# A NEW ORIENTED ADAPTIVE CROSS SEARCH ALGORITHM FOR BLOCK MATCHING MOTION ESTIMATION <br> Heng Yang, Qing Wang <br> School of Computer Science and Engineering <br> Northwestern Polytechnical University <br> Xi'an 710072, P. R. China 


#### Abstract

Block-matching motion estimation plays an important role in video coding and faster, more robust and more effective search algorithms are needed. Recently, a great number of fast block matching algorithms (BMAs) have been proposed in the literature based on the discovery of the center-biased characteristics of motion-vector distribution. In this paper, a novel oriented adaptive cross search (OACS) algorithm is proposed, where small cross, large cross and T-shape search patterns are defined and utilized adaptively. In accordance with the adaptive tracing of orientation change or optimal point, three kinds of key points are defined to decide which kind or which oriented pattern may be chosen for the next step. Experimental results on the benchmarks have shown that the OACS algorithm can provide average speed ups of $74.65 \%, 39.78 \%, 42.44 \%$, and $7.84 \%$ over DS, SDS, CDS, and SCDS, respectively. Finally, the mean absolute distortion and PSNR of luminance component are close to the results of other fast BMAs and the similar search accuracy can be maintained as expected.


## 1. INTRODUCTION

Motion estimation is the cardinal process in video coding and compression ${ }^{[1]}$. Block matching algorithm (BMA), which is a temporal redundancy removal technique between successive frames, is a fundamental part of most of the mo-tion-compensated video coding standards ${ }^{[2]}$ and has been widely adopted by current video coding standards such as H.26x and MPEG-1,2,4,7. The block- matching method divides frames into non-overlapping and regular sized blocks, or so-called macro-blocks, then seeks the bestmatched block from the previous frames within a fixedsized search window. Based on a block distortion measure, the displacement of the best-matched block will be described as the motion vector to the block in the current frame. The more accurate estimation is, the less distortion between best-matched block and current block will be. Generally, the full search (FS) method, which carries out searching for all the candidate blocks within the search window exhaustively, can find out the global best matching result. However, full search is therefore very time-consuming. In the last two decades, many well known fast algorithms have been proposed to speed up motion estimation with similar
block distortion instead of full searching strategy, some of which are three step search (3SS), new three step search (N3SS), four step search (4SS), diamond search(DS) ${ }^{[3,4]}$, square-diamond search (SDS) ${ }^{[5]}$, cross-diamond search (CDS) ${ }^{[6]}$, small cross-diamond search (SCDS) ${ }^{[7]}$, Kite-crossdiamond search (KCDS) ${ }^{[8]}$ and so on. On the discovery of the characteristic of center-biased motion vector distribution, which is that most of the motion vectors are enclosed in the central $5 \times 5$ (blocks) area, the more robust and more effective block matching algorithms are likely to be. From the statistical results of center-biased motion vector distribution, it is obvious that most of motion vectors within blocks are close to zero so that most of the blocks can be regarded as stationary or quasi-stationary blocks. In the algorithms of N3SS, 4SS, DS, SDS, CDS and SCDS, the searching criteria are emphasized on the search in the central areas in order to find the motion vector quickly.
Moreover, a parallel processing idea of coarse location and accurate orientation was proposed in the SDS algorithm ${ }^{[5]}$, which utilized square and small diamond-shaped patterns to decide the next candidate for the optimal result. CDS and SCDS both introduce cross-shaped pattern in the initial step instead of diamond-shaped ones, to the DS algorithm and employ halfway-stop technique for quasistationary or stationary candidate blocks. The difference between them is that CDS performs only the large crossshaped pattern (LCSP) as the initial step while SCDS uses both LCSP and small cross-shaped patterns (SCSP) as first the two steps ${ }^{[6,7]}$.
In this paper, a novel fast BMA algorithm, which is called oriented adaptive cross search algorithm (OACS), is proposed. Initially, two cross-shaped search patterns are utilized as search areas and then one of the four T-shaped search patterns (TSP) is adaptively used according to the orientation predicted in the last step. Experimental results show that OACS can get a faster speed than the typical BMAs and can maintain a similar distortion performance.

