ADAPTIVE ALGORITHM FOR RESTORATION OF LOSSY COMPRESSED IMAGES

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ABSTRACT

This work deals with the restoration of lossy compressed image by the use of a metaheuristic which is the Particle Swarm Optimization Algorithm. This algorithm was designed and adopted by the introduction of the Search Efficiency Function for the blind restoration of blurred images and has given excellent results. So, in the present paper we try to apply it in the enhancement of lossy decompressed images, and this application constitutes the contribution of this work. Images used have been compressed by two different compression methods, fractal and JPEG, and with different compression rates. The experimental results obtained were excellent.

KEYWORDS: lossy compression; image restoration; particle swarm optimization; Search Efficiency Function.

1 INTRODUCTION

The image is a strong media that has a semantic content. It increasingly became a means of communication present in our full daily lives. It is also an essential tool in satellite and astronomical fields, film production, and industrial computing.

We can see that compression degrade the quality of image. It includes degradations such as blurring, blocking effect defined by the rise of intensities discontinuity between adjacent blocks and ringing which is the result off truncating the high frequency (HF) BDCT coefficients.

To ameliorate the image quality and alleviate or remove degradations introduced by high compression, some algorithms are proposed, in [1,2,4,5]. Degradations can be suppressed in transform domain (e.g. DCT overcomplete wavelet representation (OWR)), spatial domain [5], or the combinations. In [8] an algorithm of postprocessing based on the theory of projections onto convex sets to represent the prior information of the original image. Learning-based image restoration scheme is proposed in [7,11,12] by suppressing compression degradations and recovering high frequency components with the priors learned from a training set of natural images.

The aim of this paper is to restore compressed images using Particle Swarm Optimization algorithm. The restoration process is a deconvolution problem. And because of the use of the PSO algorithm, the restoration process becomes an optimization problem.

The rest of the paper is organized as follows:

In Section 2, we define the compression problem. In Section 3, we introduce our proposed restoration algorithm. Section 4 shows the experimental results obtained. Finally, Section 5 concludes our contribution and merits of this work.

2 IMAGE COMPRESSION

2.1 Coding

Image data compression is generally used to solve transmission problems. The aim of efficient coding is to reduce the required transmission rate for a given picture quality. Coding is usually performed in two steps [1]:

First one is the elimination of redundancies, where the picture quality is conserved but the compression rate is generally low. And the second is coding with controlled loss of information, where the compression rate can reach high values but the picture quality is reduced.

2.2 Lossy or lossless compression

The Image compression may be lossy or lossless. Lossless compression is preferred for archival purposes and often for medical imaging, technical drawings, clip art, or comics. Lossy compression methods, especially when used at low bit rates, introduce compression artifacts. Lossy methods are especially suitable for natural images such as photographs in applications where minor (sometimes imperceptible) loss of fidelity is acceptable to achieve a substantial reduction in bit rate. The lossy compression that produces imperceptible differences may be called visually lossless.

2.3 Compression using transforms

Compression methods using transforms [1] are particularly efficient and allow high compression rates by transmitting only a few coefficients of the transformed image. Among them, the 2-D Discrete Cosine Transform (2-D DCT) [1] is widely used because of its efficiency and its ability to decorrelate the information, also its ease of implementation.

The attention, in our work, focused on two lossy techniques: JPEG and fractal compression.

JPEG is designed for compressing full-color or gray-scale images of natural, real-world scenes. To exploit this method, an image is first partitioned into non overlapped 8×8 blocks. A discrete Cosine transform (DCT) is applied to each block to convert the gray levels of pixels in the spatial domain into coefficients in the frequency domain. The coefficients are normalized by different scales according to the quantization table provided by the JPEG standard conducted by some psycho visual evidence. The quantized coefficients are rearranged in a zigzag scan order to be further compressed by an efficient lossless coding strategy such as run length coding, arithmetic coding, or Huffman coding. The decoding is simply the inverse process of encoding.

JPEG-2000 is based upon a wavelet decomposition of the original image, with up to 5 wavelet decomposition levels. Each resulting sub-band is then divided into rectangular code-blocks, and each code-block is independently coded by an arithmetic codec using progressive bit planes. The bit stream is created by using a sophisticated distortion minimization algorithm called EBCOT which gives, for each layer (bit plane), the optimum contribution of each code block.

A fractal compression algorithm first partitions an image into non overlapping 8×8 blocks, called range blocks and forms a domain pool containing all of possibly overlapped 16×16 blocks, associated with 8 isometrics from reflections and rotations, called domain blocks. For each range block, it exhaustively searches, in a domain pool, for a best matched domain block with the minimum square error after a contractive afine transform is applied to the domain=bloc. A fractal compressed code for a range block consists of quantized contractively coefficients in the affine transform, an offset which is the mean of pixel gray levels in the range block, the position of the best matched domain block and its type of isometry. The decoding is to find the fixed point, the decoded image, by starting with any initial image. The procedure applies a compressed local afine transform on the domain block corresponding to the position of a range block until all of the decoded range blocks are obtained. The procedure is repeated iteratively until it converges (usually in no more than 8 iterations). Two serious problems that occur in fractal encoding are the computational demands and the existence problem of best range-domain matches. The most attractive property is the resolution-independent decoding property.

