A Fast Block Matching Algorithm for Video Motion Estimation Based on Particle Swarm Optimization and Motion Prejudgment

Ran Ren∗
Madanmohan Manokar†
Yaogang Shi‡
Baoyu Zheng§

February 1, 2008

Abstract

In this paper, we propose a fast 2-D block-based motion estimation algorithm called Particle Swarm Optimization - Zero-motion Prejudgment (PSO-ZMP) which consists of three sequential routines: 1) Zero-motion prejudgment. The routine aims at finding static macroblocks (MB) which do not need to perform remaining search thus reduces the computational cost; 2) Predictive image coding and 3) PSO matching routine. Simulation results obtained show that the proposed PSO-ZMP algorithm achieves over 10 times of computation less than Diamond Search (DS) and 5 times less than the recent proposed Adaptive Root Pattern Searching (ARPS). Meanwhile the PSNR performances using PSO-ZMP are very close to that using DS and ARPS in some less-motioned sequences. While in some sequences containing dense and complex motion contents, the PSNR performances of PSO-ZMP are several dB lower than that using DS and ARPS but in an acceptable degree.

1 Introduction

With the increasing popularity of technologies such as digital television, Internet streaming video and video conferencing, video compression has become an essential component of broadcast and entertainment media. Among various kinds of approaches, block-based motion estimation and compression are most widely accepted ones. The block-matching algorithm (BMA) for motion estimation (ME) has been adopted in many international standards for digital video compression, such as H.264 and MPEG 4 [8]. In the framework of video coding, the statistical redundancies can be categorized by either temporal or spatial. For the purpose of reducing the temporal redundancies among frames, motion estimation was applied [4]. Block-based matching algorithms consider each frame in the video sequence formed by many nonoverlapping small regions, called the macroblocks (MB) which are often square-shaped and with fixed-size (16 × 16 or 8 × 8). Let $B_m$ represents the $m$th MB and $M$ the number of blocks, and $\mathcal{M} = 1, 2, \ldots, M$; let $\Lambda$ be the entire frame and the partition into MBs should satisfy $\bigcup B_m = \Lambda$ and $B_m \bigcap B_n = \emptyset, m \neq n$ [14]. Given a MB $B_m$ in the anchor frame, the motion estimation problem is to determine a corresponding matching MB $B'_m$ in the target frame such that the matching error between these two blocks is minimized. Then, a motion vector is computed by subtracting the coordinates of the MB in the anchor frame from that of the matching MB in the target frame. Instead of sending the entire frame pixel-by-pixel, a set of motion vectors is transmitted through the channel which greatly reduces the amount of transmission. In the decoder side, a motion compensated procedure is applied to reconstruct frames using the received motion vectors and the anchor frame. Referred to many researches, the motion estimation and encoding part consumes nearly 70–90 percent of the total amount of computation in the whole video compression procedure thus making it an active research topic in the last two decades.

There are many proposals of BMAs in literature. The most basic one is the Exhaustive Search (ES), also known as full search which simply compares the given MB in the anchor frame with all candidate MBs in the target frame exhaustively within a predefined search region. Previous research showed that ES can obtain
high matching accuracy but requires a very large amount of computation thus infeasible to implement in real-time video applications. To speed up the search, various fast algorithms for block matching which reduce the number of search candidates have been developed. Well known examples are 2-D Logarithmic Search (LOGS) [6], Three Step Search (TSS) [10], Four Step Search (4SS) [7], Diamond Search (DS) [9] which is accepted in the MPEG-4 Verification Model and widely implemented in VLSI, and the recent proposed Adaptive Rood Pattern Search (ARPS) [13] which is almost two or three times faster than DS and even achieves higher peak signal-to-noise ratio (PSNR) than that using DS.

From the optimization point of view, block-based methods can be described by the following minimization [1], \( \forall m \):

\[
\min_{d_m \in P} \varepsilon(d_m), \varepsilon(d_m) = \sum_{n \in B_m} \Phi(I_k[n] - I_{k-1}[n + d_m])
\]

where \( I_k \) is the target frame; \( I_{k-1} \) is the anchor frame; \( \varepsilon(d_m) \) is the matching error; \( d \) are the motion vectors and \( P \) is the search area to which \( d_m \) belongs, defined as \( P = n = (n_1, n_2) : -P \leq n_1 \leq P, -P \leq n_2 \leq P \). Sign of \( d \) is positive when motion of the block is towards positive direction from \( k-1 \)th frame to \( k \)th frame. And negative when motion of the block is in negative direction from \( k-1 \)th frame to \( k \)th frame. \( B_m \) is an \( N \times N \) size MB with the top-left corner coordinate at \( m = (m_1, m_2) \). The goal is to find the best displacement motion vector \( d_m \) for each MB \( B_m \), in the sense of the criterion \( \Phi \).

