A Fast Lossless Multi-resolution Motion Estimation Algorithm Using Selective Matching Units

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Abstract. We propose a new and fast multi-resolution motion estimation (MRME) algorithm using optimal matching units and scans for video coding, to significantly reduce the amount of computation in motion estimation. Our proposed algorithm has no any degradation of prediction quality compared to the original MRME algorithm. The computational reduction of our algorithm comes from fast elimination of unlikely candidate vectors. We fast eliminate inappropriate motion vectors using gradient magnitude in image data. The experimental results show that our algorithm reduces the computational amount of just 98~95% compared to full search algorithm and 55~80% compared to the original MRME algorithm. Our algorithm will be useful to real-time video coding applications such as MPEG-2 and MPEG-4 AVC.

1 Introduction

Motion estimation is defined as getting the best motion vector, which is the displacement of the coordinate of the best similar block in a previous frame for the block in a current frame. Of many approaches for motion estimation, the block-matching algorithm (BMA) is very popular in the framework of generic coding [1]-[2]. In last decades, so many BMA-based fast motion estimation algorithms have been published as follows [2]: unimodal error surface assumption (UESA) techniques[3]-[6], multi-resolution motion estimation (MRME) techniques [7]-[13], variable search range techniques with spatial/temporal correlation of the motion vectors, half-stop techniques using threshold of matching distortion, integral projection technique of matching block, low bit resolution techniques, sub-sampling techniques of matching block, successive elimination algorithm (SEA) [15]-[16], partial distortion elimination (PDE) [17], and so on.

In these fast algorithms, MRME is popular in video coding applications because of reduced computation, good prediction quality, its simplicity and easy hardware implementation. So many modified MRME algorithms of motion estimation have been reported in the last decades to further improve the original MRME algorithm. However, most of modified fast MRME algorithms can result in poor prediction quality for some cases, which can be a serious problem in actual applications [7]-[13].

In this paper, we remove only unnecessary computation in calculating block matching errors without any degradation of prediction quality compared to the original MRME algorithm. Our proposed algorithm employs multi-resolution approach, the

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PDE, spiral search, and the adaptive matching scan from image complexity of the reference block. The MRME scheme has good prediction quality with significant computational reduction at same time. The PDE algorithm reduce only computational amount without affecting prediction quality, and the spiral search algorithm increases the probability to detect the optimal motion vectors in the search range as soon as possible because most of optimal motion vectors distribute about center area of the search range. And our proposed adaptive matching scan algorithm eliminates impossible candidates fast by first calculating block matching error for complex area of the reference block. From the combined algorithms, we further reduce only unnecessary computation without any degradation of prediction quality in calculating block-matching errors.

This paper is organized as follows. In section 2, we describe our proposed algorithm, which is based on MRME scheme, PDE, spiral search algorithm, and adaptive matching scan. In section 3, experimental results for various sequences and several fast algorithms and discussions of the results are given. Conclusion is followed in section 4.

2 Proposed Algorithm Using Spiral PDE and Adaptive Matching Scan Algorithm in MRME Scheme

In this section, we propose MRME based fast block-matching algorithm applicable to the current international video coding standards. Our algorithm reduces only unnecessary computation without any degradation of prediction quality compared to the original MRME algorithm. To do that, we use multi-resolution scheme, PDE (partial distortion elimination), and adaptive matching scan, which have different orders of calculations of matching errors in the matching blocks. With the concept, we further reduce the computations compared to the conventional MRME algorithm with the same prediction quality as that of the conventional MRME algorithm. From these concepts, we can remove impossible candidates faster, resulting in further reduced computations compared to the conventional MRME algorithm. We describe adaptive matching scan algorithm with PDE and spiral search based on image complexity.