The quality of a compression method often is measured by the Peak signal-to-noise ratio (PSNR). It measures the amount of noise introduced through a lossy compression of the image, however, the subjective judgment of the viewer also is regarded as an important measure, perhaps, being the most important measure.

In this paper we deal with the lossy compression and we try to ameliorate the quality of the image by the application of our restoration algorithm.

3 PROPOSED RESTORATION METHOD

The proposed restoration method is based on Particle Swarm Optimization (PSO) as an adaptive metaheuristic.

3.1 Particle Swarm Optimization

Particle Swarm Optimization is an evolutionary tool which uses a population of candidate solutions to develop an optimal solution of a problem. The degree of optimality is measured by a fitness function defined by the user [3] and [6]. This paradigm has born in 1995 in the United States. The PSO, which has roots in artificial life and social psychology as well as engineering and computer science, differs from evolutionary computation methods in that the population members called particles which are scattered in the space of the problem [6]. The behavior of the swarm is described from a particle view angle [6]. At first, the swarm is shared out in the search space; each particle has a random velocity. Then, at any time step, each particle is able to evaluate the quality of its position and take in memory its best performance, yi equation (1) , i.e. the best position it has reached until now and its quality. It is able to question a certain number of its own kind and get from each one of them its own best performance. It chooses the best of the best performances it knows, $\hat{y}_i$ equation (2), modifies its velocity according to this information and to its own data and it moves consequently, equations (3) and (4). The search strategy of algorithms based on population as the PSO is constituted of two phases, exploration and exploitation. The first is responsible of the detection of the more promising areas in the search space, the second permit to promote the convergence of the particles toward the best detected solution [3]. The PSO can be arranged under the class of iterative methods as well as within the stochastic techniques.

Each particle in the swarm is represented by the followed characteristics [3] and [6]:

x_i: The current position of the particle i.

v_i: The current velocity of the particle i.

The update of the personal best position of a particle is as follows:

$$y_i(t+1) = \begin{cases} y_i(t) & si \quad f(x_i(t+1)) \geq f(y_i(t)) \\ x_i(t+1) & si \quad f(x_i(t+1)) < f(y_i(t)) \end{cases} \tag{1}$$

The position of the global best particle is given by:

$$\hat{y}(t) \in \{y_0, y_1, ..., y_s\} = \min\{f(y_0(t)), f(y_1(t)), ..., f(y_s(t))\} \tag{2}$$

S: denotes the size of the swarm.

The velocity of the particle is updated by:

$$v_{ij}(t+1) = wv_{ij}(t) + r_1c_1(y_{i,j}(t) - x_{ij}(t)) \; r_2c_2(\hat{y}_j(t) - x_{ij}(t)) \tag{3}$$

Where: w is the inertia weight

c_1 and c_2 are acceleration constants

r_1 and r_2 are uniformly distributed variables.

j=1: D, where D: the dimension of the search space of the considered problem.

The position of the particle i is updated by the equation:

$$x_{ij}(t+1) = x_{ij}(t) + v_{ij}(t+1) \tag{4}$$

The equation (3) is the velocity vector which drives the search process and reflects the "sociability" of particles.unavoidable.

3.2 Search Efficiency Function

The scale free movement patterns of some individuals, independent, foragers have aroused considerable interest because such patterns are known to constitute an optimal searching strategy when target sites are randomly and sparsely distributed [10]. A Search Efficiency Function (SEF) $\eta(\mu)$ was defined by [10] to be reciprocal of the mean distance travelled by a searcher before detection of a target site:

$$\eta(\mu)=L / Nl\langle l\rangle \tag{5}$$

Where $\langle l\rangle$ is the mean length of a flight- line segment and N_l is the mean number of straight- line segments traversed before arrival at a target site. The distance between successive targets is approximated by the mean distance between successive targets, λ,

$$\langle l\rangle = [(\mu-1)/(2-\mu)][(\lambda^{2-\mu} - r^{2-\mu})/ r^{2-\mu}] + \lambda^{2-\mu}/ r^{1-\mu} \tag{6}$$

This aspect of searching is captured by optimal Lévy-flights searching strategies. The search started from an arbitrary point, x0 in the interval [-λ/2, λ/2], the average number of straight- line flight- segments traversed before first reaching a target is:

$$Nl=(1/2K)[\,[(x_0+L)\,(L-x_0)/\,r^2]^{(\mu-1)/2} \tag{7}$$

Where $L=\lambda/2$ and K is the diffusivity. The searching efficiency is dependent upon the initial location of the searcher.