Particle swarm optimization (PSO) was originally proposed by Kennedy and Eberhart in 1995 [5]. It is widely accepted and focused by researchers due to its profound intelligence background 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, fuzzy system control etc. and obtained significant success. Like Genetic Algorithm (GA), PSO is also an evolutionary algorithm based on swarm intelligence. But, on the other side, unlike GA, PSO has no evolution operators such as crossover and mutation [3]. In PSO, the potential solutions, called particles, fly through the solution space by following the current optimum particles. The original intent was to graphically simulate the graceful but unpredictable choreography of a bird flock. Through competitions and cooperations, particles follow the optimum points in the solution space to optimize the problem. Many proposals indicate that PSO is relatively more capable for global exploration and converges more quickly than many other heuristic algorithms [2].

The rest of the paper is organized as follows. Section II introduces the PSO algorithm and we propose the PSO-ZMP block-matching algorithm for motion estimation in Section III. Simulation results and analysis on five video sequences are given in Section IV. Section V concludes the paper.

## 2 Particle Swarm Optimization

Particle swarm algorithm is a kind of evolutionary algorithm based on swarm intelligence. Each potential solution is considered as one particle, and these particles are distributed stochastically in the high-dimensional solution space in the initialization period of the algorithm. Through following the optimum discovered by itself and the entire group, each particle periodically updates its own velocity and position.

\[
v_{id}(t + 1) = w \times v_{id}(t) + c_1 \times \text{rand}_1(\cdot) \\
\quad \times (p_{id} - x_{id}) + c_2 \times \text{rand}_2(\cdot) \\
\quad \times (p_{gd} - x_{id})
\]

\[
x_{id}(t + 1) = x_{id}(t) + v_{id}(t + 1)
\]

\(1 \leq i \leq N, 1 \leq d \leq D\)

Where, \( N \) is the number of particles and \( D \) is the dimensionality; \( V_i = (v_{i1}, v_{i2}, \cdots, v_{iD}), v_{id} \in [-v_{\text{max}}, v_{\text{max}}] \) is the velocity vector of particle \( i \) which decides the particle’s displacement in each iteration. Similarly, \( X_i = (x_{i1}, x_{i2}, \cdots, x_{iD}), x_{id} \in [-x_{\text{max}}, x_{\text{max}}] \) 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; \( \text{rand}_1(\cdot) \) and \( \text{rand}_2(\cdot) \) 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.
In the $t+1$ time iteration, particle $i$ uses $p_g$ and $p_i$ as the heuristic information to updates its own velocity and position. The first term in Eq.1 represents the diversification, while the second and third intensification. The second and third terms should be understood as the trustworthiness towards itself and the entire social system respectively. Therefore, a balance between the diversification and intensification is achieved based on which the optimization progress is possible.

### 3 Block-matching algorithm based on PSO-ZMP

In this paper, an algorithm based on Particle Swarm Optimization (PSO) and Zero-Motion Prejudgment (ZMP) is proposed to reduce the computation and obtain satisfied compensated video quality. The PSO-ZMP algorithm consists of three sequential routines. 1) Zero-motion prejudgment; 2) Predictive image coding; 3) PSO matching. Instead of distributed stochastically in the entire matching space, we also devise a novel distribution pattern for particle initialization to bear the center-biased characteristics of common motion fields.

#### 3.1 Performance Evaluation Criterion

As widely adopted, we measure the amount of computation and the quality of compensated video sequence by Computation and Peak Signal-to-Noise Ratio (PSNR). Computation is defined as the average number of the error function evaluations per MV generation. Due to the minimum computational cost, we choose Summed Absolute Difference (SAD) as the error function which is defined as follows:

$$SAD = \frac{1}{N} N \sum_{i=1}^{N} \sum_{j=1}^{N} |I_k(i,j) - I_{k-1}(i,j)|$$

where the size of a MB is $N \times N$.

