

AN EXTENDED SMALL DIAMOND SEARCH ALGORITHM FOR FAST BLOCK MOTION ESTIMATION

Chang-Uk Jeong, Takeshi Ikenaga, and Satoshi Goto

Graduate School of Information, Production and Systems
Waseda University, Kitakyushu, 808-0135, Japan
Email: jcu@ruri.waseda.jp, {ikenaga, goto}@waseda.jp

ABSTRACT

In this paper, we propose a fast motion estimation algorithm that is suitable for searching both center-biased motion and large motion by applying the small diamond pattern used in some block-matching algorithms (BMA). The search will be terminated by a small diamond search (SDS) method after performing a large search based on a modified three-step search (3SS) strategy. The results of the experiment show an increase about 220% in the search speed compared to that of diamond search (DS) and efficient three-step search (E3SS) in a sequence that represent small motions in objects. Experimental results also demonstrate reasonable search points in the estimation of rough motions in high-resolution images, maintaining a performance better than other fast BMAs in terms of PSNR.

Index Terms—Block-matching algorithm, fast search algorithm, motion estimation, small diamond search, video compression

1. INTRODUCTION

Motion estimation (ME) method is typically used to effectively remove the temporal redundancy. In addition, the block-matching motion estimation (BMME) is the most significant part in today's video coding techniques and standards. The BMME has also been adopted by various international video compression standards, such as ISO/IEC MPEG-1, MPEG-2, MPEG-4, ITU-T H.261, H.263 [1], and recently published H.264 [2]. The block-matching algorithm (BMA) has been widely applied due to the efficiency of prediction and accuracy of estimation.

In the last few years, various fast BMAs were proposed to replace the full search (FS) algorithm with high computational complexity. The proposed BMAs use different search strategies to simultaneously satisfy the accuracy and search speed in motion estimation. In particular, the size and shape of search patterns largely affect the efficiency of algorithms. A typical algorithm of fast BMAs is the three-step search (3SS) [3]. The 3SS shows a logarithmical decrease in the size of rectangular search patterns in each search step. Even though the 3SS algorithm performs well in large search, there exists severe redundancy in calculation because it always uses a constant number of search points (SPT). Also, it overlooks large part of the center-biased motion vector (MV) distribution of real-world image sequences [4]. Some later published algorithms consider the estimation of center-biased motions and thus are more appropriate for searching real-world sequences. They are new three-step search (N3SS) [4], four-step search (4SS) [5], and block-based gradient descent search (BBGDS) [6] algorithms. In addition, most of search patterns are restricted as a rectangular shape before the diamond search (DS)

[7]–[9] and the hexagon-based search (HEXBS) [10] algorithms are proposed. The DS and HEXBS can obtain higher prediction quality even though they use fewer search points. They perform the search by applying unrestricted search steps under the diamond and hexagon-shaped distortion patterns. However, a weakness in local minimum block distortion measure (BDM) points deteriorates the performance of large search because these algorithms depend on size and shape restricted patterns. Nevertheless, new methods such as the point-oriented grouping strategy [11] continue to be proposed for speedup them. The efficient three-step search (E3SS) algorithm [12] proposed in recent years uses the three-step search strategy employed in the 3SS algorithm to perform large search and can be corresponded to the center of searching area by performing a small diamond search (SDS) process based on the unrestricted search step method. Meanwhile, the unsymmetrical-cross multi-hexagon-grid search (UMHexagonS) [13] algorithm produces an excellent search quality, but is much slower than other fast BMAs.

In this paper, we propose an extended small diamond search (ESDS) algorithm by employing the small diamond pattern used in the early searching step in the cross-diamond-hexagonal search (CDHS) algorithm [14] as a type of minimum-size patterns to find the zero motion vector (ZMV). To perform large search, the ESDS is based on the phased reduction of the large rectangular pattern and new modified search strategy of the 3SS.

2. EXTENDED SMALL DIAMOND SEARCH

The proposed ESDS algorithm arranges a 3×3 small diamond-shaped pattern (SDSP) at the center of a search window in the early searching step. The SDSP is selected as a minimum-size pattern to find the ZMV. The N3SS, DS, and E3SS require the minimum number of SPTs as 17, 13, and 13, respectively, to find the ZMV, whereas the ESDS requires only 5 SPTs. If the minimum BDM point is determined as the center of the SDSP, the search is terminated. The second searching step is implemented when the minimum BDM point is determined as the contour of the SDSP.