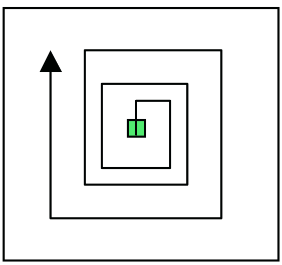
2.1 Partial Distortion Elimination (PDE) and Spiral Search Algorithm

Before describing our algorithms, we will introduce the conventional PDE and spiral search algorithm. An efficient algorithm to reduce the computational complexity efficiently is the partial distortion elimination (PDE) method [1]-[2]. It uses the partial sum of matching distortion to eliminate impossible candidates before complete calculation of matching distortion in a matching block. That is, if an intermediate sum of matching error is larger than the minimum value of matching error at that time, the remaining computation for matching error is abandoned. In the partial distortion elimination (PDE), the *kth* partial sum of absolute difference (SAD) to check during the matching is as follows:

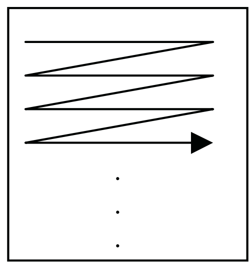
$$\sum_{i=1}^{k}\sum_{j=1}^{N}\left|f_t(i,j)-f_{t-1}(i+x,j+y)\right| \qquad k=1,2,...N \tag{1}$$

N represents matching block size in the Eq. (1). If k is smaller than N from the partial sum of absolute difference (SAD) exceed the current SADmin, then we can quit the remaining summation of matching error calculation and kick out the impossible candidate motion vector (x,y). The PDE technique has been widely used to reduce the computational load in the full search algorithm. The reduction of calculation in obtaining motion vectors with the PDE algorithm depends on how fast global minimum of matching distortion is detected. If we find the global minimum of distortion in calculation of matching error faster, computational amount for matching error in a block is further reduced and k in the Eq. (1) is determined faster.

Ability to reject impossible candidates in the PDE algorithm depends on the search strategy which makes minimum matching error be detected faster. For the purpose, spiral search method shown in Fig. 1 (a) can be used. So, combined PDE algorithm uses Eq. (1) and spiral search. Fig. 1(b) shows top-to-bottom sequential search algorithm. In general, most of motion vectors are distributed about (0,0), which is the center of the search range. Thus, we can get higher probability for obtaining minimum matching error by using the spiral search scheme. If we get less matching error faster, we can ultimately remove more computation. Therefore, we employ the spiral search and PDE algorithm in our proposed algorithms.



(a)



(b)

Fig. 1. Conventional spiral search direction and top-to-bottom sequential search: (a) spiral search direction and (b) top-to-bottom sequential search

As shown in Fig. 1(b), simple PDE algorithm means top-to-bottom matching scan based on Eq. (1) with top-to-bottom search in a given search range. Ability to reject impossible candidates in the PDE algorithm depends on the search strategy, which makes minimum matching error be detected faster. For the purpose, spiral search method shown in Fig. 1(a) is very efficient. So, combined PDE algorithm uses Eq. (1) and spiral search. As shown in the experimental results, the combined PDE algorithm rejects more the impossible candidates than simple PDE. Therefore, we employ the spiral search in the proposing matching scan algorithms.

2.2 Adaptive Matching Scan Algorithm Based on Image Complexity

2.2.1 Physical Meaning of the Relationship Between Matching Error and Image Complexity

Important thing in the PDE algorithm is that how fast impossible candidates are detected by removing unnecessary computation. To do so, we use the relationship between block matching error and image complexity of reference block using representative pixels. In this paper, we use the fact that the block-matching error is proportional to the complexity of the reference block with Taylor series expansion. The motivation of the proposing algorithm is using image complexity to find the impossible candidates faster. That is, we use image complexity and matching error for fast motion estimation. Thus, we measure image complexity and use sum of absolute difference (SAD) as matching criterion.

Usually, the matching distortion error, $d_t(p)$, is defined as the first expression in Eq. (2). Here, $f_t(p)$ represents pixel values at the block position p which represents a matching block position in the t_{th} frame, $cmv=(cmvx, cmvy)$ represents the position of the candidate motion vectors in the given search range. Additionally, the matching distortion can be approximated with the second expression of Eq. (2). It means that the matching block of the position p in the t_{th} frame can be approximated with the block of the $t\text{-}1_{th}$ frame. It has the displacement of optimal motion vector $mv=(mvx, mvy)$ of the given search range in the $t\text{-}1_{th}$ frame from the corresponding position of the t_{th} frame. Using the Taylor series expansion and taking only the first term of the series can obtain the third expression in Eq. (2). The higher order terms from the Taylor series expansion can be ignored in Eq. (2). Then, the t_{th} frame block can be exchanged approximately, with the $t\text{-}1_{th}$ frame block as the first approximation. As shown in Eq. (2), the matching distortion is expressed by the image gradient and the difference between candidate motion vectors and the optimal motion vector. The gradient and its magnitude are expressed as shown in Eq. (3).

