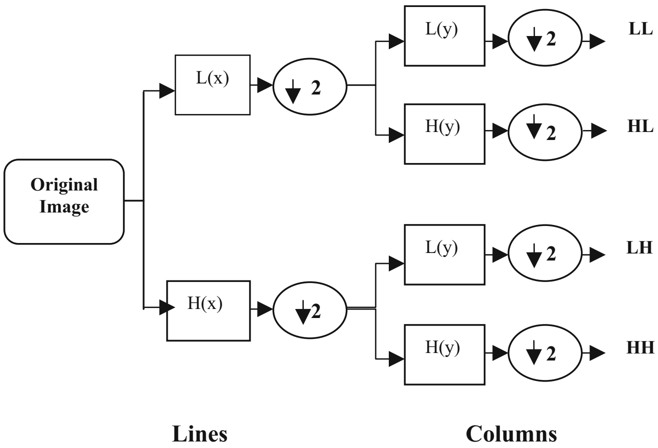

Fig. 4. Decomposition steps of an image by the discrete wavelet

Figure 5 is an example of the wavelet transformation of the Lena image at two levels of decomposition.

Fig. 5. Representation of a wavelet transform of the Lena image at 2 levels

2.3 Kohonen's Network

Kohonen's network came into existence in 1990 (Self Organizing Map) [3, 15]. It is a competitive network. It is made up of a layer of neurons reflecting the input-data presented to the network and a topological map. Self organizing map is a neural network in a single layer in which the neurons are usually arranged on a matrix. Each of these neurons is connected to the input via variable synaptic weights. The general structure of Kohonen's network is illustrated in Fig. 6. When an input is presented to

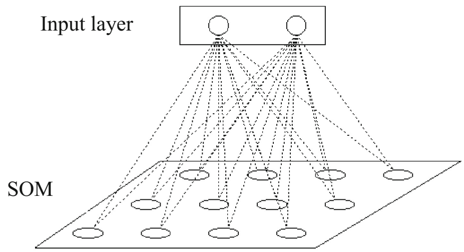

Fig. 6. Self organizing map

the network via the input layer, the neurons of the self organizing map are activated differently and a competition starts between these neurons. The neuron with the closest weight value to that of the input value is deemed the winner [17].

The adaptation of the network weight to learning is done according to the following rules:

1. Find the winner neuron in the competition as:

$$d(X, w_c) \leq d(X, w_i), \forall i \neq c \tag{7}$$

   Where
   X: input vector
   w_c: the weight vector of the winner neuron c
   w_i: the weight vector of the neuron i
2. Update weight w_i of the network:

$$w_i(t+1) = w_i(t) + h(c, i, t) * [X - w_i(t)] \tag{8}$$

   where $w_i(t)$ is the weight vector of the neuron i at time t, h is a function defined by:

$$h(c, i, t) = \begin{cases} \alpha(t), i \in N(c, t) \\ 0, \text{si non} \end{cases} avec\alpha(t) \in [0, 1] \tag{9}$$

   The function h defines the magnitude of the correction made to the winner neuron c and its neighborhood. The neighborhood, at time t, of the winner neuron c is determined by the function $N(c, t)$ which is a decreasing function over time. The final neighborhood of a neuron consists of the neuron itself. The function $h(c, i, t)$ allows assigning the same correction $\alpha(t)$ to all the neurons belonging to the neighborhood of the winner neuron at time t.

3 Image Compression by the Proposed Approach

To compress the gray level image, we first apply a logarithmic quantization to the original image using Weber-Fechner law. Second, we apply a discrete wavelet transformation to the quantified image according to the decomposition level (j) and the type of wavelet. Then, we cut the three detail sub-images (LH, HL, and HH) in a block (BS) in a definite block width (e.g. 4×4, 8×8 or 16×16) by keeping the approximation sub-image (LL). Third, we look for the codebook for each block representing the code-word with the minimum distance from the block. The index of the selected word is added to the index vector, and then we encode this vector by Huffman coding [7, 8]. The last step is to save the index vectors coded in Huffman and the approximation sub-image representing the compressed image.

