A Multi-objective Particle Swarm Optimization in Video coding technique

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***Abstract*— In video transmission and storage applications Video coding plays an important role. Today's increasing order of multimedia applications led to a lot of research works in video coding technique. In such a way that high compression ratio is obtained with the available bandwidth. The image compression using Wavelet has witnessed great success in the past decade. Motion compensation using Wavelet transform video codec performs best compression in order to meet the rate and distortion constraint in video transmission than the block based techniques. The directional features of images does not represent efficiently by the 2D DWT. Many efforts have been put in to multi-scale directional representation. In this paper, video coding using directional transform DDWT is considered .The Directional transform DDWT expansive nature is decreased by using noise shaping algorithm. By the selection of optimal coefficients of DDWT using Multi Objective Particle Swarm Optimization (MOPSO) technique the highest compression ratio is obtained. The objective functions in this video coding technique of Computation Time , Mean square error and Entropy are taken for optimization with the constraints of bits per pixel and frame rate. The standard 3D SPIHT coding is compared with the proposed method performance**

Index Terms— Dual tree Discrete Wavelet transform, Noise shaping, Multi Objective Particle swarm optimization, Mean Square Error.

I. INTRODUCTION

The transmission and storage of the video signals are not possible without compression because video information of one second requires more megabytes of memory. The available bandwidth is not sufficient for modern multimedia applications. So a lot of research works are going on compression algorithms for video coding. At high compression ratios block based coders introduce ringing effects and artifact. The wavelet based motion compensated technique on 2D+t transform for video coding, the complex motion estimation and compensation is a complicated process. So the new 3D-Wavelet based coding technique proposed. Wavelet based motion compensated video coders are recently developed. Gang Ling et al [1] and Lazer D. et al [2] used 3D temporal wavelet transforms for effective video compression. Authors showed that 3D wavelet transforms without motion compensation provides good compression performance than the motion compensated predictive technique. The popular encoding techniques such as SPIHT [3] and EZW [4] and combined with 3D wavelet results, good quality of compression. These coders provide both spatial scalability and temporal as in [5]. Continuous rate scalable application method can prove valuable in scenarios where the channel is unable to provide a constant bandwidth. Rather than terminating the session, a decoder can adjust the bit rate to use the limited resources, yet produce video of acceptable quality. Such decoders are particularly attractive because of their flexibility. Scalable video coding has the capability of reconstructing lower resolution signals from partial bit streams. J.R.Ohm had proved that motion compensated temporal wavelet coding eliminates the encoder drift problem in scalable video coding [6]. Ivan et al. [7] showed the limitations of discrete wavelet transform for multi dimensional signals such as aliasing, oscillatory nature of coefficients and lack of directionality. Dual Tree Discrete wavelet (DDWT) Transform is much suitable for video coding with the kernel functions having the capability of directional property, compensation and eliminating motion estimation process. Wang et al. showed on the suitability of Dual tree Discrete Wavelet Transform for video coding [8], [9]. Ivan et al applications of DDWT in denoising [10].

Dual tree discrete wavelet transform is a detailed type transform. Because it converts K number of samples into L number of coefficients. ($K < L$).The number of coefficients is reduced because of noise shaping algorithm [11].The significant coefficients are selected because of Multi objective optimization algorithm using PSO. Shanmugalakshmi and Thamarai reported the usage of 3-D dual tree wavelet transform with Particle swarm optimization in video coding with single objective in [12]. In [12], the single objective function of maximizing PSNR value is considered. The optimum subbands are selected using Particle swarm Optimization algorithm to improve the PSNR value with the constraints of different bitrates.

