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Sub-Pixel Motion Estimation using Wavelet Based Counterlet Transform

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***Abstract*—Better Compression of Video Frame can be achieved by high accuracy estimation and compensation of motion vectors to diminish the estimated Error between P and I frame. Compensating the motion in a video by Quarter pixel has been accurate, on the other hand coding rate of the encoder will be very slow for block matching Sub-pixel exhaustive Search, targeting this a novel Sub-pixel motion estimation procedure using wavelet-based counterlet transform (WBCT) is presented in this paper. Primarily, the optimum low occurrence sub-band whole number pixel point of the video frame block in transform domain is found out. Then by considering the optimum pixel point as a middle point to search the optimum motion vector of the subpixel using chaotic particle swarm optimization (PSO) algorithm. This optimum motion vector is then considered as initial motion vector of high occurrence sub-band in video frame block. To finish with, the high occurrence sub-band is subjected for thorough search to get optimum motion vector. As the experimental results show, the proposed methodology has better performance for search time and motion compensation effect in standard video sequences.**

***Index Terms*— Motion estimation, Subpixel, wavelet-based counterlet transform, particle swarm optimization.**

I. INTRODUCTION

In the video compression the temporal redundancies between the adjacent frames are reduced by Motion Estimation and Compensation. From pixel preservation property in moving pictures it is clear that pixels in one frame is shifted to form the pixel patterns on the adjacent frame. Hence the objects that represent the pictures in one frame is moved within the frame to represent the image in adjacent frames. Using subpixel over an integer pixel for describing the moving objects is more effective in eliminating large compensation errors in video. Large number of computations are required for motion estimation using Sub-pixel exhaustive Search algorithm. So it is imperative to cut the search period in sub-pixel motion estimation.

The overall idea of motion estimation is the video compression resulting in the reduction of the number of bits to be encoded, thus increasing the speed. Figure-1 shows the video compression process flow.

The most important part in video coding is the motion estimation. This part deals with the estimation of motion vectors from a pair of video frames which are infrequently accurate.

Many fast sub-pixel search [4] procedures anticipated for predicting motion vectors in recent times having to many compensation errors as the estimated optimum sub-pixel about the actual function is not completely identical. The motion estimation procedure based on WBCT is not accurate as the search element is an

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integer pixel. Accordingly, enhanced sub-pixel motion estimation techniques are necessary to resolve the stated issues.

In this paper, a new sub-pixel motion estimation procedure using WBCT [7] is offered. WBCT is an improvement to contourlet transform [7] which is a multi-resolution, local and more directional image transform. It can extract more information of image in effective approach without redundancy than wavelet and counterlet.

Initially we compute the optimum motion vector of integer pixel in WBCT field is calculated. Later on, a new approach to predict the motion vector in subpixel called chaotic particle swarm optimization is used.

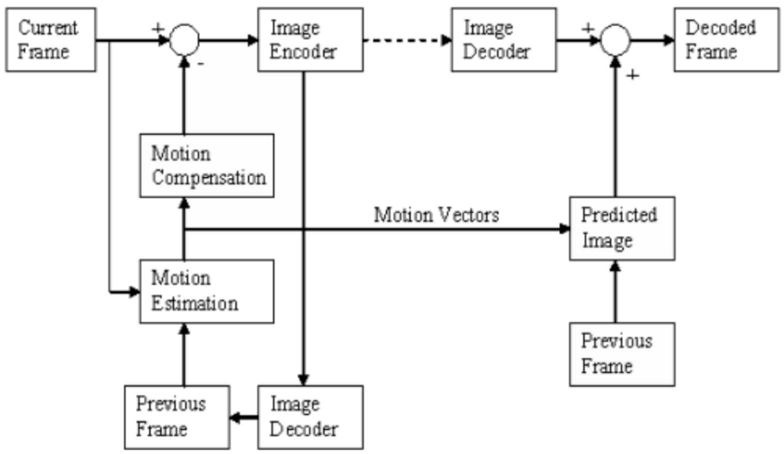


Figure 1: MPEG video compression process flow

II. METHODOLOGY

A. Sub-Pixel Full Search Motion Estimation.

Full search is nothing but the exhaustive search method, which is one of the block matching techniques [9]. The algorithm computes the cost function for each of the partitions in the frame and assures the block with best match with high PSNR. Here the approach is used in different way for the computation of the MV with more pixel accuracy. The Block Diagram below depicts the proposed search method.

