Two Step Quadrant Based Gradient Directional Descent Search For Fast Block Motion Estimation

Prabhat Kumar Singh[1], Sharad Mohan Srivastav[2], Chandan Kumar[3]

[1] Mtech Scholar Deptt. of ECE., Sagar Institute of science and technology, Rajiv Gandhi Proudyogiki Vishwavidhalaya, Bhopal.

[2]Asstt. Prof. Deptt. of ECE., Sagar Institute of science and technology, Rajiv Gandhi Proudyogiki Vishwavidhalaya, Bhopal.

[3]Deptt. of electronics and comm, AIACTR (NCT OF DELHI).

Abstract: **For motion estimation Search point pattern based is used as a fast block motion estimation algorithms, it provides significant speedup for motion estimation. the main problem is it suffers from being easily trapped in local minima. This may lead to low robustness in prediction accuracy particularly for image or video sequences wherein the video there are complex motions. The problem introduced especially in one-at-a-time search (OTS) and block-based gradient descent search (BBGDS).which provide very high speedup ratio. To improve this, the multipath search using more than one search path has been proposed to improve the robustness of BBGDS. It requires more computation, in this the computational requirement is much increased. To remove this drawback, a line searches search (LS) algorithm using multiple OTSs and gradient descent searches are reviewed or proposed in this letter. Also, we introducing a new methodology to reduce computational complexity and improve the PSNR and reduces the number of searches points. The search point patterns in each stage depend on the minima found in these different directions after finding minima we apply the three-step search to find the minima in the particular direction and thus the global minimum can be easily traced more efficiently. Experimental results show that TWO STEP QUADRANT BASED GRADIENT DESCENT SEARCH (TQBGDS) reduces computation load significantly compared with the well-known fast block motion estimation algorithms.**

Keywords: **Quadrant Based Gradient Directional Descent Search, Block Motion Estimation**

I. INTRODUCTION BLOCK MATCHING

Block matching Motion estimation (BMME) is globally adopted by video coding standards such as MPEG-2, MPEG-4, and H.264/AVC, mainly due to its simplicity and good distortion performance. Using BMME, a video frame is divided into macro non-overlapping blocks of equal size and the best-matched block is determined from reference frames to that block in the current or present frame within a predefined search window. Normally, this is performed by The most direct method is the full search (FS), which exhaustively evaluates all possible candidate blocks within the search window. However, the computational complexity of FS is very high. It has been estimated that FS could consume up to 70% of the total computation of the video encoding process. To handle this problem, many fast block matching algorithms (BMAs) [1]–[9] have been proposed. These algorithms employ different search point patterns to search for the best-matched block. To further speed up the motion estimation process, directional information is used to reduce the number of search points required in a search pattern [10].

In most real-world video sequences, local minimum points can spread over the search window, especially for sequences with complex motion contents. Thus these fast algorithms can be trapped by local minima and cannot provide satisfactory motion estimation results. Minimizing a block distortion measure (BDM), e.g., the sum of absolute difference (SAD), between this pair of blocks. The most straightforward method is the full search (FS), which exhaustively evaluates all possible candidate blocks within the search window. Search patterns switching algorithms were proposed to solve the above problem by using different search patterns to achieve higher prediction accuracy.

II. CONVENTIONAL GRADIENT SEARCH ALGORITHMS

A. One-at-a-Time Search (OTS) The strategy of OTS is to keep searching along a particular search direction until the minima found along that direction is found. The first OTS-based BMA [1] employs the OTS strategy in horizontal and then vertical direction. An example of the OTS search path is shown in Fig. 1.