## 2. ORIENTED ADAPTIVE CROSS SEARCH (OACS)

### 2.1 Search Patterns

In order to make full use of statistical characteristic of natural scene video sequences, we defined and utilized three kinds of search patterns in our OACS algorithm, which are small cross-shaped pattern (SCSP), large cross-shaped pat-
tern (LCSP), and four directional T-shaped patterns (TSPs), as shown in Fig.1. As we know, diamond or cross-shaped search algorithms have been proposed in the literature ${ }^{[3-8]}$. In the paper, the proposed TSPs are distinct patterns different with other traditional methods. TSP can be regarded as a particular kind of cross pattern since it is a transfiguration of SCSP. In addition, which pattern is selected as the candidate at the next step is the most important factor to improve the match speed. As a result, three different kinds of points are defined in the OACS framework, which are central point, adjacent point and oriented point, as shown in the left bottom of Fig.1.


Figure 1. The illustration of search patterns used in OACS

### 2.2 OACS Algorithm

The search begins at the central point of the search window. Initially, SCSP and LCSP are taken as searching areas. Then SCSP or TSP will be chosen adaptively for subsequent search step by step. The details of the procedure of the proposed OACS algorithm are summarized in the flowchart, as shown in Fig.2.

### 2.3 Analysis of OACS Algorithm

From the section 2.2, we find that the OACS algorithm is adequate for all the points nearby or far from the central point. OACS make full use of two statistical characteristics of motion distribution, and it uses three types of cross-shape pattern to focus on searching in the CCB of the search window, especially at the central area. For the far point, it uses TSP, which has oriented feature, to search along the vertical or horizontal orientation in CCB to approach to the best matching point location as fast as possible. Moreover, TSP has oriented point and adjacent point to process respectively coarse location and accurate orientation at the same time, which is based on the parallel processing criteria mentioned in ${ }^{[5]}$. All these features of OACS make it possible to find the best matching point with the fastest speed.

Table 1 shows the comparison of search points at four typical positions nearby the central point for five fast BMAs. As we know, the most scenes of the video sequence are smooth or with little motion content so that the search points


Figure 2. The flowchart of the proposed OACS algorithm
in these areas have a large impact on the average searching points (ASP) of BMAs. From Table 4, we can see that the OACS algorithm leads to fewer search points than those of other testing BMAs at four positions, $(0,0),(1,0),(1,-1)$ and $(2,0)$. For example, the OACS algorithm can reduce 8,4 and 4 search points at the position $(0,0)$ compared to the DS, SDS and CDS algorithms respectively and is as the same as that of SCDS. Furthermore, the OACS algorithm can reduce 3 and 6 search points at the positions $(1,-1)$ and $(2,0)$ comparing to the SCDS algorithm, which is recognized as the best one so far. The procedures of these four points are shown in Fig.3(a)-(d), respectively.

Moreover, for the points far from the central point, we choose point $(4,0)$ and $(4,-2)$ as the testing representatives. The former locates in the CCB and the latter was used as an example in ${ }^{[4]}$. The results of search points are listed in the most right tow columns of Table 1 , from which we can see that the OACS algorithm has distinct predominance over other BMAs for the points located in CCB. For example, it only took 17 points to seek the best result for the point $(4,0)$ whereas the DS, SDS, CDS and SCDS algorithms checked $23,22,25$ and 25 points, respectively. For the point ( $-4,-2$ ), the OACS algorithm also has good performance and need 1, 3 , and 3 search points fewer than the DS, CDS and SCDS

Table 1 Search comparison of BMAs at different positions

|  | $(0,0)$ | $(1,0)$ | $(1,-1)$ | $(2,0)$ | $(4,0)$ | $(-4,-2)$ |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| DS | 13 | 13 | 16 | 18 | 23 | 24 |
| SDS | 9 | 12 | 14 | 15 | 22 | 22 |
| CDS | 9 | 11 | 16 | 19 | 25 | 26 |
| SCDS | 5 | 11 | 16 | 19 | 25 | 26 |
| OACS | 5 | 11 | 13 | 13 | 17 | 23 |

algorithms respectively even if it needs one search point more than the SDS algorithm. Fig. 3 (e)-(f) show the search procedure of two points $(4,0)$ and $(-4,-2)$.