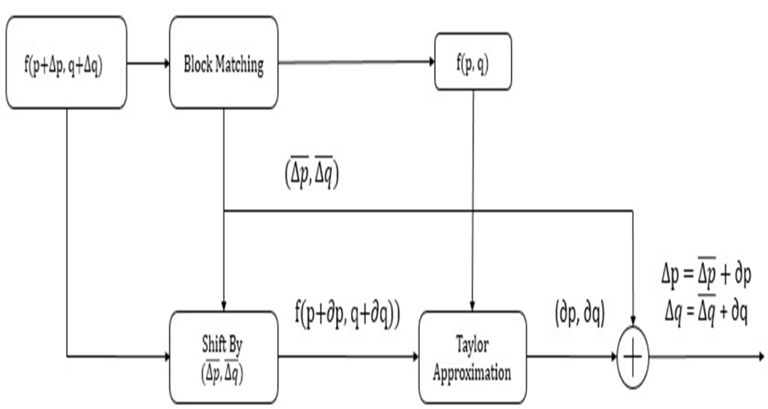


Figure 2: Block diagram of combined block matching and optical flow

Block matching usually uses sum of absolute difference (SAD) as matching criterion. The equation is as follow:

$$SAD(m,n) = \sum_{i=1}^{M} \sum_{j=1}^{N} \left| f_k(i,j) - f_{k-1}(i+m, j+n) \right| \quad (1)$$

Where M and N denote search area and $f_k(i, j)$ is the maiden point of searching.

To start with, the optimum point with the least SAD is found among the candidate points. Then the 1/4 accuracy subpixel is examined by SPFS contained by blocks of size l6x16, l6x8, 8x16, 8x8.

SPFS algorithm has the following steps:

Step 1: Compute SAD of the whole number pixel point and SAD of eight 1/2 pixel points within 3 x3 space, find out the optimum 1/2 pixel point.

Step 2: Examine eight 1/4 pixel points and estimate their SAD around the 1/2 pixel point, find out the optimal 1/4 pixel point.

From the above analysis we can observe that in each block we have to search eight 1/2 pixel points, and then search eight 1/4 pixel points, which lessens the whole speed of motion estimation

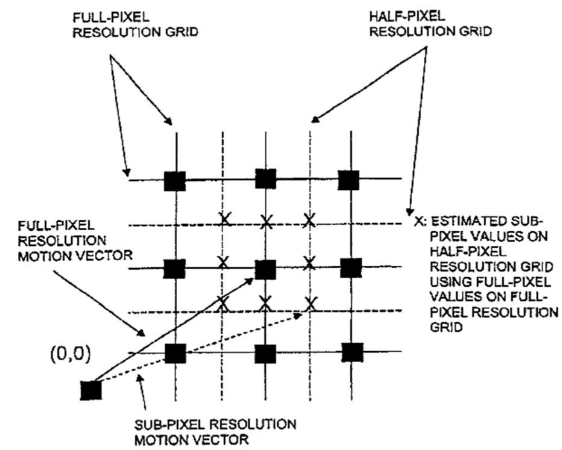


Figure 3: Principle Representation of SPFS algorithm

B. Wavelet based Counterlet transform.

Counterlet transforms (CT) are designed to capture the components with high frequency to represent the directionality. Counterlet transform also called as pyramidal directional filter banks is not orthogonal, it comes with redundancy which occurs in pyramidal stage [6]. Since CT is improvement to Wavelets which is achieved thru Laplacian Pyramid (LP) and Directional filter banks (DFB). So it is challenging to use CT video coding.

