Multi objective Particle Swarm Optimization in video coding

M. Thamarai, R. Shanmugalakshmi

Abstract— Particle Swarm Optimization (PSO) is a global optimization technique based on swarm intelligence. It simulates the behavior of bird flocking. It is widely accepted and focused by researchers due to its profound intelligence and simple algorithm 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 obtained significant success. In this paper the application of Particle swarm optimization for video coding is analyzed The application of multi objective optimization using PSO for optimal subband selection of the dualtree discrete wavelet transform is proposed and analyzed. The results are compared with the standard techniques. The video coding using PSO and Dualtree wavelet transform provides better PSNR values when compared to the PSO based Block based coders. The performance variation of the PSO based coder in various aspects such as swarm size variation and threshold value variation for frame rates are also measured.

Keywords— Dualtree Discrete Wavelet Transform, Multi objective Particle Swarm Optimization, Noise Shaping and MSE

I. INTRODUCTION

PSO was introduced by[1],[2] Eberhart and Kennedy in 1995.It is a gradientless global optimization technique, suitable for continuous variable problems. This algorithm maintains a population of particles, where each particle represents the potential solution in the search space(Optimization). PSO has the following features:

- No evolutionary operators such as crossover and mutation as in GA.
- Ease of use with fewer parameters to adjust.

The aim of PSO is to find the particle position that results in the best evaluation of a given fitness function. Each particle fly through the N dimensional search space to find the optimum solution followed by the current better performing particle.

Each particle remembers its own best position Xpbest (that is, where the function was the fittest), and of all these ,the globally best value Xgbest is determined from the particles Xpbest values. As shown in expression (1), the particles are attracted by Xpbest and Xgbest. At each iteration the particle velocity vector V_i and position vector X_i are modified according to (1) and (2).

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

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

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, $X_i = (x_{i1}, x_{i2}, \ldots, x_{iD})$, $x_{id} \ \varepsilon \ [-x_{\min}, x_{\max}]$ 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_g, p_i are the best solutions discovered so far by the group and itself respectively.

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.

The velocity of the particle is calculated based on the contributions of the following three factors:

- Fraction of the previous velocity
- The cognitive component: The cognitive component is a function of the distance of the particle from its personal best position.
- The social component: The social component is a function of the distance from the particle found so far.

The personal best position of any particle is calculated as

$$y_i(t+1) = \begin{cases} y_i(t) & \text{if } f(x_i(t+1)) \ge f(y_i(t)) \\ x_i(t+1) & \text{f } f(x_i(t+1) < f(y_i(t)) \end{cases} \quad \ldots\ldots\ldots\ldots(3)$$

where $f(x_i(t+1))$ is the fitness value of $x_i(t+1)$

The quality of the solution is measured by a fitness function. There are two types of stopping criteria are used in PSO algorithm .Maximum (or fixed) number of iterations and another one is minimum inertia weight.

A. *Video Coding and Dualtree Discrete Wavelet Transform*

Video compression plays an important role in video signal processing, transmission and storage. Video is a sequence of correlated images. This temporal redundancy can be exploited for coding and processing. Motion estimation and compensation have been the most widely used methods in video compression and become the standard approach to reduce the temporal redundancies between frames. The block matching algorithm for motion estimation has been adopted in many international standards for digital video compression, such as H.264 and MPEG 4. Wavelet based motion compensated video coders provide both temporal and spatial scalability [3].

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Continuous rate scalable applications can prove valuable in scenarios where the channel is unable to provide a constant bandwidth. Scalable video coding has the capability of reconstructing lower resolution signals from partial bit streams. J.R. Ohm [4] had proved that motion compensated temporal wavelet coding eliminates the encoder drift problem in scalable video coding this paper. The objective functions are taken as computation time, Mean square error and Entropy of the subbands. The proposed system and MOPSO problem formulation are shown in figures 1 and 2 respectively.