$$\begin{aligned} d_t(p) &= \left| f_t(p) - f_{t-1}(p+cmv) \right| \\ &\approx \left| f_{t-1}(p+mv) - f_{t-1}(p+cmv) \right| \\ &\approx \left| \tfrac{\partial f_{t-1}(p+mv)}{\partial x}(cmvx - mvx) + \tfrac{\partial f_{t-1}(p+mv)}{\partial y}(cmvy - mvy) \right| \\ &\approx \left| \tfrac{\partial f_t(p)}{\partial x}(cmvx - mvx) \right| + \left| \tfrac{\partial f_t(p)}{\partial y}(cmvy - mvy) \right| \end{aligned} \tag{2}$$

$$\begin{aligned} \left| G[f(x,y)] \right| &= \left\| \begin{bmatrix} Gx \\ Gy \end{bmatrix} \right\| = \left\| \begin{bmatrix} \frac{\partial f}{\partial x} \\ \frac{\partial f}{\partial y} \end{bmatrix} \right\| = \sqrt{G^2{}_x + G^2{}_y} \\ &\approx |Gx| + |Gy| \\ &\approx \left| f(x,y) - f(x+1,y) \right| + \left| f(x,y) - f(x,y+1) \right| \end{aligned} \tag{3}$$

2.2.2 Fast Adaptive Matching Scan Algorithms Using Image Complexity of Reference Block

By localizing the image complexity well, we can get more reduction of unnecessary computation. In general, image complexity is well localized in pieces rather than the whole span of the image or of some fixed blocks. Our proposed algorithm using adaptive matching scan based on image complexity is validated by further reduced computation. That is, if we use localization of image complexity with small square subblocks then, we can get a faster elimination of impossible candidates than that of the previous works. This is realized with the first calculations of matching error for the area of larger distortion. Our adaptive matching scan algorithm from complexity order with square subblocks can be represented as shown in Eq. (4). Local complexity of subblock is defined as spatial complexity of image data for each subblock and measured with gradient magnitude as shown in Eq. (3). The size of matching unit of square subblocks and row vectors is the same for the fair comparison. We just change the shape of the matching unit from row vectors to square subblocks to localize image complexity well.

$$\text{Partial Distortion} = \sum_{u=1}^{k} \sum_{i=1}^{N/s,} \sum_{j=1}^{N/s} \left| \begin{array}{l} f_t(i+q_u*(N/s), j+r_u*(N/s)) \\ -f_{t-1}(i+x+q_u*(N/s), j \\ \quad +y+r_u*(N/s)) \end{array} \right| \tag{4}$$

$$k=1,2,...N,\quad q_u = floor((m_u-1)/(N/s)),$$
$$r_u = (m_u-1)\%(N/s),$$
$$m_u \in local\_complexity\_order[u]$$

In Eq. (4), s is the size of a small sub-block, N is the size of matching block, and the *local_complexity_order[]* is the matching scan order according to the local complexity from the square subblocks, *(x,y)* is a candidate vector in the search range, and m_u is the index of the subblock, which is determined by gradient magnitude and arranged in the array of *local_complexity_order[u].* The operation, *floor(alpha),* rounds off the alpha. The operation, *(alpha)%(beta),* calculates remainder after division of *(alpha/beta). k* is variable because of PDE scheme.

Our proposed algorithm employs the MRME scheme, the PDE, the spiral search, and the adaptive matching scan from the image complexity of the reference block. As described previously, the MRME scheme has good prediction quality with significant computational reduction at same time. The PDE algorithm reduce only computational amount without affecting prediction quality, and the spiral search algorithm increases the probability to detect the optimal motion vectors in the search range as soon as possible because most of optimal motion vectors distributes about center area of the search range. And our proposed adaptive matching scan algorithm eliminates impossible candidates fast by first calculating block matching error for complex area of the reference block. From the combined algorithms, we further reduce only computation without any degradation of prediction quality in calculating block-matching errors.

3 Experimental Results

To compare the performance of the proposed algorithm with the conventional algorithms, we use 100 frames of ‘foreman’, ‘car phone’, ‘trevor’, and ‘clair’ image sequences. In these sequences, ‘foreman’, and ‘car phone’ have big motions compared with other image sequences, while ‘clair’ is almost inactive sequences compared with first three sequences. ‘trevor’ sequence has intermediate motions.