The second step in search uses a rectangular pattern that is a half of the search window. In a 15×15 small search window (maximum displacement $W = \pm 7$), a 9×9 rectangle that is a half of the search window becomes the search pattern. As shown in Fig. 1, 8 SPTs marked at the outside of the SDPS using dots are the elements of the large rectangle-shaped pattern (LRSP) arranged at the center of a search window. If the minimum BDM point on the SDSP used in the early searching step becomes the minimum BDM point in the second searching step again, it skips the third and fourth searching step and performs the SDS algorithm of the final step in order to search center-biased motions. The second searching step is critical in the decision that selects either large search or central search.

In the third step in search, the LRSP used for the large search in

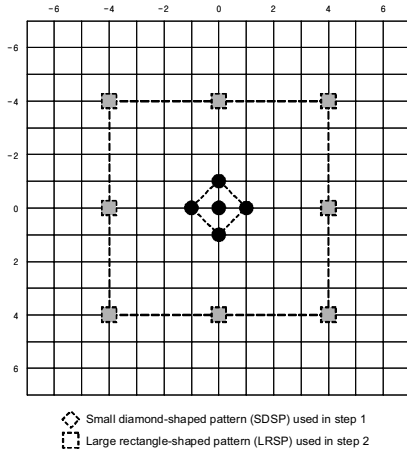


Fig. 1. The SDSP used in the first step and the LRSP used in the second step of the ESDS. The ESDS uses only 5 SPTs to find the ZMV. If the SPTs are not recognized as the ZMV, it adds 8 SPTs on the LRSP in the next step.

a search window, which represents more than $W=\pm 15$ (31×31), shows a logarithmical decrease in its size up to 9×9 . Thus, in a small search window ($W=\pm 7$), it skips this process and then comes to the fourth step. The LRSP reduced by half are arranged at the center of a search window as pattern center in which each reduced pattern shows a constant number of SPTs as 8. Because the distance between the SDSP used in the early searching step and the LRSP used in the second searching step becomes more distant in proportion as the size of a search window increases, it is important to consider the third search process as a countermeasure against the existence of a global minimum BDM point in the area between two patterns. The performance of the third searching step not only enhances the internal search of the LRSP, but also modifies the search direction. Fig. 2 shows the search points on the SDSP and LRSPs used up to the third searching step for $W=\pm 15$.

The proposed algorithm implements the fourth step in search that applies a large search strategy employed in the 3SS after completing the internal reducing process of rectangular patterns. First, it is necessary to reduce the size of the LRSP, which corresponds to the minimum BDM point in the previous step, to half of the original size. Because the point always exists on the 9×9 rectangular pattern for $W=\pm 7$, the size becomes 5×5 . In the case of $W=\pm 15$, because the size determined in the second search process is reduced from 15×15 to 9×9 , the LRSP will be reduced by 9×9 if one of the search points on the 15×15 LRSP is the minimum BDM point. In addition, if the minimum BDM point in the previous step is a point of the search points on the 9×9 LRSP, the LRSP will be reduced by 5×5 . Then, the half-reduced LRSP of the objective pattern is arranged with the minimum BDM point in the previous step as the center and is able to be searched and compared. In addition, this process is repeatedly performed until the size of the LRSP is reduced to 5×5 , different from that of the 3SS. Fig. 3 illustrates certain search patterns and SPTs in the fourth searching step for the search window of $W=\pm 15$. The number of SPTs on the reduced and arranged LRSP can be determined as 5, 7, and 8 according to the location of the minimum BDM point in the previous step as illustrated in Fig. 3.

In the final step of the ESDS, it performs the SDS algorithm (Fig. 4). Because the SDS is performed as a manner of the unrestricted search step, the number of SPTs is always changing. In addition, it

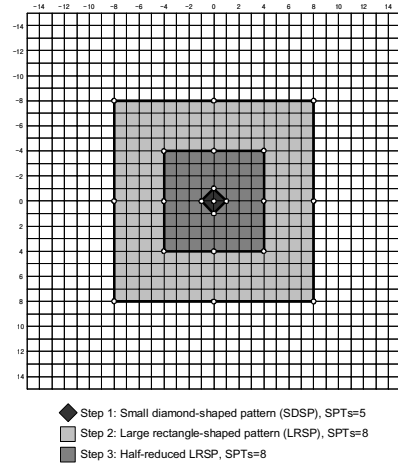


Fig. 2. The SDSP and LRSPs used up to the third step of the ESDS for a search window, $W=\pm 15$.