3.3 Proposed Method

In a previous work we have used the PSO, this powerful optimization tool, in image restoration [13] which was converted on an optimization problem. It has given good results. Due to these results, we tried to use this tool in blind image restoration, since, in most of cases information about the degradation process are limited or unknown.

In this case we used the SEF (5) as cost function [14], where there is no need of information about the degradation and tried to find the solution. This solution constitutes, in our case, the restored image. The procedure is as follows:

The proposed algorithm [14]

1. We introduced the decompressed image into the algorithm as initial solution;
2. Generate a population of similar images;
3. Fitness evaluation: SEF as cost function;
   - N_l computing from (7)
   - $\langle l\rangle$ computing from (6)
   - $\eta(\mu)$ computing from (5)
4. When the maximum of (5) is reached we got the optimum solution;
   - get the personal best of each particle (image)
   - deduce the global best of the swarm
5. Repeat steps : 2 and 3 until maximum iteration is reached

6. Restored image is obtained.

4 RESULTS AND DISCUSSION

To test the behavior of this algorithm we have used Lena image (256X256) as test image, Fig. 1. To evaluate the performances of our algorithm we have choose the use of PSNR metric in dB.

$$PSNR = 10 log_{10} (255^2/MSE) \quad (8)$$

Where, MSE is the Mean Square Error between the original image and the restored image.

Figure 01: Test Image: Lena

The decompressed images are obtained by fractal and JPEG for different compression rates values (CR). Then they were treated by our algorithm. Some resulting images are presented in Fig. 2 and Fig. 3.


CR= 0.06


(a) CR= 0.75 (b)

Figure 02: FIC Images: a. Decompressed, b. Restored


CR= 0.1


(a) CR= 0.70 (b)

Figure 03: JPEG Images: a. Decompressed, b. Restored

Tables 1 and 2 summarize the PSNR results of enhanced images according to different values of compression rates with both compression methods.

Where DI is the decompressed image and RI is the restored image.

Table 01: PSNR results in dB of JPEG images

Results	PSNR values in dB		
	Compression ratio values	**PSNR of DI**	**PSNR of RI**
	0.10	20.09	25.0350
	0.20	23.5	30.2695
	0.30	27.1	41.5092
	0.40	29.4	43.5497
	0.50	30.7	44.4491
	0.60	32.2	46.5173
	0.70	32.6	48.7055
	0.90	33.2	51.4707

Table 02: PSNR results in dB of fractal (FIC) images

Res ults	PSNR values in dB		
	Compression ratio values	**PSNR of DI**	**PSNR of RI**
	0.06	20.4	28.2023
	0.19	23.6	34.0353
	0.27	24.9	44.8160
	0.36	25.1	45.6906
	0.41	25.2	54.0387
	0.56	28.2	60.1852
	0.75	29.8	65.9205
	0.82	30.1	68.6403
	0.95	30.5	80.3246

The variation of PSNR of restored images upon compression ratio is presented in Fig. 4.

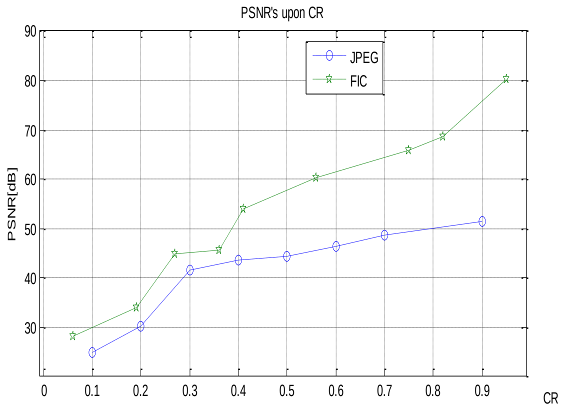

Figure 04: PSNR variation of restored images upon CR

The objective quality of image restoration is evaluated by the Peak Signal-to-Noise Ratio (PSNR). The higher the PSNR is, the smaller the difference between the restored image and the original image is and better are the results.

Fig. 2 and Fig. 3 visualize the amelioration in the images quality, and tables 1 and 2 shows the high values of PSNR obtained by our algorithm. The results we got demonstrated the efficiencies of the proposed method. It can be observed that this proposed algorithm can help to improve the image quality in terms of PSNR, curves in Fig. 4 shows that our algorithm has performed better with fractal images than the JPEG ones. Meanwhile the proposed method can generate images with better visual qualities.

Results obtained qualify this algorithm as one of the best in solving restoration problems whatever the state of the concerned image.

5 CONCLUSION

We have proposed an evolutionary method based on Particle Swarm Optimization (PSO) algorithm for a blind restoration of lossy compressed images. Since the compression operation is important in information communication, the compressed image has artifacts that influence on the quality communication. Our method has been applied on images compressed by two different methods, and according to PSNR results obtained; we can say that our algorithm is adaptable whatever the artifact is. Also, the results obtained have been compared to other methods [2, 8], and they showed better results.

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