International Journal of Computational Engineering Research (IJCER) ISSN: 2250-3005
National Conference on Architecture, Software system and Green computing

A New Image Compression Scheme with Wavelet Packets for Best Basis Selection Using Improved Pso

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Abstract

This project presents a new image compression scheme with wavelet packets for best basis selection using PSO and improved PSO. The PSO is utilized to find out the best wavelet packet basis for image compression. Wavelet packet transform provides a more precise analysis to image, which not only decomposes the low frequency components but also decomposes high frequency components. The wavelet packet-based library contains a number of wavelet packet basis .If we choose different wavelet packet , we will get different image features and achieve different compression effect. In this project, we propose a modified PSO structure for best basis image wavelet packet selection to achieve max PSNR and Compression Ratio.

We are employing two parallel PSO prediction structure to initially find best optimal Partition pattern size and Best Threshold Finding in second Step of Prediction. Compared with the existing PSO method compression algorithm implemented in MATLAB software, the novel method manages to find out the best wavelet packet basis and achieves better compression capability. The PSO can automatically access and accumulate the information in the search space and adaptively control the search process to gain the global optimal solution. PSO is simple and has fast optimization ability. To facilitate the implementation of PSO in image compression ,a fitness function is designed in terms of Mean Square Error(MSE) and sum of all the all the entropy values of the node(ESUM) which obtained from PSO optimal wavelet packet coefficients.

I. Introduction

In recent years wavelet image compression technology has become a hot research topic. In the wavelet transform, we can move high frequency components and reserve the low-frequency coefficients to compress image because most signal energy is concentrating in low frequency sub-band. However, to some images with rich detail texture, wavelet transform cannot be well described their frequency characteristics. Wavelet packet transform provides a more precise analysis to image which not only decomposes the low frequency components but also decomposes high frequency components. As we know wavelet packet-based library contains a number of wavelet packet basis. If we choose different wavelet packet we will get different image features and achieve different compression effect.

II. Wavelet Packet Decomposition

The wavelet transform is actually a subset of a far more versatile transform, the wavelet packet transform .Wavelet packets are particular linear combinations of wavelets. They form bases which retain many of the orthogonality, smoothness, and localization properties of their parent wavelets. The coefficients in the linear combinations are computed by a recursive algorithm making each newly computed wavelet packet coefficient sequence the root of its own analysis tree. Wavelet packet decomposition (WPD) (sometimes known as just wavelet packets) is a wavelet transform where the signal is passed through more filters than the discrete wavelet transform (DWT).

From the point of view of compression, the standard wavelet transform may not produce the best result, since it is limited to wavelet bases that increase by a power of two towards the low frequencies. It could be that another combination of bases produce a more desirable representation for a particular signal. The best basis algorithm by Coifman and Wickerhauser finds a set of bases that provide the most desirable representation of the data relative to a particular cost function (e.g. entropy). The wavelet decomposes the image, and generates four different horizontal frequencies and vertical frequencies outputs. These outputs are referred as approximation, horizontal detail, vertical detail, and diagonal detail. The approximation contains low frequency horizontal and vertical components of the image. The decomposition procedure is repeated on the approximation sub-band to generate the next level of the decomposition, and so on. It is leading to well known pyramidal decomposition tree. Wavelet packets are better able to represent the high frequency Information. Wavelet packets represent a generalization of Multiresolution decomposition. In the wavelet packets decomposition, the recursive procedure is applied to the coarse scale approximation along with horizontal detail, vertical detail, and diagonal detail, which leads to a complete binary tree. After wavelet packet decomposition, the image will produce a complete tree. Wavelet packet decomposition will have various forms because of the wavelet packet library including a number of wavelet packet components.

LL_1LL_2	LL_1HL_2	HL_1LL_2	HL_1HL_2
LL_1LH_2	LL_1HH_2	HL_1LH_2	HL_1HH_2
LH_1LL_2	LH_1LH_2	HH_1LL_2	HH_1HL_2
LH_1LH_2	LH_1HH_2	HH_1LH_2	HH_1HH_2

Fig1 The structure of two level decomposition of wavelet packet

Therefore, selecting the appropriate wavelet packet will achieve better results for a given image. we use PSO to optimize high frequency coefficients generating by the complete wavelet packet decomposed and compress the image using the gained best wavelet packet basis.