The motion estimate quality between the original $I_{ogn}$ and the compensated video sequences $I_{cmp}$ is measured in PSNR which is defined as:

$$PSNR = 10 \log_{10} \frac{I_{max}^2}{\sigma^2}$$

$$\sigma^2 = MSE = \frac{1}{N} N \sum_{k=0}^{K} \sum_{i=0}^{N} \sum_{j=0}^{N} (I_{ogn}(i,j,k) - I_{cmp}(i,j,k))^2$$

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

#### 3.2 Zero-Motion Prejudgment

Zero-Motion Prejudgment (ZMP) was firstly introduced in [13]. Data shown in [13] represented that in most of test sequences, more than 70% of the MBs are static which do not need the remaining search. So, significant reduction of computation is possible if we perform the ZMP procedure before the follow-up predictive coding and PSO matching routine. We first calculate the matching error (SAD in this paper) between the MB in the anchor frame and the MB at the same location in the target frame and then compare it to a predetermined threshold, saying $\Delta$. If the matching error is smaller than $\Delta$, we consider this MB static which do not need any further motion estimation, and return a $[0,0]$ as its motion vector (MV).

#### 3.3 Predictive Image Coding

Based on the center-biased characteristics in video sequences, that is, certain MBs are highly correlated in local regions of the frame, the encoder creates a prediction of a region of the current frame based on previously encoded and transmitted frames. If the frame is processed in raster order, the current-encoded MB should have four patterns of region of support (ROS) that consists of the neighboring blocks whose MVs will be used to compute the predicted MV for prediction in Fig. 1 due to the limited computational cost. Experiment mentioned in [13] shows there is little PSNR difference using these four ROS patterns in the predictive coding routine, and ROS type D consumes least amount of computation because of its simplest structure. Thus, ROS pattern D is adopted in this paper.
3.4 Selection of Search Patterns

Due to the spatial correlation characteristics between MBs in one frame, during the initiation period of the PSO matching routine, we distribute the particles in four specific patterns (Fig. 2) with a view to reduce the computational cost but to achieve higher PSNR.

Since frames are processed in raster order, the MB in the top-left corner in the frame, cannot be predictive coded because there is no reference MB for prediction in the current-encoded frame. Thus, for this condition, we simply skip the predictive coding and begin PSO searching routine directly with the initial positions of particles in the pattern type B in Fig. 2.

For those MBs located at the leftmost column of frames, their reference MBs used in predictive coding are in the other side of the frame, thus may not be highly correlated and inefficient in prediction. So, we also solely perform the PSO searching routine in this case, with the pattern type D in Fig. 2. And, for the last leftmost MB been processed in the frame, that is, the MB in the bottom-left corner, we use the pattern type C in Fig. 2 instead.

Otherwise, pattern type A in Fig. 2 is adopted. We put four particles in a rood shape with size zero (size refers to the distance between any vertex point and the center-point) in the adjacent MBs and four particles in a rood shape with size one, and then rotate it by angle \( \pi/2 \). With two rood shape in difference size, we try to balance the global exploration and local refined search in order for broader searching space as well as higher matching accuracy. Moreover, we distribute particles equally in all directions (8 particles in 8 directions) with a view to, in stochastic condition, find the matching MB in each direction with equal possibility.

Notably, if the position of a particle in the during initialization and a PSO run is out of the boundary of the image frame, we simply put the particle in the position nearest to its intended position.

3.5 Stopping Criterion

Generally, there are two widely adopted stopping criteria. One is Fixed-iteration, that is, given a certain iteration time, saying \( N \), the search stops after \( N \) times of iteration. The other is Specified-threshold. During a PSO run, the most-fitted value found by the entire group \( p_g \), called the “best so far” value will be updated by the particles. For minimization problems, we specify a very small threshold \( \varepsilon \), and if the change of \( p_g \) during \( t \) times of
iteration is smaller than the threshold, we consider the group best value very near to the global optimum, thus the matching procedure stops. Due to the center-biased characteristics of real-world motion fields, we adopt the fixed-iteration method in this paper for reducing the computational cost.

3.6 Summary of Our Method

We incorporate the ZMP, the predictive coding and the PSO matching routines together and propose a block-matching algorithm for motion estimation based on PSO and ZMP. The algorithm can be summarized in the pseudocode below:

Algorithm 1: PSO-ZMP BMA

1: for Each frame $i$ do
2:   for Each MB $j$ do
3:     $zmpcost \leftarrow SAD(I_{i-1}(j), I_i(j))$
4:     if $zmpcost < \cdot$ then
5:       Consider MB $j$ static
6:       motionVect = $[0, 0]$
7:       Continue
8:     else
9:       if MB $j$ in the leftmost column of frame $i$ then
10:          if MB $j$ = 1 then
11:             Initial particles in pattern B, Fig. 2
12:          else if MB $j$ in the bottomright corner of frame $i$ then
13:             Initial particles in pattern C, Fig. 2
14:          else
15:             Initial particles in pattern D, Fig. 2
16:          end if
17:       else
18:         Initial particles in pattern A, Fig. 2
19:     Predictive image coding routine
20:   end if
21:   Begin PSO matching routine
22:   for Each iteration time $t$ do
23:     for Each particle $p$ do
24:       Evaluate $SAD$ using Eq. 3 and update $P_g, P_p$
25:       Update velocity using Eq. 1
26:       Update position using Eq. 2
27:     end for
28:   end for
29: end if
30: end for
31: calculate the motion vector and output
32: end for