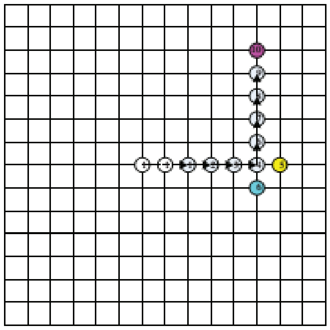


Fig.1 one step search

If, for example, the current minimum BDM point is at position (0, 1) and the upper-direction OTS is performed, then the point immediately above it, i.e., point (0, 2), will be searched. If point (0, 2) has lower distortion than (0, 1), point (0, 2) will be set as the current minimum distortion point. Point (0, 3), which is above point (0, 2), will then be searched. The search continues until the minimum point is closeted between two higher values, or until the search window boundary is reached. As OTS follows the descending gradient path in a particular direction, it can be considered as a 1-D gradient descent search in that direction.

In summary, the OTS performs 1-D gradient descent search on the error surface twice. Although it uses fewer search points compared with other fast BMAs, its prediction quality is low. This is because a 1-D gradient descent search is insufficient to estimate the global minimum position.

B. Block-Based Gradient Descent Search BBGDS performs 2-D gradient descent search. An example of BBGDS search path is shown in Fig. 2.

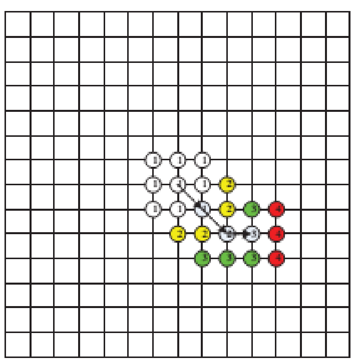


Fig.2 Block based gradient descent search

The eight adjacent points must be BBGDS searches correspond to the eight directions. They cover all the possible directions from the search center. In other words, BBGDS is basically two-dimensional gradient descent search and then one-at-a-time moves toward the global minimum following a descending gradient path.

It has a better prediction quality in terms of PSNR than OTS algorithm.

C. Multipath Search BBGDS provides a very high speed-up ratio in motion estimation but it is easily trapped in the local minima causing low robustness in prediction accuracy. One reason is that BBGDS only uses one single minimum distortion point found in a search step as the search center of the next step. Therefore, while the steepest descending gradient path is considered, other gradient descending paths will be ignored. But it may lead to a problem of global minima. Since the steepest descending gradient path searches a local minimum point instead of a global one, algorithms that consider all the candidate paths should have better prediction quality. Based on this idea, the MPS algorithm was proposed. Basically, MPS is a BBGDS using multiple descending gradient paths. Fig. 3 shows an example of MPS.

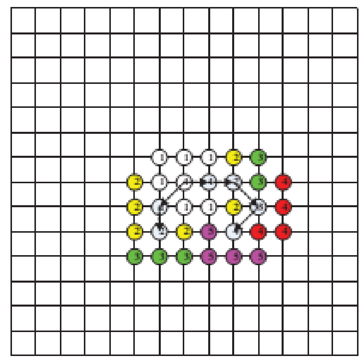


Fig 3. Multipath search

However, MPS is not efficient because it increases the number of points to search all candidate descending gradient paths. Experiments show that MPS can improve the robustness of BBGDS but with the significantly increased computational requirement, especially for complex motion sequences.

D. In Directional gradient search, The strategy of OTS is a 1-D gradient descent search in a particular direction, and the conventional OTS motion estimation algorithm performs OTS twice in the search window. A 2-D gradient descent search algorithm, e.g., BBGDS, performs better than a 1-D search algorithm. MPS is a multiple paths search algorithm for improving the performance of BBGDS, but it is not very efficient in terms of computational complexity.