Wavelet based counterlet transform [10] is derived by replacing pyramidal filter by wavelet filter then by taking directionality of CT as an advantage to eliminate redundancy. First the wavelet will decompose the video frame in to one low frequency and three high frequency components, followed by Directional filer bank will decompose the sub band in to 2^n directions

C. Chaotic PSO.

This algorithm corresponds to swarm intellect, swarms are the cluster of organisms or animals that are seen in numerous all around. Here we use the same kind of evidence and induce this intelligence into the artificial systems [5].

Let us consider the examine space where we initialize the set of particles, these particles are obtained by finding the global maxima of the search space. Each particle initialized will have a location and a fitness value, and these particles are not static, they keep on moving with a velocity. Each particle p^i will have a location vector $p^i(p_n^i, p_2^i, \ldots p_{n-1}^i)$, a velocity vector $v^i(v_n^i, v_2^i, \ldots v_{n-1}^i)$ and a fitness value. This works in an iterative method, at every iteration each particle can take one chance to move with magnitude of velocity, such that if the velocity is large then the particle also take larger step and if the velocity is small then step taken by particle will be also small. A step here means the amount by which the particle can move within the search space.

Since all the particles are positioned at different positions of search space and initialized randomly in search area so they are expected to have fitness function which is useful in calculating fitness value using which we can allot some velocity

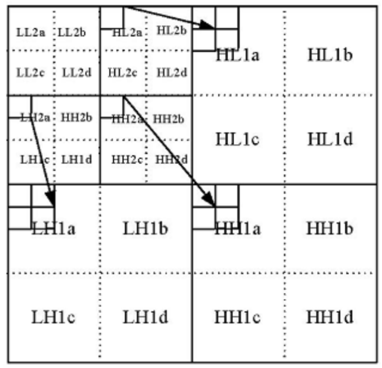


Figure 4: Image structure after WBCT

A position of particle i at any time t+1 ($p^i(t+1)$) is given by position of particle i at time t and the velocity of the particle at time t,

$$p^i(t+1) = p^i(t) + v^i(t) \tag{2}$$

The PSO equation for calculating velocity is

$$v^i(t+1) = v^i(t) + c_1 r[p^i - pb^i] + c_2 r[p^i - pg^i] \tag{3}$$

Where C_1 and C_2 are constants between 0 and 1 which controls the amount of variation in velocity. C_1 value express the intension of the particle to go near the local best whereas C_2 value express the intension of the particle to go near the global best, r is the random variable which is used to present some randomness in the procedure, another attribute is that v^i is always limited to v^{max} as if it's too far the particle will reach high velocity resulting in false global best.Later a randomness called chaos is introduced using the equation

$$Y_{m+1} = 1 - 2Y_m^2 ; \qquad -1<Y_m<1 \tag{4}$$

Where m=0, 1, 2, 3…. and Y_m is a chaotic sequence

The variable will be initialized using the equation (4) if the particles goes to local optimal positions. To obtain the dimension transform of the every chaotic variable for its optimal value equation (5) is used

$$Y_m^{'} = \left(\frac{\max - \min}{2}\right) Y_m + \frac{\max + \min}{2} \text{ ; m=0, 1, 2….} \tag{5}$$

Where, $Y_m^{'}$ is a sequence in transform domain, with max and min as maximum and minimum values of the transform domain

III. Experimental Results and Analysis

To validate the proposed algorithms for video compression the results below are obtained. For the computation we considered standard CIF format test videos which are first split into frames and the algorithms are applied for two frames and the PSNR's are tabulated along with the time taken for their computation