The problem of Optimizing with single objective often gives to unacceptable results with respect to the other objectives. So a suitable multi objective solution that simultaneously optimizes every objective function is almost impossible. The One solution for this multi objective problem is finding a set of solutions that satisfies all the objectives in an acceptable level. At the same time it does not dominate by any other solution. In this paper, video coding is formulated as a multi objective problem and the objective factors are identified such as Computation time, Entropy and MSE,

The video sequence is decomposed by 3-D dual-tree real discrete wavelet transform. Noise edging method is used to select the important coefficients from the vast DDWT coefficients. Because of the multi objective PSO algorithm [MOPSO], the dual tree subband coefficients with high energy content are identified. The identified subband coefficients in each plane are encoded by using EZW algorithm technique. This paper is framed as follows: Section II illustrates the PSO and multi objective PSO. Video coding process using multi objective PSO is explained in section III, In section IV shows the experimental results. Conclusion is summarized in section V.

II. PARTICLE SWARM OPTIMIZATION [PSO]

Particle Swarm Optimization (PSO) is a global optimization technique based on swarm intelligence. It simulates the behavior of bird flocking [13]. It is widely accepted and focused by researchers due to its profound intelligence and simple structure. Currently PSO has been implemented in a wide range of research areas such as functional optimization, pattern recognition, neural network training and fuzzy system control etc., and is successful. In PSO, each potential solution is considered as one particle. The system is initialized with a population of random solutions (particles)and searches for optima (global best particle), according to some fitness function, by updating particles over generations; that is, particles “fly” through the N-dimensional problem search space to find the best solution by following the current better-performing particle. When compared to Genetic Algorithm, PSO has very few parameters to adjust and easy to implement. The variants of PSO’s such as Binary PSO, Hybrid PSO, Adaptive PSO and Dissipative PSO are used in various image processing applications.

For binary PSO [14], particle position represents position in binary space. Hybrid PSO combines the basic mechanism of PSO and the natural selection mechanism, which is usually utilized by Evolutionary Computation methods such as GAs.

Around 10% of PSO applications are devoted to image and video analysis applications. Image analysis applications include iris recognition, fruit quality grading, face detection and recognition, image segmentation, synthetic aperture radar imaging, Image fusion and Image registration etc., Video application includes MPEG optimization, motion estimation, object tracking, body posture tracking and traffic incident detection.

. Benjamin D. defined sparse signal recovery using PSO for Image compression [15]. Images are compressed with compressive sampling and then reconstructed with PSO techniques. Several enhancements to the basic PSO algorithm are discussed to improve signal recovery accuracy. Fractal image compression is one of the image compression techniques in the spatial domain but it involves more computational time due to global search. In order to reduce the computational time and acceptable quality of the decoded image in this technique, PSO algorithm is proposed [16].

Recently PSO has been extended to deal with multiple objective optimization problems [17]. The fixed population size MOPSO and variable population size PSO (Dynamic PSO) are used throughout the evolution process to explore the search space to discover the non dominated individuals (particles).

In PSO, we assume that the problem is in a D-dimensional space, which includes many particles; each particle represents a feasible solution of optimization problem. On every iteration, each particle updates itself by the two extreme values, one is individual extreme value pbest, which is personal best value for that particle p_{id}, and the other is the global best value for that particle (gbest) p_{gd}. Each particle adjusts its flight speed and direction according to current rate, pbest and gbest using Eq.1 and Eq. 2 repeatedly.

$$v_{id}(t+1) = wv_{id}(t) + c_1 rand_1(.)(p_{id} - x_{id}) + c_2 rand_2(.)(p_{gd} - x_{id}) \quad (1)$$

$$x_{id}(t+1) = x_{id}(t) + v_{id}(t+1), 1 \le i \le N, 1 \le d \le D \quad (2)$$

Where N is the number of particles and D is the dimensionality; $V_i = (v_{i1}, v_{i2}, \ldots, v_{iD}), v_{id}\ \varepsilon\ [-v_{\min}, v_{\max}]$ is the velocity vector of particle i, which decides the particle’s displacement in each iteration. Similarly, X_i = (x_{i1}, x_{i2}, … , x_{iD}), $x_{id}\ \varepsilon\ [-x_{\min}, x_{\max}]$ is the position vector of particle i which is a potential solution in the solution space.