III. TWO STEP QUADRANT BASED GRADIENT DESCENT SEARCH (TQBGDS)

In this section, a 2-D, Two-step quadrant based gradient descent search (TQBGDS) descent search are proposed. It outperforms TQBGDS by considering all descending gradient paths while achieving lower computational complexity than MPS by using one-step search in eight directions. Fig 4 two-step quadrant based gradient descent search For Fast Block Motion Estimation directional gradient search shown in fig 5, using two-step quadrant based gradient descent search on the reference frame in diagonal directions is proposed. It starts searches from the center, searches in all directional gradients. Where it found the minima it stops the searching, and indicates the minima as distortion by indicating it as a motion vector. If it is at the center of the search window then it shows there is no motion occurs. The search point patterns in each stage depend on the minima found in these eight directions, and thus the global minimum can be traced more efficiently.

directional gradient descent search algorithm using, two step quadrant search. First, apply the searching technique in the reference frame. Searches start from the center of the search window, it calculates the mad value of the center, then it starts moving toward all diagonal, vertically and horizontal directions. It will give better accuracy and improves picture quality in terms of PSNR quality. Fig 5

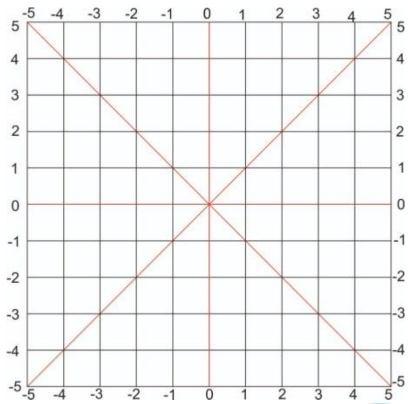


Fig.5 Directional Based

Two-step quadrant based gradient descent search (TQBGDS) descent search algorithm using, OTS's and two step quadrant based search. First, apply the searching technique in the reference frame. Searches start from the center of the search window, it calculates the mad value of the center, then it start moving toward all eight directions. These eight directions are shown in Fig.5 and each of the eight directional searches uses the OTS strategy. In OTS, the point-by-point search along a direction is continued if a newly searched point has lower distortion than the previously searched point. Otherwise, the search in that direction stops. The minimum distortion found by each directional search is set as a directional minimum (DIRECTIONAL_MIN). Apply two-step search in minima directional gradient quadrant as shown in fig 5. It will be an efficient searching technique for the low complex video sequences, it will helpful to find the minimum in the first search round itself. it is also efficient for complex video sequences by using a two-step search. It may give less prediction error and the number of search point per each frame. It may also improve prediction quality in terms of PSNR. So, two-step quadrant based gradient descent search is effective for the notion estimation

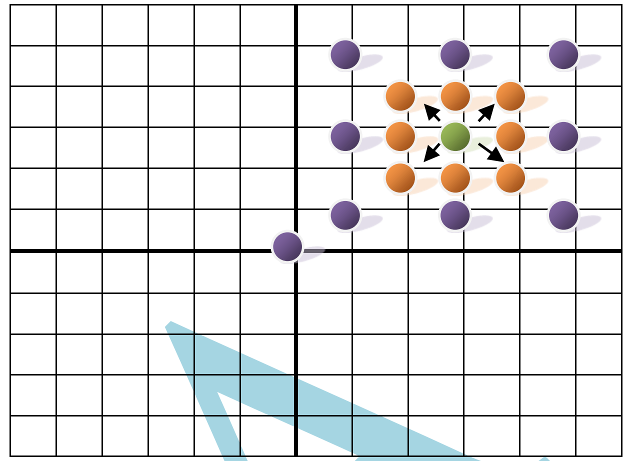


Fig 6

The proposed TSQBGD algorithm can be summarized as follows

Step 1: Calculate the BDM of the search window center and set the value as CURRENT_MIN.

Step 2: For each of the eight directions of the point with CURRENT_MIN
(a) perform point-by-point directional OTS;
(b) set the minimum BDM found in the current direction as a DIRECTIONAL_MIN.
(c) apply two-step search at the quadrant,where the current min found.

Step 3: If no point with DIRECTIONAL_MIN is found (i.e., the current search center is still the minimum point), go to Step 5; otherwise, go to Step 4.

Step 4: DIRECTIONAL_MINs are compared. The lowest one is set as CURRENT_MIN. This is the end of a search round. Go to Step 2 with updated CURRENT_MIN and its corresponding position.