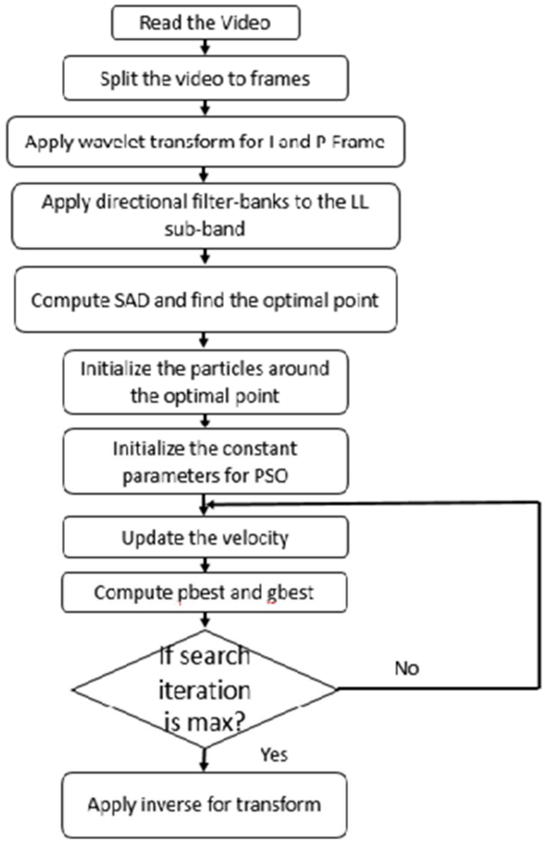


Figure 4: Flowchart in WBCT Domain

TABLE I: PSNR IN DB FOR DIFFERENT TEST VIDEO SEQUENCES

FRAMES	METHOD	PSNR in DB
Foreman	SPFS	33.39
	WBCT	33.89
Suzie	SPFS	36.3131
	WBCT	38.76
City	SPFS	30.2480
	WBCT	41.87
Salesman	SPFS	29.6465
	WBCT	23.86

TABLE II: RUNNING TIME RATIO OF DIFFERENT TEST VIDEO SEQUENCES

FRAMES	METHOD	PSNR in DB
Foreman	SPFS	1
	WBCT	0.34
Suzie	SPFS	1
	WBCT	0.43
City	SPFS	1
	WBCT	0.30
Salesman	SPFS	1
	WBCT	0.59

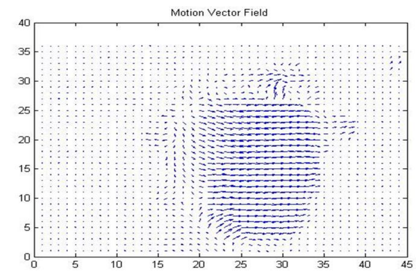
We can perceive from the above Table 1 that the average PSNR of the test sequnces after applying the proposed algorithm is increased by 4%-7%. As Chaotic PSO is presented for compensation we can see the reduction in running time ratio by 50-60% on an average besouse of not following regular block matching method instead going with random vector search using Chaotic PSO.Camparative results with motin vectors for standard test video frames are shown in figures 5 and 6

(a)Reference frame

(b)Candidate frame

(c) SPFS

(d)Proposed method



(e) Quiever Plot

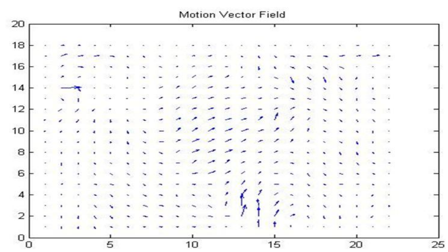
Figure5 : Results of foremen showing motion vectors

(a)Reference frame

(b)Candidate frame

(c) SPFS

(d)Proposed method



(e) Quiever Plot

Figure 6: Results of Suzie showing motion vectors

We can perceive from the above Table 1 that the average PSNR of the test sequnces after applying the proposed algorithm is increased by 4%-7%. As Chaotic PSO is presented for compensation we can see the reduction in running time ratio by 50-60% on an average besouse of not following regular block matching method instead going with random vector search using Chaotic PSO.Camparative results with motin vectors for standard test video frames are shown in figures 5 and 6

IV. Conclusion

In this paper an improved sub-pixel motion estimation algorithm based on WBCT is proposed. The purpose is to compensate the motion in video frames in sub-pixel level. Proposed algorithm uses the WBCT to capture the more video frame features in high frequency effectively. Then to reduce the search points in sub-pixel level after finding the integer point in WBCT domain chaotic PSO is applied. Experimental results show the comparison between the SPFS and proposed algorithm proving that proposed algorithm gives better results in terms of PSNR and running time ratio for the different Video test sequence considered for experimentation

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