4 Experiments and Results

We’ve tested our PSO-ZMP algorithm on five test video sequences: Akiyo, Container, Mother & Daughter, News and Silent within 100 image frames (except 90 frames in Akiyo due to the limitation of the sequence length).

4.1 Experimental Settings

4.1.1 PSO Parameters

PSO matching is the core routine in our algorithm. In this paper, to balance between computational cost and compensated video quality, we adopt the standard PSO with inertia weight $[11, 12]$ which is widely considered as the defacto PSO standard. We use the fixed-iteration stopping criterion with max 5 iterations. The max velocity
Table 1: ZMP threshold ∆ for five test video sequences

| Sequence      | Format | ZMP Threshold ∆ |
|---------------|--------|-----------------|
| Akiyo         | QCIF   | 384             |
| Container     | QCIF   | 512             |
| Mot. & Dau.   | QCIF   | 384             |
| News          | QCIF   | 512             |
| Silent        | QCIF   | 384             |

is set to 5. The inertia weight $w$ decreases linearly from 0.9 to 0.4 during a PSO run and two acceleration factors $c_1$, $c_2$ are set to 2.0, as commonly did.

4.1.2 Motion Estimation Parameters

- We divide a whole image frame into 16 × 16 MBs in the simulation.

- We select a ZMP threshold ∆ for each test video sequence correspondingly based on data obtained in experiments. The parameters are shown in Table 1.

- We do not restrict the range of candidate matching MBs rigidly by a search window $P$. Instead, through the fixed-iteration and the setting of max velocity, particles search for the matching MB in an area more flexible and adaptable.

4.2 Results and Analysis

Fig. 3 and fig. 4 below show the simulation results on five test video sequences. For comparison, the performance of DS, ARPS, GA-ZMP, the BMA based on the genetic algorithm and PSO-ZMP algorithm are examined. Average peak signal-to-noise ratio (PSNR) per frame of the reconstructed video sequence is computed for quality measurement and documented in Table 2. The computational gain of our PSO-ZMP to DS (or ARPS) is defined by the ratio of matching speed to that of our method, which is shown in Table 3.

From the results obtained, PSO-ZMP shows significant computational reductions while acceptable drops in peak signal-to-noise ratio (PSNR). Notably, in sequence Akiyo and Mother & Daughter, our method achieves very close PSNR performance (max difference 1.09dB in Mother & Daughter) with 12.04 and 12.44 times of computation reductions compared to ARPS. In sequence Silent, News and Container, the PSNR performances using our method are 2-4 dB (max difference 4.04dB in Silent) less than that of ARPS and DS. But, in those sequences, compared to DS, PSO-ZMP consumes over 8-12 times less of computation to that of DS and 3-6 times less to that of ARPS. Referred to [14], a PSNR higher than 40dB typically indicates an excellent image (i.e., being very close to the original), between 30-40dB usually means a good image (i.e., the distortion is visible but acceptable); between 20-30dB PSNR is quite poor; and finally, a PSNR lower than 20dB is unacceptable. For all five sequences tested, PSO-ZMP algorithm achieves PSNR higher than 30dB in most of the frames, thus the PSNR droppings are in an acceptable degree.

Compared to GA-ZMP which incorporates genetic algorithm and zero-motion prejudgment (ZMP), our PSO-ZMP algorithm achieves superior performances on average PSNR and computation on all five test sequences. With the evolution operators such as crossover and mutation, GA consumes more amount of computation which leads to 1.5-2 times more computations than that using PSO. Meanwhile, our algorithm with PSO and ZMP incorporated obtains higher average PSNR compared to that using GA because PSO is more capable for the global exploration and local exploitation [3].