The quality of the solution is measured by a fitness function; w is the inertia weight which decreases linearly during a run; c_1, c_2 are both positive constants, called the acceleration factors which are generally set to 2.0; $rand_1$ (.) and $rand_2$ (.) are two independent random number distributed uniformly over the range [0, 1]; and p_{gd}, p_{id} are the best solutions discovered so far by the particle in the group and itself respectively.

$v_{id}(t+1)$ -velocity of the particle at time (t+1) and

$x_{id}(t+1)$ -position of the particle at (t+1)

In Eq. 1, the first part is momentum which is effect of the current state of the particle; the second part is the individual cognitive part which adjusts particle’s flight to its own positions; the third part is the community part which guides the particle’s flight to the group’s best position. The balance between the three parts determines the PSO’s searching ability.

PSO as developed by the authors comprises a very simple concept, and it can be implemented in a few lines of computer code. It requires only primitive mathematical operators and is computationally inexpensive in terms of both memory requirements and speed.

Basic Concepts of Multi Objective Optimization

Most of the problems in the real world are multi objective in nature and may have multiple optimum olutions for different objectives.

Eckart Zitzler and Macro Laumanns [18] define the general Multi-Objective Optimization Problem as follows

Def. 1: Find the vector

$$\vec{x}^* = \left[x_1^*, x_2^*......, x_n^*\right]^T \quad \text{(Solution)} \tag{3}$$

which satisfies the p inequality constraints:

$$g_i(\vec{x}) \leq 0 \qquad i = 1,2,..., p \tag{4}$$

and the q equality constraints:

$$h_i(\vec{x}) = 0 \quad i = 1,2,..., q \tag{5}$$

and optimizes the vector function:

$$\vec{f}(\vec{x}) = [f_1(\vec{x}), f_2(\vec{x}),..., f_l(\vec{x})]^T \tag{6}$$

The constraints given by equations.4 and 5 define the feasible region Ω (solution region) and any point in Ω defines a feasible solution. The l components of the vector $\vec{f}(\vec{x})$ are the criteria to be considered. The constrains $\vec{g}_i(\vec{x})$ and $\vec{h}_i(\vec{x})$ represent the restrictions imposed on the decision variables. The vector $\vec{x}^*$ denotes the optimum solution. When there are several objective functions, the concept of optimum changes lead to "trade-off" solutions rather than a single solution.

Multi Objective PSO

Solving Multi objective optimization problems using PSO is discussed in [19]. PSO is particularly suitable for multi objective optimization because of high speed of convergence. Abdullak et al. reported the usage of Genetic Algorithm for multi objective problems [20]. PSO is tried for multi objective optimization in two approaches (single objective and multi objective) in [21]. The multi objective PSO is used for Image segmentation [22] and filter bank design [23] optimization problems.

In order to handle multiple objectives, PSO must be modified before being applied to MO problems. In most approaches, the major modifications involve the selection kprocess of global best and personal best. Cello et al [24] developed a grid based global best selection process and employed a second population to store the non dominated solutions. From the second population, using Roulette wheel selection, the global best is selected randomly. The personal best is selected according to the Pareto dominance.

In Vector evaluated particle swarm optimization VEPSO, n no. of swarms are used to solve n number of objectives. In VEPSO algorithm, when one swarm updates the velocities of the particle, the other swarm is used to find the best particle to follow. In vector evaluated Genetic algorithm - non pareto approach, fractions of the next generation or sub populations are selected from the old generation according to the objectives separately. After shuffling all the sub populations together, cross over and mutation are applied to generate new populations. In the proposed work, the weighted aggregate approach is used to find the optimal subbands of the DDWT. The fitness function of the MOPSO combines the MSE, ESUM-Entropy of the various subbands and Computation time as objective functions with different weightage values.

III. MULTI OBJECTIVE PSO VIDEO CODING

At the expense of less number of bits, the video sequence may be transmitted and reconstructed with good quality. The input video sequence is decomposed using dual tree discrete wavelet transform (DDWT). The DDWT coefficients are reduced to desired numbers using noise shaping process. The coefficients after noise shaping are subjected to MOPSO block, where the optimal number of sub bands are selected based on objective functions. The selected subbands are encoded using EZW algorithm and the parameters PSNR, Computation time are measured for different frame rates and bits/pixel values. The block diagram of the proposed system is shown in **Fig.1**.