From the aforementioned analysis, the OACS algorithm can speed up searching and is the fastest one among the testing BMAs. Especially, for the points in the central area and in the CCB, OACS has an obvious predominance. In addition, from the aspect of search pattern, the SCSP used in OACS is the same as the small diamond search pattern (SDSP) used in DS, SDS, CDS and SCDS algorithms. The TSP is a transformation of SCSP and it has an oriented point for coarse location. However, the candidate points used for the coarse location by the TSPs are fewer than those of the large diamond search pattern (LDSP) used in DS, CDS and SCDS, which is the disadvantageous aspect to result in the local optimal, not the global one.







$$
\begin{array}{lll}
\hline \text { (1) First step } & 2 \text { Second step } & 3^{\text {Third step }}
\end{array}
$$

$\begin{array}{ll}\text { (a) } \mathrm{MV}=(0,0) & \text { (b) } \mathrm{MV}=(1,0)\end{array}$
(c) $\mathrm{MV}=(1,-1) \quad$ (d) $\mathrm{MV}=(2,0)$
(e) $M V=(4,0) \quad$ (f) $M V=(-4,-2)$

Figure 3. The search procedure of six typical examples by the proposed OCAS algorithm. Each candidate is marked with its step number, within which only one is the minimum BDM point (filled by red color).

## 3. EXPERIMENTAL RESULTS

To verify the efficiency of OACS algorithm, it was implemented on the platform of JVT reference software JM73 ${ }^{[11]}$. In order to compare the OACS algorithm with other traditional BMAs, the DS, SDS, CDS, SCDS algorithm are also implemented on this platform.

In the experiment, we encode and decode eight well known sequences for testing, which are "Salesman", "Carphone", "MissAmerican", "Grandmother" (QCIF, 176×144, 150 frames), "Foreman"(CIF, $352 \times 288,100$ frames), "Flower garden", "Table tennis" and "Football" (SIF, $352 \times 240$, 100
frames). Among them, image sequences of "Miss American" and "Grandmother" consist of gentle, smooth and low motion content whilst there are moderate motion contents in the sequences of "Salesman", "Carphone" and "Foreman". Moreover, fast and large motion with camera zooming can be found in "Table Tennis" and camera panning with translation and rigorous motion content can be found in the sequences of "Flower garden" and "Football", respectively. In the experiment, we encoded the sequence at 30 fps , where the CABAC entropy coder was used for all tests, a search range of $16(33 \times 33)$, one reference frame, IPPP... encode sequence type, and QP is preset to 28 for I frame and all P frames.

The proposed OACS algorithm is compared against the five existing BMAs: FS, DS, SDS, CDS and SCDS by: (1) average searching point (the average number of search point used to find motion vector), i.e., ASP, which is the criterion of searching speed; (2) peak signal-to-noise ratio (PSNR) of luminance component, which stands for the criterion of searching accuracy.

In Table 2 and 3, we summarize the experiment results of each BMAs using the eight video sequences on ASP and PSNR of luminance component, from which we can find out that it took OACS the smallest average number of searching points per block. It speeds up more than 150 times compared with FS and achieves $74.65 \%$, $39.78 \%$, $42.44 \%$ and $7.84 \%$ speed improvement over DS, SDS, CDS, SCDS, respectively. By observing the result tabulated in Table 8, we can find out that no matter what degree and types of motion content the video sequences contain, PSNR of luminance component obtained by using OACS just decreases slightly (at most 0.08 db averagely) compared to FS and nearly as the same as those of DS, SDS, CDS and SCDS.