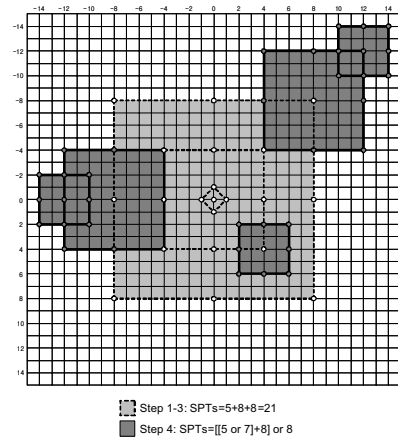


Fig. 3. Examples of the search patterns and search points used in the fourth step for $W=\pm 15$.

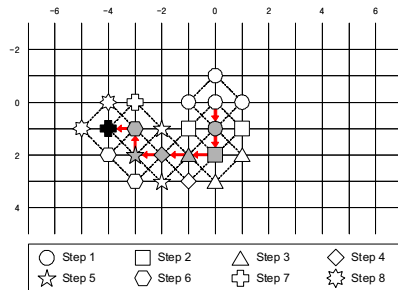


Fig. 4. An example of the MV $(-4, 1)$ search path in the SDS algorithm.

uses a few number of search points and is simple in implementation. Fig. 5 illustrates examples in the search using the ESDS algorithm for the search window size $W=\pm 15$. Each search step in the ESDS can be summarized as follows:

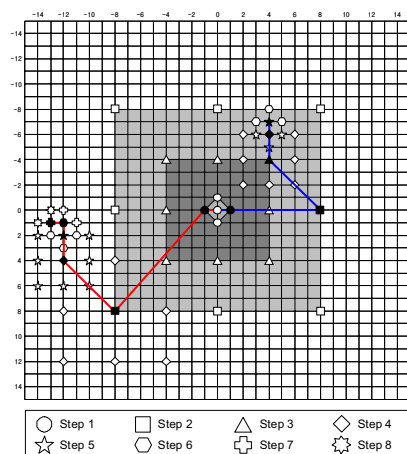


Fig. 5. Two examples of search paths in the ESDS for $W=\pm 15$.

Step (1): Search of SPTs on the SDSP

5 searching points on the SDSP are arranged at the center of a search window. If a minimum BDM point is determined as the center of the search window, the search will be terminated (MV=ZMV). Otherwise, it implements Step (2).

Step (2): Search of SPTs on the LRSP

The LRSP here is a half of the search window. The center point of the LRSP is set at the center of the search window. 8 SPTs on the pattern are compared with the minimum BDM point in the previous step. If a SPT in Step (1) is determined as the minimum BDM point, the process moves to Step (5). Otherwise, it implements the next step, Step (3).

Step (3): Reduction of the LRSP

It reduces the LRSP to half size. If the reduced size of the LRSP is smaller than 9×9 , the process moves to Step (4). Otherwise, it arranges the reduced LRSP at the center of the search window and compares 8 SPTs on the pattern with the minimum BDM point in the previous step. Then, it repeats Step (3).

Step (4): Large search of the LRSP

It reduces the size of the LRSP that corresponds to the minimum BDM point in the previous step as its half size. If the reduced size is determined to be smaller than 5×5 , the process moves to Step (5). Otherwise, the reduced LRSP is adopted with the minimum BDM point as its center, and SPTs are searched. Then, it repeats Step (4).

Step (5): Implementation of the SDS algorithm

It moves the center of the SDSP to the minimum BDM point in the previous step. Then, it searches the other SPTs on the SDSP. If the minimum BDM point is the center of the SDSP, it terminates the search. Otherwise, it repeats Step (5).