The standard separable discrete wavelet transform (DWT) provides a multi-resolution representation of a signal and has established an impressive reputation for video compression. Several recently proposed DWT-based video coders have achieved coding efficiency similar to or slightly better than block-based hybrid video coders in [5].

But the poor directional selectivity of the multidimensional DWT can lead to checkerboard artifacts at low bit rate. The DT-CWT is an over complete transform with limited redundancy (2^m:1 for m-dimensional signals). This transform has good directional selectivity and its subband responses are approximately shift-invariant as in [6]. The 2-D DT-CWT gives superior results for image processing applications compared to the DWT.

In [7], Selesnick et al introduced a 3-D version of the dual-tree wavelet transform and showed that it has superior motion selectivity. The major challenge to apply the 3-D complex DDWT for video coding is it's over completeness with 8:1 redundancy. By choosing the real parts of the wavelet coefficients, perfect reconstruction is obtained with the motion selectivity retained. This reduces the redundancy to 4:1. To reduce the number of coefficients, Kingsbury proposed an iterative projection-based noise shaping (NS) scheme [8], which modifies previously chosen large coefficients to compensate for the loss due to small coefficients because of thresolding. In paper [9] Wang, discussed about the enhancements in the DDWT based video coding technique.

B. Multiobjective PSO

Recently PSO has been extended to handle multiple objective problems and is reported in [10].PSO is particularly suitable for multi objective optimization because of high speed of convergence. Abdullak et al.[11] reported the usage of Genetic Algorithm for multi objective problems. When compared with GA, PSO has memory and few parameters to adjust. The multi objective PSO is used for Image segmentation [12] and filter bank design [13] 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 process of global best and personal best. Cello et al [14] 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 this paper section II presents the video coding problem formulation using multi objective optimization and section III presents the Optimal subband (DDWT Subband) selection algorithm using MOPSO. Section IV the video coding results and conclusion is in section V.

II. VIDEO CODING USING MULTI OBJECTIVEPSO

The video coding is formulated as a multi objective problem. The redundancy of the dualtree discrete wavelet transform (4:1) for video signal is eliminated using the multi objective PSO. The weighted aggregate MOPSO approach is used in

this paper. The objective functions are taken as computation time, Mean square error and Entropy of the subbands. The proposed system and MOPSO problem formulation are shown in figures 1 and 2 respectively.

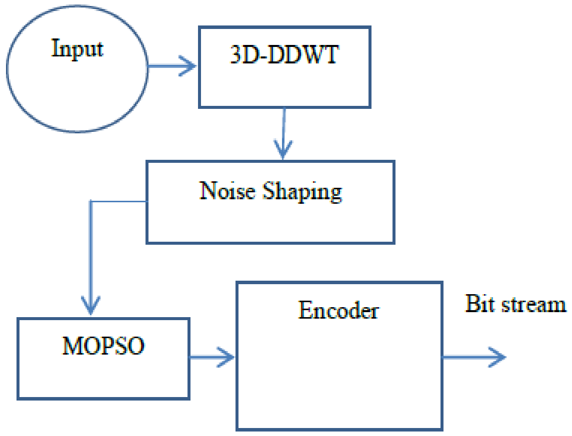

Fig.1 proposed video coding system using MOPSO

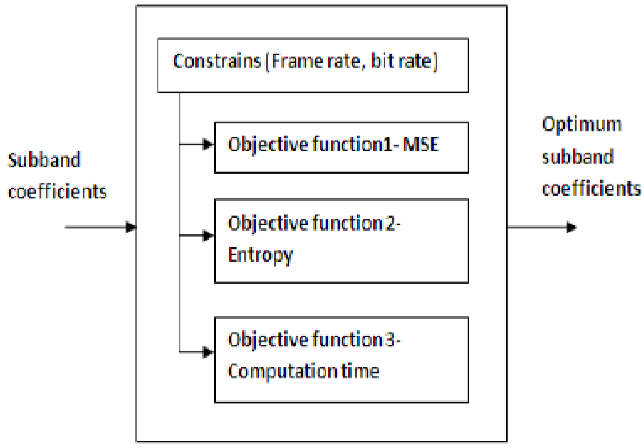

Fig.2 MOPSO problem formulation

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 subbands 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.2** shows the video coding multi objective problem formulation. The objective functions are Means 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 threshold and the number of particles are taken for analysis.