4 Experimental Study and Results

In our work, we compare two compression methods: the classic method and the new method using Weber-Fechner law. We change the compression parameters: the wavelet decomposition level (j), the size of the input block (BS) and the size of Self Organization map (SOM). To evaluate our new approach, we use three compression evaluation criteria: the compression ratio (CT), the means square error (MSE) and the Peak Signal to Noise Ratio (PSNR).

- The compression ratio gives a measurement of the performance of the compression methods of still images. Also, it is an evaluation criterion for the compression algorithms. The compression ratio is defined by:

$$TC = \left(1 - \frac{k'}{k}\right) * 100 \quad (10)$$

where TC: the compression ratio, k': the number of bits per pixel in the compressed image and k: the number of bits per pixel in the original image (k = 8 for the images in gray level).
- MSE (Means Square Error), in the context of the compression method with losses, can measure the quality of the reconstructed image with respect to the original image.

$$MSE = \frac{1}{m * n} \sum_{i=1}^{m} \sum_{j=1}^{n} (I(i,j) - J(i,j))^2 \quad (11)$$

where m and n represent the dimensions of the image, I and J stand for the original image as well as the reconstructed image.
- PSNR (Peak Signal to Noise Ratio) measures the signal to noise ratio. The signal represents the original image, whereas the noise represents the difference between the original image and the image reconstructed after compression.

$$PSNR = 10 * \log_{10}\left(\frac{(2^n - 1)^2}{MSE}\right) \quad (12)$$

The following tables correspond to the tests carried out on Einstein, House, Boat and Lena gray level images of the size 512*512 pixels (Fig. 7). We use the Haar wavelet transform because we show in [16] it is better for the reconstructed image quality by the comparison to other types of wavelets.

Einstein.bmp House.bmp Boat.bmp Lena.bmp

Fig. 7. Original Images.

By using the same compression parameters, the analysis of the Tables 1, 2, 3 and 4 show that the compression ratio (the number of bits per pixel) of the image compressed by the new approach is improved with respect to the former approach. In this work, we present a subjective comparison between the synthetic images compressed by the classic approach and our new approach which utilizes Weber-Fechner law. Both compressions are made at the same compression ratio.

Table 1. Experimental compression results of einstein image

Classic approach				Weber-Fechner approach				Parameters
Nbpp	CR(%)	MSE	PSNR	Nbpp	CR(%)	MSE	PSNR	
4.490	43.87	34.627	32.736	2.957	63.02	34.240	32.785	J = 1; BS = 2; SOM = 16
3.879	51.51	34.390	32.766	2.612	67.34	33.637	32.862	J = 1; BS = 2; SOM = 8
2.606	67.42	41.796	31.919	1.770	77.86	43.441	31.751	J = 1; BS = 4; SOM = 16
2.255	71.81	42.927	31.803	1.554	80.56	45.755	31.526	J = 1; BS = 4; SOM = 8
1.818	77.27	44.37	31.659	1.132	85.84	55.845	30.660	J = 1; BS = 4; SOM = 2
1.624	79.70	44.803	31.617	0.988	87.64	56.049	30.645	J = 1; BS = 16; SOM = 2
1.237	84.53	96.691	28.276	0.977	87.78	102.899	28.006	J = 2; BS = 4; SOM = 8
0.638	92.25	103.63	27.975	0.438	94.51	115.736	27.496	J = 2; BS = 8; SOM = 8
0.487	93.91	104.61	27.934	0.299	96.25	116.937	27.451	J = 2; BS = 16; SOM = 8
0.438	94.52	103.32	27.988	0.266	96.66	122.282	27.257	J = 2; BS = 16; SOM = 2
0.138	98.27	188.588	25.375	0.092	98.84	219.585	24.714	J = 3; BS = 16; SOM = 2