3. EXPERIMENTAL RESULTS

The search speed can be verified by the average number of search points per block (Avg. SPT) and the speed up ratio with respect to the FS (Speedup). The sum of absolute difference (SAD) algorithm is used to measure the BDM. The basic block size used in simulations is 16×16 and search window sizes are configured as $W=\pm 7$, $W=\pm 15$, and $W=\pm 31$, respectively. The average peak signal-to-noise ratio (PSNR) per frame shows the search quality. Test sequences used in this experiment are “Claire” (CIF 360×288 , 100 frames), “Football” (CIF 360×240 , 200 frames), “Coastguard” (CIF 352×288 , 200 frames), “Stefan” (CCIR601 720×480 , 200 frames), “Susie” (CCIR601 720×486 , 90 frames), and “Garden” (CCIR601

720×486 , 90 frames). Tables 1–6 compare the performance between the proposed ESDS algorithm and other BMAs, such as the FS, 3SS, N3SS, DS, extended hexagon-based search (EHS) [13], and E3SS. From Table 1, in the “Claire” sequence that shows a tendency of quasi-stationary motions, it is evident that the ESDS shows an increase in the search speed more than 220% by searching about 6 SPTs, which are 7 SPTs fewer than that of the DS and E3SS. However, the prediction accuracy can be maintained as an equivalent level for other algorithms. In the case of the CIF sequences of “Football” and “Coastguard”, which include large-scale motions, it demonstrates the highest PSNR and a good search speed as shown in Tables 2 and 3. The performance on the “Stefan” sequence including tough and rough sports scene with the resolution of 720×480 is shown in Table 4. The proposed ESDS shows a remarkable performance in the search quality for the “Stefan” sequence compared to that of the N3SS, DS, and EHS. Also, it shows that 2–3 SPTs are determined as a gain even though it shows a similar aspect of the PSNR compared to that of the E3SS. In addition, the proposed algorithm achieves the highest PSNR compared to other fast algorithms for the “Susie” and “Garden” sequences as shown in Tables 5 and 6. Fig. 6 illustrates the average PSNR per frame and the average number of search points per block for CCIR601 “Stefan” sequence with $W=\pm 31$. The figure shows that the proposed algorithm demonstrates faster search speed than other fast BMAs except for the DS and EHS in most frames. We can also see the proposed ESDS maintains an outstanding search quality compared to other fast BMAs.

4. CONCLUSIONS

This paper proposes an extended small diamond search (ESDS) algorithm using the SDSP and the LRSP. The proposed ESDS algorithm logarithmically decreases the size of the LRSP in a large search window and arranges the reduced LRSP at the center. Then, it uses a modified large search of the 3SS. In the last search step, it finishes the search using the SDS algorithm. The results of the experiment show that the proposed algorithm represents better search quality compared with other fast BMAs while it shows more computing gains than that of the DS and E3SS. Moreover, the proposed algorithm provides stronger flexibility than other BMAs because it demonstrates satisfying performances in both quasi-stationary and rough motions.

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Table 1. Performance comparisons for CIF “Claire”

| BMA | Max. Displacement $W=\pm 7$ | | | Max. Displacement $W=\pm 15$ | | |
|------|-----------------------------|---------|--------|------------------------------|---------|--------|
| | Avg. SPT | Speedup | PSNR | Avg. SPT | Speedup | PSNR |
| FS | 225.000 | 1.000 | 41.184 | 961.000 | 1.000 | 41.186 |
| 3SS | 25.000 | 9.000 | 41.092 | 33.000 | 29.121 | 41.061 |
| N3SS | 17.405 | 12.927 | 41.167 | 17.396 | 55.243 | 41.129 |
| DS | 13.225 | 17.013 | 41.161 | 13.226 | 72.660 | 41.162 |
| EHS | 11.330 | 19.859 | 41.093 | 11.330 | 84.819 | 41.094 |
| E3SS | 13.425 | 16.760 | 41.137 | 13.422 | 71.599 | 41.136 |
| ESDS | 6.030 | 37.313 | 41.133 | 6.047 | 158.922 | 41.134 |

Table 2. Performance comparisons for CIF “Football”

| BMA | Max. Displacement $W=\pm 7$ | | | Max. Displacement $W=\pm 15$ | | |
|------|-----------------------------|---------|--------|------------------------------|---------|--------|
| | Avg. SPT | Speedup | PSNR | Avg. SPT | Speedup | PSNR |
| FS | 225.000 | 1.000 | 23.922 | 961.000 | 1.000 | 25.333 |
| 3SS | 25.000 | 9.000 | 23.608 | 33.000 | 29.121 | 24.337 |
| N3SS | 25.552 | 8.806 | 23.662 | 28.229 | 34.043 | 24.263 |
| DS | 21.793 | 10.324 | 23.506 | 23.898 | 40.213 | 24.241 |
| EHS | 17.869 | 12.592 | 23.479 | 19.080 | 50.367 | 24.200 |
| E3SS | 22.150 | 10.158 | 23.673 | 25.476 | 37.722 | 24.498 |
| ESDS | 18.703 | 12.030 | 23.624 | 23.561 | 40.788 | 24.607 |