A. Optimal Subband Selection Using MOPSO

In order to find the best wavelet subband basis, we adopt minimum entropy principle .We have calculated the sum of all the entropy values of the node(ESUM) of the selected subbands. Fitness function for PSO is designed considering both 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. [15] used MSE and ESUM as objective functions for selecting the best wavelet packet. In the proposed work, the fitness function is defined as follows with three objective functions:

Fitness=α_1MSE+α_2ESUM+α_3Computation time (4)

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 constraints considered are different frame rates and different number of particles and threshold values.

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(5)

$$\sigma_\varepsilon = \sum_{k=1}^{K}\sum_{i=1}^{N}\sum_{J=1}^{N}\left((Iorg(i,j,k) - I_{\mathrm{Re}\,con}(i,j,k)\right)^2 \qquad (5)$$

$Iorg(i,j,k)$ - Original Image frame in the video sequence

$I_{\mathrm{Re}\,con}(i,j,k)$ - Reconstructed frame after encoding the video sequence where K is the number of frames in the video sequence.

III. OPTIMAL SUBBAND 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 Equation.(4)

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 est fitness value, then P_{gd} (global best) is updated. Update each particle's velocity and position according to the Eq.1 and Eq. 2.

Step 6: Continue the exploration process until a pre specified iterations are satisfied. Declare the global optimum value as the solution. For the given constraints in terms of different frame rates, 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 particle updating parameter is taken as the inertia weight w =0.9.

IV. RESULTS

The video sequence is first grouped into frames and is subjected to DDWT decomposition. The filter bank used for DDWT is as discussed in [6]. After DDWT decomposition the number of coefficients is minimized using Noise Shaping algorithm. The number of coefficients is fixed as 17,000 and the multiplication factor value (1.8) are assigned to the Noise shaping algorithm to identify energy concentrated subband coefficients. The standard video sequences Foreman, Rhinos are used to test the performance of the proposed method. The average PSNR values of these sequences under various conditions like various thresholds, various number of particles is given in Table-I. The two video sequences Foreman and rhinos are tested to measure the performance of the algorithm.

Table I Performance of MOPSO with threshold variation and particle variations

No. of Particles	PSNR (dB)							
	Threshold :30		Threshold:40		Threshold:50		Threshold:100	
	Foreman	Rhinos	Foreman	Rhinos	Foreman	Rhinos	Foreman	Rhinos
30	38.445	36.9335	37.9583	36.1166	36.3977	35.4412	36.3977	35.4412
40	33.0654	32.928	33.5056	33.6533	33.80007	33.7979	30.589	33.2226
50	38.3755	33.942	34.7123	35.1151	36.9844	34.9056	37.7452	34.2821

The average value of PSNR, MSE and Computation time for the two video sequences, Foreman and Rhinos are shown in Table- I. The performance is measured for various threshold values and various number of particles.

The number of particles are varied as 30,40 and 50.The PSNR variation for the particles with threshold value of 30 and threshold of 30, 40, 50 and 100 are given in Table- I. The increase in particle numbers increases the PSNR value.

Table-II gives the PSNR variation with threshold variation with the number of particles as 30.

Increase in the threshold value decreases PSNR. The computation time for various threshold values are shown in Table-III. For both the sequences the computation time decreases with increasing threshold.