Table 2. Experimental compression results of house image

Classic approach				Weber-Fechner approach				Parameters
Nbpp	CR(%)	MSE	PSNR	Nbpp	CR(%)	MSE	PSNR	
4.396	45.05	95.531	28.329	2.592	67.59	96.560	28.282	J = 1; BS = 2; SOM = 16
3.716	53.55	100.827	28.095	2.251	71.861	98.822	28.182	J = 1; BS = 2; SOM = 8
2.607	67.41	111.318	27.665	1.707	78.66	119.358	27.362	J = 1; BS = 4; SOM = 16
2.284	71.45	112.99	27.600	1.447	81.90	123.361	27.219	J = 1; BS = 4; SOM = 8
1.826	77.17	115.71	27.497	1.069	86.63	139.326	26.690	J = 1; BS = 4; SOM = 2
1.667	79.16	116.372	27.472	0.954	88.07	144.335	26.537	J = 1; BS = 16; SOM = 2
1.188	85.15	295.88	23.419	0.852	89.34	297.751	23.392	J = 2; BS = 4; SOM = 8
0.642	91.97	327,871	22.974	0.427	94.65	336.749	22.857	J = 2; BS = 8; SOM = 8
0.495	93.81	345,151	22.751	0.307	96.15	344.926	22.753	J = 2; BS = 16; SOM = 8
0.448	94.40	367,421	22.479	0.276	96.55	363.384	22.527	J = 2; BS = 16; SOM = 2
0.141	98.23	528.691	20.898	0.094	98.81	654.78	19.969	J = 3; BS = 16; SOM = 2

Table 3. Experimental compression results of boat image

Classic approach				Weber-Fechner approach				Parameters
Nbpp	CR(%)	MSE	PSNR	Nbpp	CR(%)	MSE	PSNR	
4.864	32.20	71.972	29.559	3.161	60.47	67.74	29.822	J = 1; BS = 2; SOM = 16
4.025	49.68	76.681	29.283	2.777	65.28	72.495	29.527	J = 1; BS = 2; SOM = 8
2.703	66.21	87.312	28.720	2.043	74.46	92.124	28.487	J = 1; BS = 4; SOM = 16
2.374	70.32	88.727	28.650	1.687	78.90	97.617	28.235	J = 1; BS = 4; SOM = 8
1.964	75.45	92.864	28.452	1.182	85.21	125.068	27.159	J = 1; BS = 4; SOM = 2
1.742	78.22	93.392	28.427	1.099	86.25	113.826	27.568	J = 1; BS = 16; SOM = 2
1.252	84.35	222.975	24.648	1.057	86.78	241.295	24.305	J = 2; BS = 4; SOM = 8
0.666	91.67	233.746	24.443	0.496	93.79	268.219	23.845	J = 2; BS = 8; SOM = 8
0.517	93.53	235.984	24.402	0.352	95.59	269.455	23.825	J = 2; BS = 16; SOM = 8
0.468	94.15	232.396	24.468	0.312	96.08	278.112	23.688	J = 2; BS = 16; SOM = 2
0.144	98.20	418.641	21.912	0.105	98.67	492.372	21.207	J = 3; BS = 16; SOM = 2

Table 4. Experimental compression results of lena image

Classic approach				Weber-Fechner approach				Parameters
Nbpp	CR(%)	MSE	PSNR	Nbpp	CR(%)	MSE	PSNR	
4.755	40.56	34.60	32.739	2.763	65.45	34.885	32.704	J = 1; BS = 2; SOM = 16
3.958	50.52	36.902	32.460	2.399	70.008	37.253	32.419	J = 1; BS = 2; SOM = 8
2.673	66.58	43.062	31.789	1.790	77.616	46.277	31.477	J = 1; BS = 4; SOM = 16
2.312	71.11	44.289	31.667	1.494	81.32	48.185	31.301	J = 1; BS = 4; SOM = 8
1.892	76.35	46.754	31.432	1.062	86.71	54.738	30.747	J = 1; BS = 4; SOM = 2
1.677	79.03	47.458	31.367	0.937	88.28	56.842	30.584	J = 1; BS = 16; SOM = 2
1.258	84.27	129.087	27.022	0.915	88.55	135.757	26.803	J = 2; BS = 4; SOM = 8
0.657	91.77	135.75	26.803	0.444	94.44	155.445	26.215	J = 2; BS = 8; SOM = 8
0.507	93.66	138.216	26.725	0.308	96.149	156.748	26.178	J = 2; BS = 16; SOM = 8
0.464	94.21	137.228	26.756	0.273	96.58	162.486	26.022	J = 2; BS = 16; SOM = 2
0.151	98.11	289.429	23.515	0.097	98.77	340.524	22.809	J = 3; BS = 16; SOM = 2

