

Abstract

Motion estimation (ME) is an significant segment in video coding. Many ME process have been there to reduce the complexity of video coding. One of the useful processes is Block Matching (BM) process. There were so many algorithms for BM process. One of the simplest algorithm is Full Search Algorithm (FSA). But the search points delivered by this is very high, so in this paper a new algorithm based on Improved Artificial Bee Colony (IABC) was introduced to reduce the search points. IABC is optimization algorithm; it will randomly select search location and compare. In this all the algorithms compared based on the search location and the Peak-Signal-Noise-Ratio (PSNR) Values

Keywords: Motion Estimation, Block Matching, Full Search Algorithm, Improved Artificial Bee colony, PSNR.

Introduction

Motion estimation is a very important part in video coding. To estimate motion there are several ME methods are there, one of the useful and simplest method is block matching process. In a BM process a video is divided into multiple numbers of frames, each frame is divided into equal size non-overlapping blocks. Each block in the current frame the best matching block is identified in the previous frame, aiming to minimize the Sum of Absolute Difference (SAD). There were so many BM algorithms are there. In FSA block in the current frame compared with all other block in the previous frame, so it is delivering the most accurate motion vector. But it is a exhaustive search. In order to decrease the computational complexity of the BM process, several BM algorithms have been proposed. Sometimes delivering false motion vector, Holding well for slow-moving sequences but failing for other kind of movements in a video sequences. Affect the accuracy of the detection of motion vectors due to noise or illumination changes, Computation time also very high. So in this paper IABC algorithm is introduced, it is reducing the search points using fitness calculation approach.

Basics of Block Matching Process

The purpose of a block matching algorithm is to find a matching block from a frame i in some other frame p , which may appear before or after i the video sequence, increasing the effectiveness of interframe video compression and television standards conversion.

The search area for a good macro block match is constrained up to P pixels on all four sides of the corresponding macro block in previous frame. This ' P ' is called as the search parameter. Larger motions require a larger P and the larger the search parameter the more computationally expensive the process of motion estimation becomes. Usually the macro block is taken as a square of side 16 pixels, and the search parameter P is 7 pixels

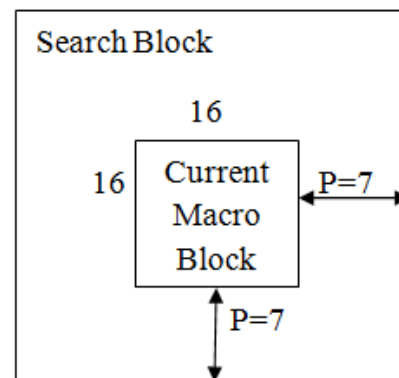


Fig 1 Measurement of the search area and the block

The idea is represented in Fig 1. The matching of one macro block with another is based on the output of a cost function. The macro block that results in the least cost is the one that matches the closest to current block.

Motion Estimation and Block Matching

For motion estimation through a BM algorithm, the current frame of an image sequence I_t is divided into non-overlapping blocks of $N \times N$ pixels. For each template block in the current frame, the best matched block within a search window (S) of size $(2W + 1) \times (2W + 1)$ in the previous frame I_{t-1} is determined, where W is the maximum allowed displacement. The position difference between a template block in the current frame and the best matched block in the previous frame is called the motion vector. Under such perspective, BM can be approached as an optimization problem aiming for finding the best MV within a search space.

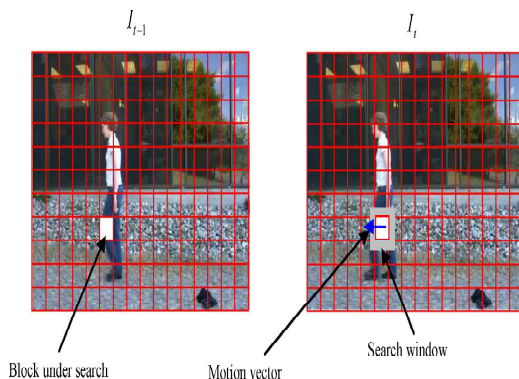


Fig 2 Block matching procedure

The most well-known criterion for BM algorithms is the sum of absolute differences (SAD). It is considering a template block at position (x, y) in the current frame and the candidate block at position $(x + \hat{u}, y + \hat{v})$ in the previous frame I_{t-1} .

$$SAD(\hat{u}, \hat{v}) = \sum_{j=0}^{N-1} \sum_{i=0}^{N-1} |g_t(x+i, y+j) - g_{t-1}(x+\hat{u}+i, y+\hat{v}+j)|$$

Where $g_t(\cdot)$ is the gray value of a pixel in the current frame I_t and $g_{t-1}(\cdot)$ is the gray level of a pixel in the previous frame I_{t-1} .

In the context of BM algorithms, the FSA is the most robust and accurate method to find the MV. It tests all possible candidate blocks from I_{t-1} within the search area to find the block with the minimum SAD. For the maximum displacement of W , the FSA requires $(2W + 1)^2$ search points. For instance, if the maximum displacement W is ± 7 , the total search points are 225. Each SAD calculation requires $2N^2$ additions and the total number of additions for the FSA to match a 16×16 block is 130,560. Such computational requirement makes the application of FSA difficult for real time tasks.

Existing Systems

The full search algorithm (FSA) is the simplest block matching algorithm that can deliver the optimal estimation solution with respect to a minimal matching error as it checks all candidates one at a time.