Table-IV gives the variation of computation time with variation in the number of particles. The particles are varied from 10 to 50 and the increases with increase in the number of particles. In all the above mentioned tables the number of iterations is taken as 5. The PSNR variation with particle variation is also given in Table-V.The particles are varied from 10 to 50 and the increase in PSNR value is from 32 to 38 for the Foreman sequence and it varies from 31to 34 for the rhinos sequence. The PSNR values of different frames are calculated and tabulated. Table-VI gives the PSNR variation with the fixed number of particles as 30 and threshold value as 30.

Table-II PSNR Variation with Threshold

Threshold	PSNR(dB)	
	Foreman	Rhinos
30	38.4	36.9
40	37.9	36.1
50	36.4	35.4
100	36.2	35.3

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Table-III Computation time variation with threshold

No. of Particles	Computation time(Sec)	
	Foreman	Rhinos
10	67	69
20	97	103
30	120	137
40	410	440
50	601	580

Table-IV Computation time variation with number of particles

Threshold	Computation time(Sec)	
	Foreman	Rhinos
30	105.71	103.693
40	97.245	97.1
50	95.34	95.56
100	94.78	94.68

Table-V PSNR performance with various number of particles

No. of Particles	PSNR(dB)	
	Foreman	Rhinos
10	32.2	31.6
20	33.8	31.7
30	38.4	36.9
40	33.1	32.9
50	38.4	33.9

Table-VI PSNR performance with various frames

Frame Number	PSNR (dB)	
	Foreman	Rhinos
10	38.4403	33.6957
20	38.0816	34.234
30	38.083	35.381
40	38.1423	36.032
50	38.1976	36.4328
60	38.2244	36.6248
70	43.9423	36.9335
80	38.4495	36.4328

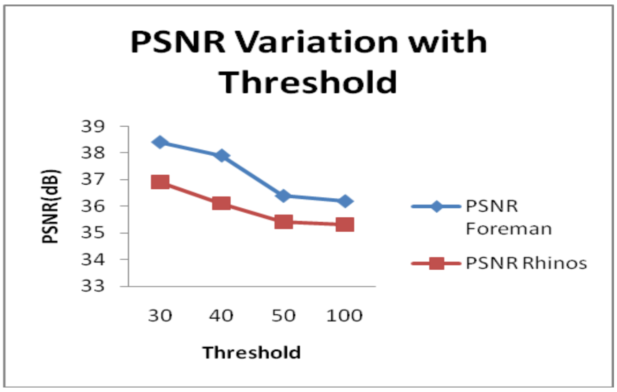

Fig 3 PSNR variation with threshold variation with fixed the no. of particles as 30

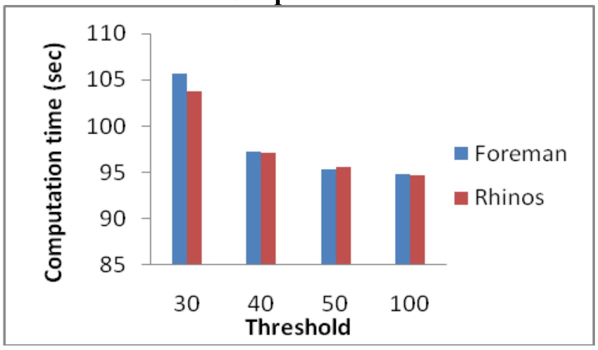

Fig 4.Computation time variation with threshold with fixed no. of particles as 30

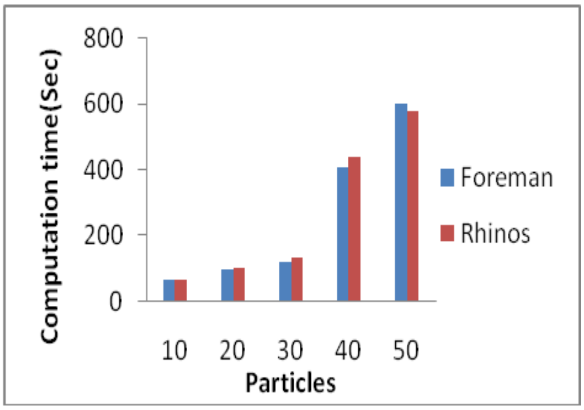

Fig.5. Computation time variation with no. of particles with constant threshold value of 30