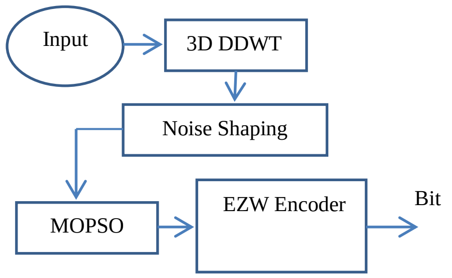

Fig.1 Block diagram of the proposed video coding system

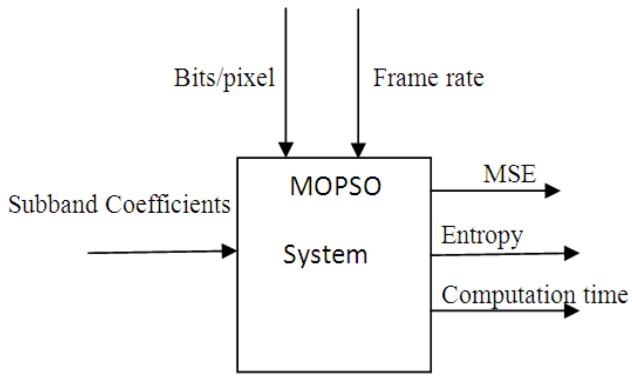

Fig.2 MOPSO block in the proposed system

MOPSO Problem Formulation

Fig.2 shows the video coding multi objective problem formulation. The objective functions are Mean Square Error

(MSE), Computation Time and Entropy of the subbands (ESUM)). All the three are minimization functions. The fixed population size MOPSO is used throughout the evolution process to explore the search space to discover the non dominated individuals (particles). Here the constraints are frame rate and bits per pixel. The bits/pixel values are taken as 0.3, 0.5 and 0.8. A frame rate of 5 Frames/sec is taken for analysis.

Optimal Sub-band Selection Using MOPSO

Minimum entropy principle is adapted here to find the best wavelet subband sets. The sum of all the entropy values of the node (ESUM) of the selected subbands is calculated. Fitness function for PSO is defined by considering MSE, ESUM and Computation Time. In PSO process, the fitness function values are in descending order and the minimum is the global optimum value. Chunjuan et al. used MSE and ESUM as objective functions for selecting the best wavelet packet [25].

In the proposed work, the fitness function is defined as follows with three objective functions:

$$\text{Fitness}=\alpha_1\text{MSE}+\alpha_2\text{ESUM}+\alpha_3\text{Computation time} \quad (7)$$

The constraints considered are 0.3 or 0.5 0r 0.8 bits/pixel and a frame rate of 5 Frames/sec.

Where α_1,α_2 , α_3 are constants and their (weightage values) values are taken as 0.4 and 0.3 and 0.3 respectively.

The Entropy sum is calculated for each set of subbands as Entropy of (LL, LH, HL, HH).

The computation time varies with respect to the size of the subband sets and the average mean square error (MSE) σ_ε is calculated as per equation

$$\sigma_\varepsilon = \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{J=1}^{N}\left((I_{org}(i,j,k) - I_{recon}(i,j,k)\right)^2 \quad (8)$$

$I_{org}(i,j,k)$ - Original Image frame in the video sequence

$I_{recon}(i,j,k)$ - Reconstructed frame in the video sequence

where K is the number of frames in the video sequence.

Optimal sub-band selection Algorithm

Step 1: Divide the video sequence into group of Frames. Apply 3D Dual tree wavelet transform and subject the coefficients to noise shaping algorithm. The result is the reduced number of coefficients.

Step 2: Initialization of population: Set of randomly selected subband coefficients are considered as Particles. Each particle is initialized as the multiplication of randomly initialized '0' and '1' matrix with the subband of DDWT coefficients matrix.