5 Conclusion

In this paper, we have proposed a fast block-based motion estimation algorithm based on Particle Swarm Optimization (PSO) with novel particle initiation patterns. Applied successfully in many functional and combinatorial optimization problems, PSO is proved to have a relevant stronger ability in global exploration. In addition, a zero-motion prejudgment (ZMP) routine is incorporated into the PSO BMA to further reduce the computational
Figure 3: Simulation results on Akiyo, Container and Mother & Daughter
Figure 4: Simulation results on News and Silent
Table 2: Average PSNR performance of DS, ARPS and PSO-ZMP

| Sequence   | DS    | ARPS  | GA-ZMP | PSO-ZMP |
|------------|-------|-------|--------|---------|
| Akiyo      | 43.50 | 43.49 | 42.07  | 42.39   |
| Container  | 36.34 | 36.13 | 32.36  | 33.15   |
| Mot. & Dau.| 40.46 | 40.57 | 35.66  | 39.48   |
| News       | 36.66 | 36.61 | 35.02  | 35.29   |
| Silent     | 36.68 | 36.46 | 31.62  | 32.64   |

Table 3: Computational gain to ARPS and to DS

| Sequence   | ARPS to DS | PSO-ZMP to DS | PSO-ZMP to ARPS | PSO-ZMP to GA-ZMP |
|------------|------------|---------------|-----------------|-------------------|
| Akiyo      | 2.44       | 12.04         | 4.94            | 1.47              |
| Container  | 2.24       | 8.10          | 3.62            | 1.54              |
| Mot. & Dau.| 2.22       | 12.44         | 5.62            | 1.61              |
| News       | 2.32       | 9.85          | 4.25            | 1.68              |
| Silent     | 2.25       | 8.60          | 3.82            | 2.17              |

cost of the algorithm. Simulation results show that the PSO-ZMP BMA proposed requires less amount of com-
putation and achieves PSNR in a acceptable degree of drop. while close and acceptable PSNR performance
compared to widely accepted ARPS and DS BMA. Moreover PSO just consumes a few lines of codes due to its
simplicity which makes the PSO-ZMP algorithm attractive for hardware implementation.

In the future, variants of PSO might be applied to strengthen the global searching ability and the accelerate
the convergence speed. And, to speed up the search and avoid being trapped in local minima, a multiresolution
procedure may be used.

Acknowledgment

The authors would like to thank Qian Wu for helping us make the nice search pattern figures and Yuxuan Wang
for the invaluable discussion and proofreading.

References

[1] A.Bovik. *Handbook of image and video processing*. Publishing house of Electronics Industry and Elsevier,
Beijing, China, second edition, 2006.

[2] R.C.Eberhart and Y.H.Shi. Particle swarm optimization: developments, applications and resources. In
*Proc. The IEEE Congress on Evolutionary Computation*, Piscataway, NJ.

[3] R.C.Eberhart and Y.H.Shi. Comparison between genetic algorithm and particle swarm optimization. In
*Proc. The IEEE Congress on Evolutionary Computation*, 1998.

[4] F. Dufaux and F. Moscheni. Motion estimation techniques for digital tv: A review and a new contribution.
*Proc.IEEE*, 83(6), June.

[5] J.Kennedy and R.C.Eberhart. Particle swarm optimization. In *Proc. IEEE International Conference on
Neural Networks*, Perth, Australia, 1995.

[6] J.R.Jain and A.K.Jain. Displacement measurement and its application in interframe image coding. *IEEE
Trans. Commun.*, COM-29, Dec.

[7] L.M.Po and W.C.Ma. A noval four-step search algorithm for block motion estimation in video coding. *IEEE
Trans. Circuits Syst. Video Technol.*, 6, Aug.
[8] I. E. G. Richardson. *H.264 and MPEG-4 video compression*. Wiley, Chichester, England, 2003.

[9] S.Zhu and K.K.Ma. A new diamond search algorithm for fast block-matching motion estimation. In *Proc. Int. Conf. Information, Communications and Signal Processing (ICICS)*, volume 1, pages 292–296, Sept.9-12 1997.

[10] T.Koga, K.Inuma, A.Hirano, Y.Iijima and T.Ishiguro. Motion compensated interframe coding for video conferencing. In *Proc. Nat. Telecommunication Conf.*, pages G.5.3.1–G.5.3.5, Nov.29-Dec.3 1981.

[11] Y.H.Shi and R.C.Eberhart. Empirical study of particle swarm optimization. In *Proc. IEEE Congress on Evolutionary Computation*, 1999

[12] Y.H.Shi and R.C.Eberhart. A modified particle swarm optimization. In *Proc. IEEE Congress on Evolutionary Computation*, 1998

[13] Y.Nie and K.K.Ma. Adaptive rood pattern search for fast block-matching motion estimation. *IEEE Trans. Image Processing*, 11(12), Dec.

[14] Y.Wang, J.Ostermann and Y.Q.Zhang. *Video Processing and Communications*. Tsinghua University Press and Prentice Hall, Beijing, China, 2002.