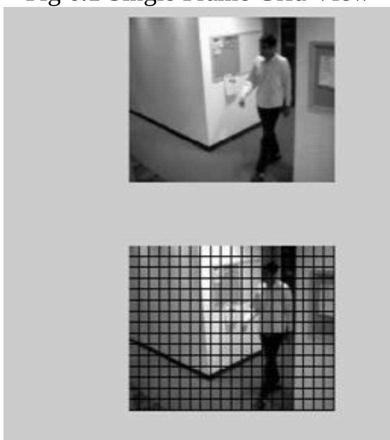
Step 5: The algorithm is completed. Return with the final motion vector (MV) pointing to the position with CURRENT_MIN

IV. RESULTS

The idea behind block matching is to divide the current frame into a matrix of 'macro blocks' that are then compared with a corresponding block and its adjacent neighbors in the previous frame to create a vector that stipulates the movement of a macro block from one location to another in the previous frame.

Take in-built Matlab video. Converted it into small non-overlapping macro blocks. The size of macro block are taken as 8*8 (row*column). Then, the grid view is shown below the image.

Fig 6.1 Single Frame Grid View



	AKIYO		NEWS		COASTGUARD		FOREMAN		STEFAN	
T	PSNR	NO. OF SEARCH POINTS	PSNR	NO. OF SEARCH POINTS	PSNR	NO. OF SEARCH POINTS	PSNR	NO. OF SEARCH POINTS	PSNR	NO. OF SEARCH POINTS
0.1	43.040	8.550	36.722	9.424	29.868	14.236	32.307	17.975	23.913	15.681
0.2	43.040	8.548	36.722	9.403	29.868	13.922	32.306	17.450	23.913	14.993
0.3	43.040	8.541	36.721	9.318	29.868	13.439	32.300	16.813	23.912	14.200
0.4	43.040	8.528	36.716	9.195	29.867	12.938	32.285	16.046	23.912	13.613
0.5	**43.041**	**8.552**	**36.750**	**9.100**	**29.870**	**12.404**	**32.270**	**15.300**	**23.921**	**13.196**
0.6	43.040	8.498	36.704	9.025	29.853	11.735	32.234	14.613	23.904	12.894
0.7	43.39	8.485	36.697	8.965	29.833	11.228	32.191	14.024	23.886	12.598
0.8	43.38	8.475	36.682	8.905	29.807	10.960	32.136	13.471	23.844	12.250
0.9	43.38	8.464	36.661	8.836	29.762	10.823	32.075	12.898	23.735	11.808

The video sequences of vipmen are taken and the reference frame and current frames are converted into small macro blocks the size of each block as 8*8 by using block process technique. And the motion vector shown where ever motion occurs in the blocks process in fig 6.2

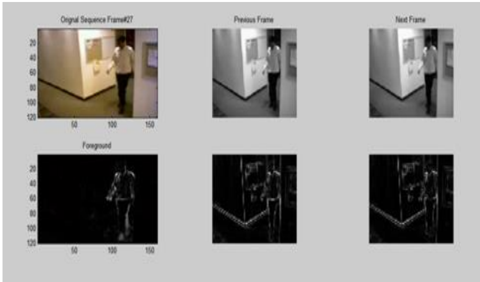
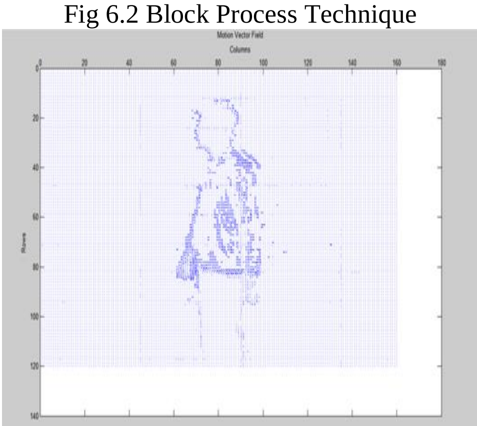


Fig 6.2 Block Process Technique



and the motion vector are shown in the below fig 6.3.