III. Particle Swarm Optimization

Particle swarm optimization (PSO) is a computational method that optimizes a problem by iteratively trying to improve a candidate solution with regard to a given measure of quality. PSO optimizes a problem by having a population of candidate solutions, here dubbed particles, and moving these particles around in the search-space according to simple mathematical formulae over the particle's position and velocity. Each particle's movement is influenced by its local best known position and is also guided toward the best known positions in the search-space, which are updated as better positions are found by other particles. This is expected to move the swarm toward the best solutions.PSO is a powerful optimization tool. It is a stochastic algorithm and the PSO operation itself is complicated and difficult to understand. The performance of a PSO based search can be changed by varying the values of the PSO parameters, inertia weight '*w*', cognitive and social acceleration constants '*c1*' and '*c2*' respectively, thereby giving it the flexibility to optimize its own performance.

Figure gives the vector representation of the PSO search space. In figure , *Vpd* and *Vld* represent the effect of '*Pbest*' and '*Gbest*' on the individual. The basic PSO velocity and position update equations are given below.

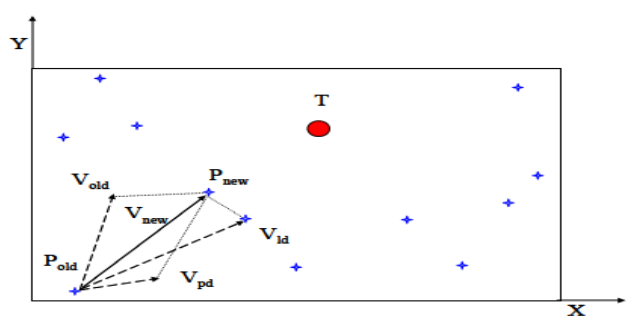


Fig .2 Vector representation of PSO (T is the target)

$$V_{new} = w \times V_{old} + c_1 \times rand \times (P_{best} - P_{old})$$
$$+ c_2 \times rand \times (G_{best} - P_{old})$$

$$P_{new} = P_{old} + V_{new}$$

V_{new} is new velocity calculated for each particle

V_{old} is Velocity of the particle from the previous iteration

P_{new} is New position calculated for each particle
P_{old} is Position of the particle from the previous iteration
w is Inertia weight constant
C_1 & C_2 is Cognitive and social acceleration constants
rand Generates a random value in the range [0 1]

In the particle swarm optimization algorithm, we assume the problem in an D-dimensional space, which including many particles. Each particle represents a feasible solution of Optimization problems. on every iteration each particle update itself by two extreme value, one is Individual extreme value pbest ,the other is global optimal value gbest. Each particle adjusts its flight speed and direction according to current rate, pbest and gbest using formula

$$v_{id}(t+1) = w^* v_{id}(t) + c_1 * r_1 * (pb_{id}(t) - x_{id}(t))$$
$$+ c_2 * r_2 * (gb(t) - x_{id}(t))$$
$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1)$$

Where i=1,2,....m; d=1,2,.....D; r_1,r_2 is the random number on the range **[0,1],** t is iteration, c_1, c_2 are learning factors which control the particle's effect by own best position and and group best position respectively. The formula for the flight speed consists of three part, the first part is a momentum part which is effected by the particle current state; the second part is the individual cognitive part, which adjusts particles flying to their own best position; the 2third part is the community part which guides the particles flying to their group best position. The balance among three parts determines the PSO's searching ability

IV. Pso Based Best Basis Selection

We know after three degree complete wavelet packet decomposition, the image will get four layer coefficients. The 0^{th} layer is original image, the first layer has3 high-frequency coefficients, the second layer has 3+3*4=15 high frequency Coefficients, and the third layer has 3+3*4+3*4*4=63 high frequency coefficients. We select high frequency components based on PSO to get the best wavelet packet basis and compress image with it.

We define the second layer high-frequency coefficients node number 15 as the Problem dimension, through optimizing second layer node to determine which node on the first and third layer should be cut, so we get the best wavelet packet Basis to image compression. We take a random values in each dimension with 0 & 1, if the node value is 1, the node will be decomposed on the next layer otherwise it will not be decomposed on next layer, so we get third layer decomposed high frequency Node coefficients The Mean Square Error is used to evaluate the image compression quality. The Smaller MSE is, the smaller image is distorted. In information theory Entropy can measure information laws, the information regularity is strong when Entropy is small. In order to find best wavelet packet basis, we adopt the Minimum Entropy. We calculate the sum of all the entropy values of the node(ESUM) obtained from PSO Optimal wavelet packet coefficients according to the above encoding rule.