We presented experimental results with the original full search (FS), the three-step search (TSS) [2], the new three-step search (NTSS) [3], the original multiresolution

resolution motion estimation (MRME) [1]-[2]. We further reduced computational complexity of MRME scheme as described previously with the partial distortion elimination (PDE) algorithm and adaptive matching scan algorithm which is our proposed algorithm.

The matching block size is 16 x 16 pixels and the search window is 31 x 31 pixels. Image format is QCIF (176 x 144) for each sequence and only forward prediction is used. Sum of absolute difference (SAD) as error criterion for finding motion vector is employed. The simulation results are shown in terms of average number of checking rows with the reference of that of full search without any fast operation and peak signal-to-noise ratio (PSNR). The average checking rows is used because the comparison for the partial distortion and the minimum distortion in the conventional PDE algorithm is performed in the unit of line-by-line of matching blocks. Here, the experiment were carried out by skipping zero and two frames. Therefore, the resulting frame rate is 30, and 10 frames per second (fps). All figures for the average checking rows of our proposed algorithm in the tables were considered with overhead computations for complexity measure.

We measured the image complexity with three directions of three neighboring points. The three directions are the right point, the below point, and the diagonal right bottom point from the corresponding point. Of course, we can extend to eight directions instead of three directions. In our experiments, the three directions were the most appropriate considering the trade-off between the computational amounts and the reduction of checking rows. The reduction of checking rows from more than three directions ones were close to that of three directions with only increased overhead computation. Also, all the matching scan algorithms employed spiral search scheme to make use of the distribution of motion vectors.

Table 1 present experimental results for average PSNR of several algorithms with 30 fps (frames per second). The average PSNR in these tables means the prediction quality for each algorithm. In these tables, we can see that the MRME schemes produce the prediction quality close to the full search (FS) algorithm. Our proposed MRME algorithms have the same prediction quality as that of the original MRME algorithm because our algorithm reduces only unnecessary computations without affecting the prediction quality. In general, it is reported MRME schemes has better prediction quality than that of TSS and NTSS in actual video sequences [1]-[2]. Generally, NTSS algorithm shows good prediction quality in inactive image sequences because it is operated with center-biased search method. Our test image sequences are QCIF format, thus motions in the sequences are not large.

Table 1. Experimental results for average PSNR of several algorithms with 30 fps

	Foreman	Car phone	Trevor	Clair
Original FS	34.43	33.44	33.28	41.29
Original MRME	33.89	33.27	33.21	41.29
TSS	33.84	33.24	33.21	41.29
NTSS	34.33	33.40	33.26	41.29

Table 2. Computational reduction ratio of several algorithms with 10 fps

	Foreman	Car phone	Trevor	Clair
Original FS	100 %	100 %	100 %	100 %
Original MRME	9%	9%	9%	9%
Fixed Direction	4.56%	4.20%	3.97%	2.11%
Adaptive Direction	4.04%	3.86%	3.69%	1.98%
TSS	11.11%	11.11%	11.11%	11.11%
NTSS	10.52%	9.65%	7.96%	7.68%

Table 3. Computational reduction ratio of several algorithms with 30 fps

	Foreman	Car phone	Trevor	Clair
Original FS	100 %	100 %	100 %	100 %
Original MRME	9%	9%	9%	9%
Fixed Direction	3.91%	3.62%	2.92%	1.75%
Adaptive Direction	3.37%	3.29%	2.74%	1.70%
TSS	11.11%	11.11%	11.11%	11.11%
NTSS	8.67%	8.70%	7.98%	7.61%

Table 2 ~ 3 present the computational reduction ratio for several algorithms for 10 fps and 30 fps. We can see that the MRME schemes obtain significant computational reduction compared to other TSS and NTSS algorithms. Additionally, the MRME schemes get good performance about computational reduction and prediction quality. Especially, our proposed algorithm, spiral search based adaptive matching MRME, obtains the most computational reduction ratio in MRME schemes, which include the original MRME and the spiral search based fixed matching MRME. There are three MRME schemes in the tables. The original MRME doesn't employ any fast method, and the MRME with fixed direction uses the spiral search method and the PDE method with the sequential fixed top-to-bottom matching direction. And our proposed algorithm, MRME with adaptive direction, uses the spiral search and the PDE with adaptive matching direction. To set the reference of computational reduction, we put the computation of the FS as 100%.