Artificial Bee Colony (ABC) is proposed to reduce the number of search locations in the BM process. The algorithm uses a simple fitness calculation approach which is based on the Nearest Neighbor Interpolation (NNI) algorithm in order to estimate the fitness value for several candidate solutions. As a result, the approach can substantially reduce the number of function evaluations yet preserving the good search capabilities of ABC. The proposed method achieves the best balance over other fast BM algorithms, in terms of both estimation accuracy and computational cost.

Improved Artificial Bee Colony Algorithm

In fixed pattern the search operation is conducted over a fixed subset of the total search window. Although such approaches have been algorithmically considered as the fastest, they are not able to eventually match the dynamic motion-content, sometimes delivering false motion vectors

Alternatively, evolutionary approaches such as genetic algorithms (GA) and particle swarm optimization (PSO) are well known for delivering the location of the global optimum in complex optimization problems. Despite of such fact, only few evolutionary approaches have specifically addressed the problem of BM, such as the Light-weight Genetic Block Matching (LWG), the Genetic Four-step Search (GFSS) and the PSO-BM. Although these methods support an accurate identification of the motion vector, their spending times are very long in comparison to other BM techniques.

ABC is one of the useful algorithm. But it is also facing some challenging problems. The convergence speed of the ABC algorithm is typically slower than those of the representative population-based algorithms when handling the unimodal problems, since it cannot utilize the information adequately to determine the most promising search direction. The ABC algorithm can also easily get trapped in the local optima when solving complex multimodal problems. These weaknesses have restricted the wider applications of the ABC algorithm.

In IABC the blocks are randomly selected and fitness value calculated. Employee bee is appointed for each and every selected block. The employee bee is finding a new block from the neighborhood and calculating the fitness value. The

fitness value is high means replace the value. The value is not improved for certain number of iteration will be removed. Finally improved solution will remain.

In IABC first of all the video is divided into multiple numbers of frames and each frames divided into equal size non-overlapping blocks. In that select five random search locations around the current location. Compute fitness value for each search location. Select another location around the randomly selected location and calculate the fitness value, so totally five new locations from the neighborhood. Calculate the fitness value for those locations. Compare the values with neighborhood location values, the highest value location will be remain another one will be neglected. If the values are not improved for more than two iteration

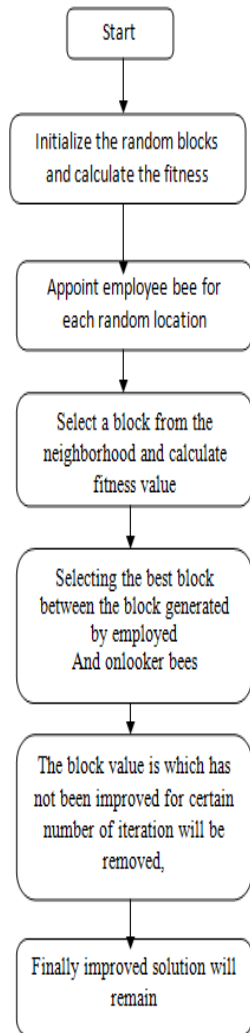


Fig 3. Improved Artificial Bee Colony for Block Matching

for the window size of ± 7 the search location will be neglected, using this method reduce the number of search location will be reduce.

Performance Metrics

A. Distortion Performance

First, all algorithms are compared in terms of their distortion performance which is characterized by the Peak-Signal-to-Noise-Ratio (PSNR) value. Such value indicates the reconstruction quality when motion vectors, which are computed through a BM approach, are used. In PSNR, the signal comes from original data frames whereas the noise is the error introduced by the calculated motion vectors. The PSNR is thus defined as:

$$PSNR = 10 \cdot \log_{10} \left(\frac{255^2}{MSE} \right)$$

Where, MSE is the mean square between the original frames and those compensated by the motion vectors.

$$MSE = \frac{1}{m \cdot n} \sum_{i=0}^{m-1} \sum_{j=0}^{n-1} [I(i, j) - K(i, j)]^2$$

Where I is reference frame, K is current frame.

$$SIR = \frac{(N2 - N1)}{N2} \times 100\%$$

Where N2 is the number of searching points used in algorithm 2(IABC). N1 is the number of searching points used in algorithm 1(DS, ABC).

Table 3 Search points of BM algorithms

Algorithm	Akiyo	Foreman
FSA	220.8687	220.8687
DS	11.56	13.43
ABC	11.98	10.47
IABC	9.67	8.78

Table 2 PSNR value of BM algorithms

Algorithm	Akiyo	Foreman
FSA	29.446	31.376
DS	30.565	30.654
ABC	29.209	31.260
IABC	29.106	30.987

Table 3 Average Speed Improvement Rate (SIR) in percentage

TEST SEQUENCE	IABC over DS	IABC over ABC
Akiyo	19.168	23.887
Foreman	52.961	19.248

Conclusion

Though ABC is a good algorithm to find a matching block to reduce the search location further IABC is introduced. IABC is an improved technique of ABC, it is used to find the best matching block. The method is able to save computational time by identifying which fitness value can be just estimated or must be calculated instead. As a result, the approach can substantially reduce the number of function evaluations, yet preserving the good search capabilities of IABC. The performance of IABC-BM has been compared to other existing BM algorithms by considering different sequences which present a great variety of formats and movement types.

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