Step 3: Apply inverse dual tree wavelet transform. The reconstructed image is obtained. Calculate MSE, PSNR and Computation time values. The optimum subband selection time is the computation time of the PSO algorithm.

Step 4 Calculate each particle's fitness value according to the Eq.7

Step 5: If the particle's fitness value is better than the particle's best fitness value, then P_{id} (individual best) is updated. If the fitness value is better than the global best fitness value, then P_{gd} (global best) is updated. The particle's velocity is the probability of a particular subband to be included in the set of subbands. The position updating is the inclusion or deletion of a particular subband in the particle's set of subbands. The particles velocity and position updating are determined based on the global best particle. The set of subbands in the particles are modified according to the subbands in the global best particle.

Step 6: Continue the exploration process until a pre specified iterations are satisfied. Declare the global optimum value as the solution (Optimum set of subbands).

For the given constraints in terms of bits/pixel and frame rate, the PSNR, MSE and the Computation time are measured. According to the weighted aggregate approach the best particle – set of optimum subband coefficient is selected. The selected subbands are encoded using EZW algorithm. The average value of PSNR and is calculated for different bit rates.

The particle updating parameters are taken as the inertia weight w =0.9 (fixed value) for each iteration and c_1=2,c_2=2,

The number of particles used: 30,

Number of iterations: 10

PSNR value of the sequence is calculated as

$$PSNR = 10\log\left(\frac{I_{\max}^2}{\sigma_\varepsilon}\right) \quad (9)$$

Where $I_{\max}^2$ =255, and σ_ε -Mean square error.

The PSNR is calculated with MOPSO for different frame and bit rates using Eq.9.

IV. RESULTS

The video sequence is first grouped into 5 frames and it is subjected to DDWT decomposition. The filter bank used for DDWT is as discussed by Ivan (2003). After DDWT decomposition the number of coefficients is minimized using the Noise Shaping algorithm. The number of coefficients is fixed as 16,384 and the multiplication factor value (1.8) are assigned to the Noise shaping algorithm to identify energy concentrated subband coefficients. For testing The standard video sequences Rhinos ,Foreman and Akiyo are used and the performance of the proposed method was analyzed. In Table-1 the average PSNR value of Rhinos Foreman and Akiyo sequences under various methods such as DWT+ 3D SPIHT, DDWT and MOPSO with DDWT are given.

The standard 3-D SPIHT algorithm is compared with result. From the Table1, it is concluded that for a video sequence which has many motions and edges such as, DDWT with MOPSO, Foreman sequence outperforms SPIHT by more than 1 dB. In the other two sequences its performance is better than the SPIHT. In Table 2 the performance measurements for the Foreman sequence for various bit rates are shown. Due to the increase in number of bit/pixel results in considerable increase in PSNR value for all the method.

The Proposed MOPSO's PSNR performance for the compression ratio of 0.9 bpp is around 1.3 dB (Foreman sequence) greater than the 3D SPIHT and around 4 dB greater than the DDWT (without MOPSO) Techniques. The computation time (Searching time for the best particle) is around 45 to 50 seconds. It is based on the selected set of DDWT subbands length.

TABLE 1- AVERAGE PSNR PERFORMANCE COMPARISON OF THE PROPOSED TECHNIQUE

Video sequence	3D SPIHT +DWT	DDWT	MOPSO +DDWT
	PSNR	PSNR	PSNR
Foreman (5 Frames)	34.563	33.7974	35.7958
Rhinos (5 Frames)	32.3440	31.9967	33.129
Akiyo (5 Frames)	35.788	34.346	36.96

TABLE 2- AVERAGE PSNR COMPARISION AT DIFFERENT BITS PER PIXEL

Encoding Algorithm	Bits per Pixel BPP	PSNR(dB)
DWT+ 3D SPIHT	.4	33.2107
	.6	35.8953
	.9	36.8344
DDWT	.5	29.1861
	.6	32.8848
	.9	33.8309
DDWT+MOPSO	.4	34.3168
	.5	36.1138
	.9	37.8592