Fig. 2 ~ 3 represent average checking rows of high-resolution for “foreman” and “clair” sequences with 30 fps. We can find obvious difference in the computational reduction between the sequential matching scan MRME and our adaptive matching scan MRME. Our proposed MRME algorithm with adaptive matching scan shows better performance than the sequential matching scan algorithm for all the frames and all the frame rates of each sequence in these figures.

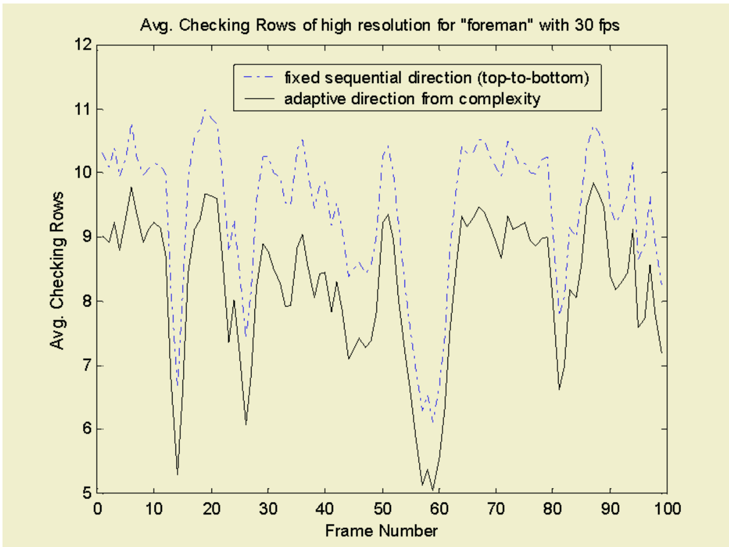


Fig. 2. Average checking rows of high resolution for “foreman” sequence with 30 fps

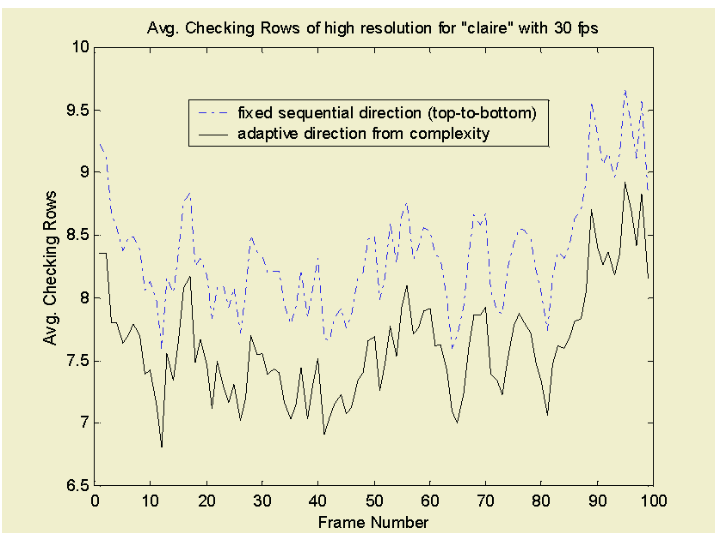


Fig. 3. Average checking rows of high resolution for “clair” sequence with 30 fps

From the above experimental results, we can conclude that the MRME scheme is excellent in terms of the prediction quality and the computational reduction compared to other fast motion estimation algorithms, and our proposed adaptive matching scan MRME algorithm obtains more computational reduction than other MRME schemes, meanwhile keeping the same prediction quality compared to the original MRME scheme.

4 Conclusions

In this thesis, we proposed MRME based fast block-matching algorithms applicable to the current international video coding standards. In our algorithm, we used image complexity, multi-resolution motion estimation, partial distortion elimination (PDE), and adaptive matching scan, which has different orders for matching error calculation in the matching blocks. The experimental results showed that our algorithm reduces the computational amount of just 98~95% compared to full search and 55~80% compared to the original MRME. Our algorithm can be applicable to real-time video coding applications such as MPEG-2 and MPEG-4 AVC encoders.

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