The reconstructed images are compared with the original images in terms of PSNR according to the number of bits per pixel (Nbpp). Actually, Figs. 8, 9, 10 and 11 indicate that the visual quality metric (PSNR) of the compressed images of the approach using Weber-Fechner law (green curve) in terms of the compression ratio (Nbpp) improves with respect to the classic approach (blue curve). We notice that there is a significant improvement in the quality of the reconstructed image if the compression ratio is higher than 1 bits per pixel since the shape of the green curve (new approach) is going up for the four images. Also, there is a little improvement if the compression ratio is less than 0.5 bits per pixel. According to the four figures, we notice a significant drop in the image quality metric (30.6 to 28 for the image Instein, 26.5 to 23 for the image House and 27.5 to 23.3 for the image Boat) if the number of bits per pixel (NBPP) is between, approximately, 1 and 1.7 and the second drop if the NBPP is less than 0.5 for the reconstructed images. This significant degradation of the image quality is due to the change of the wavelet transform level to another level.

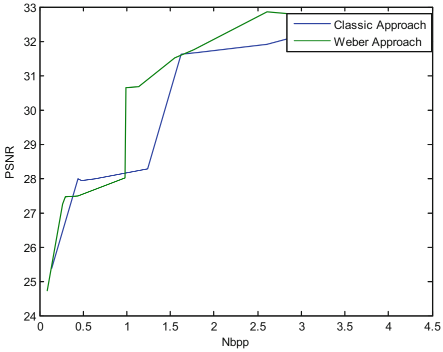

Fig. 8. PSNR = F(Nbpp) of Einstein image

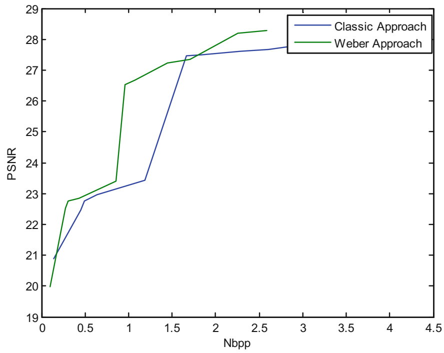

Fig. 9. PSNR = F(Nbpp) of house image

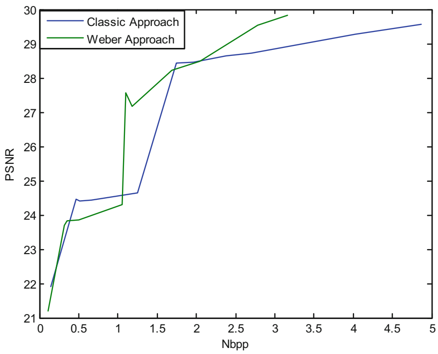

Fig. 10. PSNR = F(Nbpp) of boat image

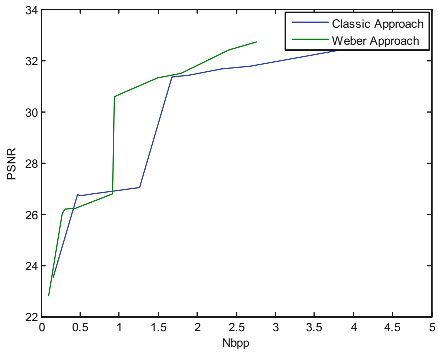

Fig. 11. PSNR = F(Nbpp) of lena image

5 Conclusion and Future Scope

In this paper, we have enhanced the compression quality of a still-image-compression approach based on the discrete wavelet transformation and neural networks by adding a new pre-treatment phase to quantify the signals of the original image through the use of the principle of Weber-Fechner law. We notice that the new approach is better than the classic approach in terms of quality according to the compression ratio feature if the number of bits per pixel is higher than 0.5. To boost our approach, we will quantify the original image in a semi-logarithmic manner by using the law of compression ‘A’ which is used in mobile telephone networks.

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