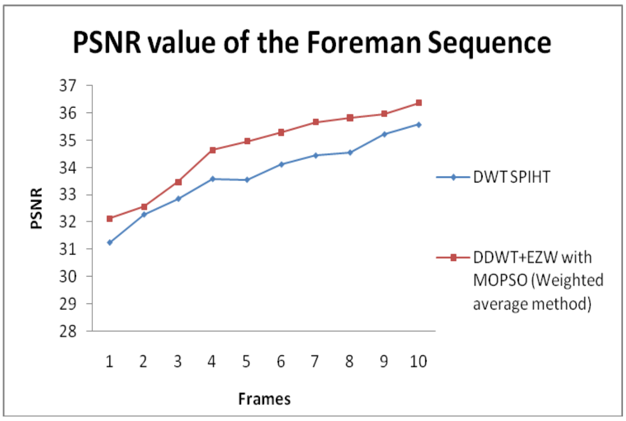

Fig.3 Foreman Sequence Average PSNR value plot

Fig.3 The different frames of Foreman sequence variation PSNR value showed. The PSNR value is higher than the SPIHT. The PSNR value the variation is less in case of DDWT+MOPSO. There is a very small change in PSNR values if number of frames is increased.

The reconstructed and original video frames of Rhinos and Foreman sequences are shown in figures 4(a) and 4(b) respectively.

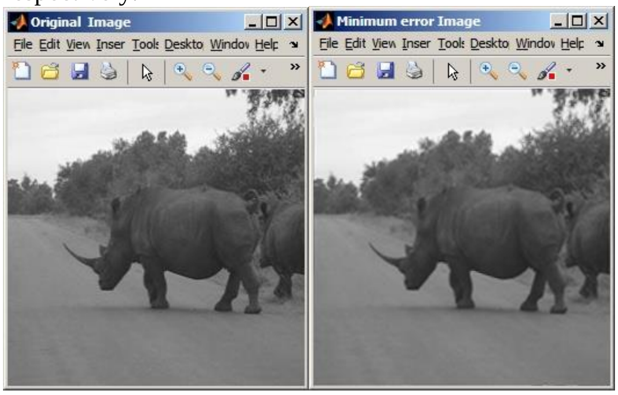

Fig 4. (a) Original frame -21 in Rhinos sequence and its low error reconstructed Frame using technique of MOPSO

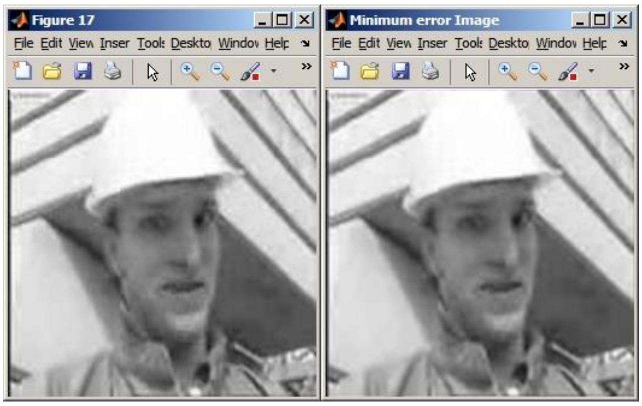

Fig 4. (b) Original frame -51 in Foreman sequence and its low error reconstructed frame using technique of MOPSO

Fig.4 Reconstructed Video frames using MOPSO: weighted aggregate approach.

V. CONCLUSION

In this paper, a video coding technique with a weighted aggregate MOPSO method combined with 3-D dual tree wavelet transform is proposed. By using video sequences the performance of the proposed method is tested .The standard DWT+SPIHT coding method is compared with the obtained test result. Comparing with the existing standard technique the obtained results are better. In future, the other approaches for Multi objective optimization and also the variants of the PSO will be taken to improve the performance analysis of the system and reduce the computational complexity of MOPSO computation part.

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