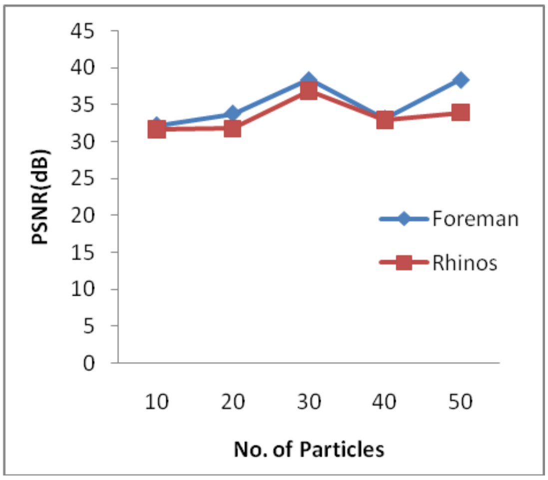

Fig.6 PSNR variation with number of particles with constant threshold 30

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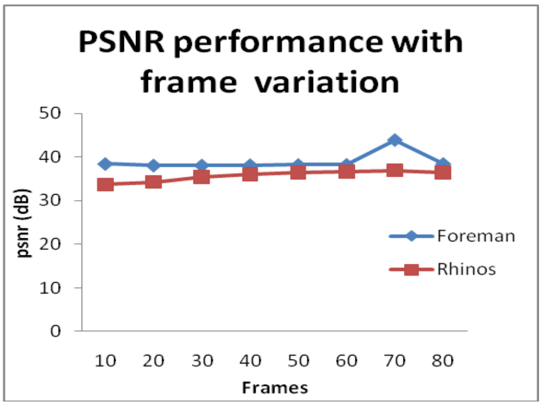

Fig.7. Average PSNR Variation with frame variations No. of Particles 30, threshold 30

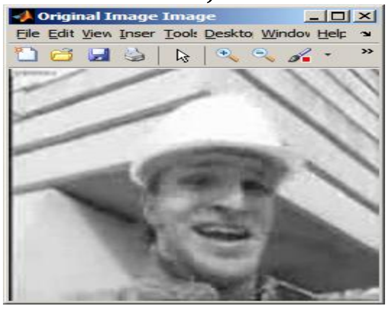

Fig.8.Original image of Foreman sequence

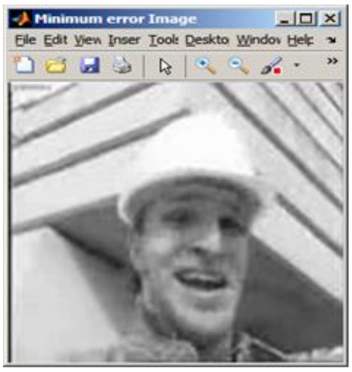

Fig.9.Minimum error Frame of Foreman sequence

From fig.3,it is concluded that the increase in threshold results in the decrease of computation time. As shown in fig 4, for the threshold value of 100, both the sequences computation time is almost equal. Fig.5 shows the increase in computation time with increase in number of particles (Swarm size).Also the increase in the number of particles results increase in PSNR value as shown in fig.6.

The PSNR performance of the weighted aggregate MOPSO method for various frame rates is shown in fig7.The original frame in the Foreman Sequence and its reconstructed frame using MOPSO (Minimum error image) are shown in Figure 8 and 9 respectively.

V. CONCLUSION

The video coding using MOPSO with dualtree discrete wavelet transform is analyzed under the conditions of variation in Noise shaping threshold, variation in number of particles.. The performance is measured with different conditions like swarm size variation and frame rate variation. It is concluded that for optimum PSNR with less computation time, the number of particles should be 30 and threshold value as 30. In future the performance is measured by means of using other MOPSO approaches with variable swarm size.

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