Proceedings of
National Conference on Innovative Trends in Computer Science Engineering (ITCSE-2015)
held at BRCMCET , Bahal on 4th April 2015

Line Searches for Fast Block Motion Estimation

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Abstract: Search point pattern-based fast block motion estimation algorithms provide significant speedup for motion estimation but usually suffer from being easily trapped in local minima. This may lead to low robustness in prediction accuracy particularly for video sequences with complex motions. This problem is especially serious in one-at-a-time search (OTS) and block-based gradient descent search (BBGDS), which provide very high speedup ratio. A multipath search using more than one search path has been proposed to improve the robustness of BBGDS but the computational requirement is much increased. Totackle this drawback, a line searches search (LS) algorithm using multiple OTSs and gradient descent searches on the error surface in different directions is proposed in this letter. The search point patterns in each stage depend on the minima found in these different directions, and thus the global minimum can be traced more efficiently. Experimental results show that DADDGDS (LINE SEARCH) reduces computation load significantly compared with the well-known fast block motion estimation algorithms.

I. INTRODUCTION

BLOCK MATCHING motion estimation (BMME) is widely 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 non-overlapping blocks of equal size and the best matched block is determined from reference frames to that block in the current frame within a predefined search window. Normally, this is performed byThe most straightforward 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 tackle 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]. However, these algorithms rely primarily on the unimodal error surface assumption, which assumes that matching error monotonically decreases toward the global minimum. 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. However,
the computational complexity of FS is very high.Search patterns switching algorithms [11], [12] were proposed to solve the above problem by using different search patterns to achieve higher prediction accuracy. However, the performance of these algorithms depends highly on the accuracy of the motion content estimators, and some of these estimator are complex in practical implementation.

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 minimum point along that directions 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. 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. This is an efficient searching strategy because it does not waste effort in probing into unknown terrain of the error surface. Moreover, it is also easy to be implemented in hardware, and data access is efficient because a search point is always adjacent to the previous search point. 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. The eight adjacent points which BBGDS searches correspond to the eight directions. They cover all the possible directions from the search center. In other words, BBGDS performs a small-scale 2-Dgradient descent search and then one-at-a-time moves toward the global minimum following a descending gradient path. BBGDS has a much better prediction quality in terms of PSNR than OTS algorithm.

C. Multipath Search

BBGDS provides very high speed-up ratio in motion estimation but it is easily trapped in the local minima causing lowrobustness in prediction accuracy. One reason is that BBGDSonly uses one single minimum distortion point found in asearch 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. Since the steepest descending gradient path may lead to 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. For each of the candidate paths, the compact square-shaped search point pattern of BBGDS is used. The algorithm converges when there is no new descending gradient path found. Fig. 3 shows an example of MPS. However, MPS is not efficient because it uses many points to search all candidate descending gradient paths. Experiments show that MPS can improve the robustness of BBGDS but with significantly increased computational requirement, especially for complex motion sequences.

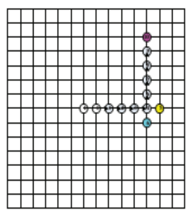

Fig. 1. Example of OTS algorithm.

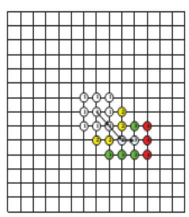

Fig. 2. Example of BBGDS.

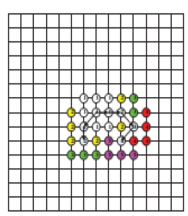

Fig. 3. Example of MPS algorithm.

D. Directional gradient search

The strategy of OTS is a 1-D gradient descent searching a particular direction, and the conventional OTS motion estimation algorithm performs OTS twice in the search window.

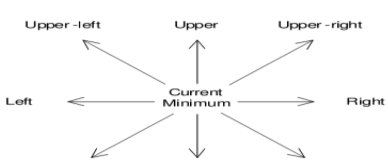

Fig 4 directional gradient search

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. In this section, a novel 2-D gradient descent search algorithm called directional gradient descent search (DGDS)is proposed. It outperforms BBGDS by considering all descending gradient paths while achieving lower computational complexity than MPS by using OTS in eight directions.

Diagonal And Adjacent Diagonal Directional Gradient Descent Search (LINE SEARCH)

Diagonal and adjacent diagonal directional gradient descent search shown in fig 5, using multiple OTSs and gradient descent searches on the reference frame in diagonal directions is proposed. It starts searches from center, and then searches in directions of all gradients. Where it found the minimum it stops the searching, and indicates the minimum as 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 sixteen directions, and thus the global minimum can be traced more efficiently.

Diagonal and adjacent diagonal directional gradient descent search algorithm using, multiple OTS's and gradient descent searches. First apply searching technique in the reference frame. Searches start from centre of the search window, it calculate the mad value of the centre, then it start moving toward all diagonal, adjacent diagonals and vertically and horizontal directions. In the first search round it find the minimum in the search window. No need to go for further search round. It will give better accuracy and improves picture quality.

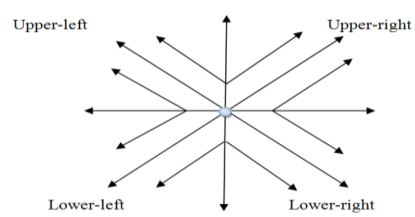

Fig 5 DADDGDS

III.CONCLUSION

Diagonal and adjacent diagonal directional gradient descent search algorithm using, multiple OTS's and gradient descent searches. First apply searching technique in the reference frame. Searches start from centre of the search window, it calculate the mad value of the centre, then it start moving toward all diagonal, adjacent diagonals and vertically and horizontal directions. In the first search round it find the minimum in the search window.

It will be efficient searching technique for the low complex video sequences, it will helpful to find the minimum in the first search round itself. it is efficient gradient descent technique to find the minimum distortion for low complex video. It may give less prediction error and the number of search point per each frame are less it may very effective for the low complex motion in a video. It may also improves prediction quality in terms of PSNR.

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