We design a fitness function for the PSO which take into consideration both MSE & ESUM. In the particle optimization process, the fitness function values are in descending order and the minimum is the global optimum value.

$$fitness = \alpha_1 \times MSE + \alpha_2 \times ESUM$$

$$MSE = \frac{1}{M \times N} \sum_{m=0}^{M-1} \sum_{n=0}^{N-1} (X(m,n) - \hat{X}(m,n))^2$$

Where α_1, α_2 are unitary coefficients. $M \times N$ is the size of the image. X(m,n) and $\hat{X}$(m,n) are pixel gray value of the original image and compression image respectively. In order to evaluate the performance of the proposed method, we select some images with rich details. The proposed the best wavelet packet compression algorithm based on PSO is compared with global threshold best wavelet packet compression algorithm using different wavelet packet function in three degree wavelet packet decomposition

Pso Based Best Basis Algorithm

We describe the detail steps of the best wavelet packet basis image compression algorithm based on PSO as following:

STEP1: Initialise Random wavelet Packets partition Size.

STEP2: Apply wavelet packets partitions into the image and segment into interclass sectors.

STEP3: Each sector holds an index and update it as local best1 and the Threshold Process will begin.

STEP4: With the Updated Partition size, initialize random soft Threshold value for each sectored index.

STEP5: Encode the Image sectors with the corresponding assigned Thresholds and reconstruct it using Reverse decoding scheme.

STEP6: Update the Threshold and compression value as local best.

STEP7: Compare these local best Thresholds and update it as Global best if it is better than the Existing Global best.

STEP8: Repeat these steps until Max Threshold iterations are reached.

STEP9: Memorize the Partition sector and Threshold values and their corresponding MSE and entropy. If it is not satisfied with fitness criterion then Transfer the control for assigning different Partition size (step 1).

STEP10: The exploration process continues until the Fitness or iteration time is Met.

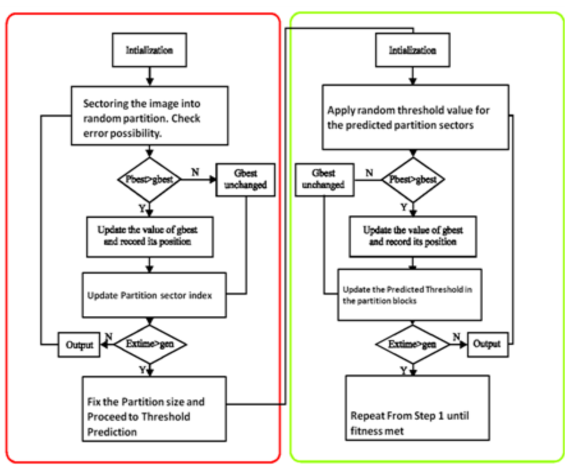
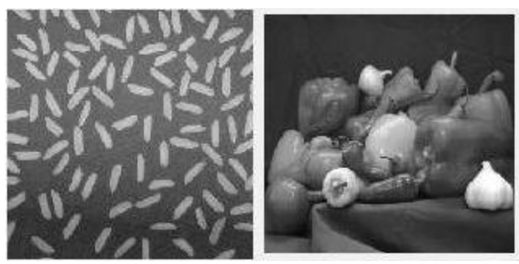


Fig 3 Operational Flow Chart

V. EXPERIMENTAL RESULTS

Original image

Without improved PSO



With improved PSO

PSNR without improved PSO	PSNR with improved PSO	Encoding Time	Decoding Time
32.5174	37.7218	0.583446	0.255903
27.6927	32.9456	0.498332	0.132234
23.3171	28.6053	0.493268	0.089798
18.1956	23.6283	0.486027	0.066927
14.9800	19.3778	0.482788	0.059175
11.0256	16.143	0.495149	0.053215

TABLE 1 Rice Image

PSNR without improved PSO	PSNR with improved PSO	Encoding Time	Decoding Time
26.2582	31.8301	0.525043	0.171721
21.9823	26.9904	0.508682	0.110406
17.5032	22.5632	0.481330	0.077673
15.3204	20.0389	0.480546	0.060484
14.4283	17.0694	0.488969	0.061795

TABLE 2 Pepper Image

In order to evaluate the performance of the proposed method we have selected some images with rich details. We can see from the experimental results & visual effects, the proposed method provide better results then existing methods.

VI. Conclusion and Future Work

In this paper we have proposed a modified PSO algorithm to improve the performance of PSO to select the best wavelet packet basis. The PSNR values of the compressed image obtained from proposed method are better then existing PSO method.

The PSO is used to choose the best wavelet packet basis. To facilitate the the implementation of PSO in image compression, a fitness function is designed in terms of MSE and sum of node entropy. Different wavelet packet functions or different threshold have different impact in image compression.

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