Fig 6.3 Motion Vector

V. CONCLUSION

Two-step quadrant based directional gradient descent search algorithms have been proposed in this letter. The proposed TSQBD is a 2-D gradient descent search algorithm. It outperforms other fast BMAs by considering all descending gradient paths while maintaining lower computational complexity by using OTS on eight directions. In addition, a fast DGDS (FDGDS) with even better speedup is also proposed. Compared with other fast BMAs, FDGDS provides higher prediction quality and higher speed. It is also very robust as it works well in videos with different motion contents

REFERENCES

[1]. R. Srinivasan and K. R. Rao,"Predictive coding based on efficient motion estimation," IEEE Trans. Commun., vol. 33, no. 8, pp. 888–896, Aug. 1985.

[2]. T. Koga,K. Iinuma, A. Hirano, Y. Iijima, and T. Ishiguro, "Motion compensated interframe coding for video conferencing," inProc. Nat. Telecommun. Conf., New Orleans, LA, Dec. 1981, pp. G5.3.1-G5.3.5.

[3]. R. Li, B. Zeng, and M. L. Lio, "A new three-step search algorithm for block motion estimation, "IEEE Trans. Circuits Syst. Video Technol., vol. 4, no. 4, pp. 438–443, Aug. 1994.

[4]. L. M. Po and W. C. Ma,"A novel four-step search algorithm for fast block motion estimation, "IEEE Trans. Circuits Syst. Video Technol., vol. 6, no. 3, pp. 313–317, Jun. 1996.

[5]. L. K. Liu and E. Feig, "A block-based gradient descent search algorithm for block motion estimation in video coding.

[6]. J. Y. Tham, S. Ranganath, M. Ranganath, and A. A. Kassim,"A novel unrestricted center-biased diamond search algorithm for block motion estimation,"IEEE Trans. Circuits Syst. Video Technol., vol. 8, no. 4, pp. 369–377, Aug. 1998.

[7]. C. Zhu, X. Lin, and L. P. Chau, "Hexagon-based search pattern for fast block motion estimation,"IEEE Trans. Circuits Syst. Video Technol., vol. 12, no. 5, pp. 349–355, May 2002.

[8]. C. H. Cheung and L. M. Po,"A novel cross-diamond search algorithm for fast block motion estimation,"IEEE Trans. Circuits Syst. Video Technol., vol. 12, no. 12, pp. 1168–177, Dec. 2002.

[9]. C. H. Cheung and L. M. Po,"Novel cross-diamond-hexagonal search algorithms for fast block motion estimation,"IEEE Trans. Multimedia, vol. 7, no. 1, pp. 16–22, Feb. 2005.

[10]. B. Kim, S. Song, and P. Mah,"Enhanced block motion estimation based on distortion-directional search patterns,"Pattern Recognition Lett., vol. 27, no. 12, pp. 1325–1335, Sep. 2006.

[11]. I. Ahmad, W. Zheng, J. Luo, and M. Liou,"A fast adaptive motion estimation algorithm," IEEE Trans. Circuits Syst. Video Technol.,vol.16, no. 3, pp. 420–438, Mar. 2006.

[12]. K. H. Ng, L. M. Po, and K. M. Wong,"Search patterns switching for motion estimation using rate of error descent,"in Proc. Int. Conf. Multimedia Expo, Beijing, China, 2007, pp. 1583–1586.

[13]. S. Goel and M. A. Bayoumi,"Multi-path search algorithm for blockbased motion estimation," in Proc. IEEE Int. Conf. Image Process., Atlanta, GA, 2006, pp. 2373–2376.

[14]. Lai-Man Po, Ka-Ho Ng, Kwok-Wai Cheung, Ka-Man Wong, Yusuf Md. Salah Uddin, and Chi-Wang Ting "Novel Directional Gradient Descent Searches for Fast Block Motion estimation," in proc. IEEE transactions on circuits and systems for video technology, vol. 19, no. 8, august 2009.