## 4. CONCLUSION

In the paper, a novel block matching algorithm for motion estimation, called as oriented adaptive cross search (OACS), is proposed. Traditionally, most of the methods put emphasis on diamond or cross shaped areas. Based on the summarization of some typical block matching algorithms and statistical knowledge of motion vector distribution of natural scene video sequences, we proposed four directional Tshaped patterns, apart from small cross-shaped pattern (SCSP) and large cross-shaped pattern (LCSP), to adaptively decide the optimal searching area step by step. The searching procedure and flowchart are discussed in the paper whilst the details for six examples, four of which are close to the center of the block and the other two points are far from the center, are shown in the paper. Moreover, the performance of the proposed OACS algorithm is evaluated with the full search and other four traditional fast algorithms, including diamond search, small diamond search, crossdiamond search and small cross-diamond search on eight typical video sequences. Experimental results have shown
that OACS achieves on average $74.65 \%, 39.78 \%, 42.44 \%$ and $7.84 \%$ speed improvement over DS, SDS, CDS and SCDS algorithms, respectively. Especially, for the sequences containing strong motion content, for example, camera zooming and panning, or shot change, the OACS algorithm improves the search efficiency undoubtedly and maintains a similar accuracy compared to DS, SDS, CDS and SCDS algorithms.

## ACKNOWLEDGEMENT

The work described in the paper was supported by National Science Fund (60403008), Aerospace Innovation Fund and Aviation Science Fund (03I53065), P. R. China.

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Table 2. The average number of searching points(ASP) and average speedup ratio(ASR) of BMAs on 8 testing sequences

|  | FS | DS | SDS | CDS | SCDS | OACS |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Miss American | 1089 | 13.24 | 9.30 | 9.32 | 5.96 |  |
| Grandmother | 1089 | 13.06 | 9.10 | 9.09 | 5.86 |  |
| Carphone | 1089 | 13.87 | 9.87 | 10.05 | 7.77 | 5.31 |
| Salesman | 1089 | 13.11 | 9.13 | 9.15 | 5.40 |  |
| Foreman | 1089 | 14.46 | 10.56 | 10.79 | 9.58 | 5.33 |
| Table Tennis | 1089 | 14.08 | 10.15 | 10.47 | 8.68 |  |
| Football | 1089 | 15.37 | 11.48 | 12.23 | 10.22 | 8.28 |
| Flower Garden | 1089 | 13.71 | 10.28 | 10.13 | 7.44 |  |
| ASP | 1089 | 13.86 | 9.98 | 10.17 | 7.70 | 9.39 |
| ASR | 1 | 78.6 | 109.1 | 107.1 | 141.4 | 7.85 |

Table 3 Comparison of luminance component PSNR of BMAs on 8 test sequences (dB)

|  | FS | DS | SDS | CDS | SCDS | OACS |
| :--- | :---: | :---: | :---: | :---: | :---: | :---: |
| Miss American | 40.14 | $40.10(-0.04)$ | $40.11(-0.03)$ | $40.12(-0.02)$ | $40.11(-0.03)$ | $40.12(-0.02)$ |
| Grandmother | 36.54 | $36.53(-0.01)$ | $36.54(0.00)$ | $36.54(0.00)$ | $36.54(0.00)$ | $36.54(0.00)$ |
| Carphone | 36.94 | $36.87(-0.07)$ | $36.85(-0.09)$ | $36.87(-0.07)$ | $36.87(-0.07)$ | $36.86(-0.08)$ |
| Salesman | 35.53 | $35.53(0.00)$ | $35.52(-0.01)$ | $35.51(-0.02)$ | $35.52(-0.01)$ | $35.52(-0.01)$ |
| Foreman | 36.65 | $36.63(-0.02)$ | $36.60(-0.05)$ | $36.60(-0.05)$ | $36.60(-0.05)$ | $36.60(-0.05)$ |
| Table Tennis | 34.06 | $34.05(-0.01)$ | $34.04(-0.02)$ | $34.05(-0.01)$ | $34.05(-0.01)$ | $34.04(-0.02)$ |
| Football | 33.26 | $33.24(-0.02)$ | $33.23(-0.03)$ | $33.24(-0.02)$ | $33.24(-0.02)$ | $33.23(-0.03)$ |
| Flower Garden | 33.35 | $33.34(-0.01)$ | $33.34(-0.01)$ | $33.34(-0.01)$ | $33.33(-0.02)$ | $33.33(-0.02)$ |
| Avg PSNR loss | 0 | -0.023 | -0.03 | -0.025 | -0.026 | -0.029 |