Table 3. Performance comparisons for CIF “Coastguard”

| BMA | Max. Displacement $W=\pm 7$ | | | Max. Displacement $W=\pm 15$ | | |
|------|-----------------------------|---------|--------|------------------------------|---------|--------|
| | Avg. SPT | Speedup | PSNR | Avg. SPT | Speedup | PSNR |
| FS | 225.000 | 1.000 | 29.687 | 961.000 | 1.000 | 29.811 |
| 3SS | 25.000 | 9.000 | 29.366 | 33.000 | 29.121 | 28.953 |
| N3SS | 21.937 | 10.257 | 29.529 | 20.640 | 46.560 | 28.950 |
| DS | 17.648 | 12.749 | 29.425 | 17.692 | 54.318 | 29.483 |
| EHS | 14.832 | 15.170 | 29.387 | 14.838 | 64.766 | 29.436 |
| E3SS | 19.228 | 11.702 | 29.533 | 18.764 | 51.215 | 29.535 |
| ESDS | 17.999 | 12.501 | 29.508 | 17.907 | 53.666 | 29.618 |

Table 4. Performance comparisons for CCIR601 “Stefan”

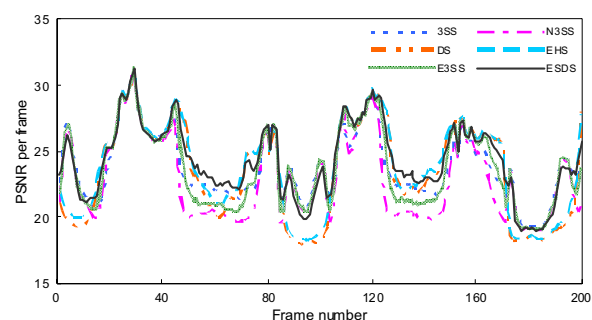
| BMA | Max. Displacement $W=\pm 15$ | | | Max. Displacement $W=\pm 31$ | | |
|------|------------------------------|---------|--------|------------------------------|---------|--------|
| | Avg. SPT | Speedup | PSNR | Avg. SPT | Speedup | PSNR |
| FS | 961.000 | 1.000 | 24.434 | 3969.000 | 1.000 | 25.998 |
| 3SS | 33.000 | 29.121 | 23.277 | 41.000 | 96.805 | 23.057 |
| N3SS | 27.100 | 35.461 | 22.900 | 27.199 | 145.924 | 21.930 |
| DS | 21.504 | 44.689 | 21.944 | 21.702 | 182.886 | 21.981 |
| EHS | 17.683 | 54.346 | 22.249 | 17.903 | 221.695 | 22.360 |
| E3SS | 24.460 | 39.289 | 23.289 | 25.773 | 153.998 | 22.776 |
| ESDS | 21.051 | 45.651 | 23.122 | 23.411 | 169.536 | 23.411 |

Table 5. Performance comparisons for CCIR601 “Susie”

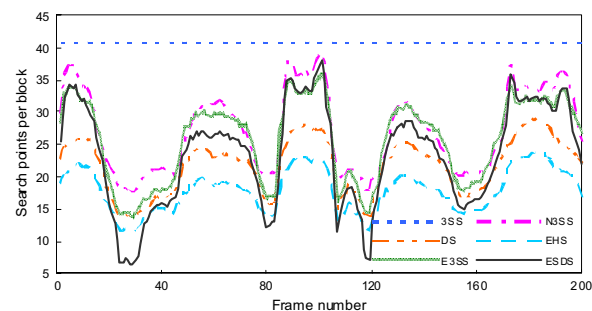
| BMA | Max. Displacement $W=\pm 15$ | | | Max. Displacement $W=\pm 31$ | | |
|------|------------------------------|---------|--------|------------------------------|---------|--------|
| | Avg. SPT | Speedup | PSNR | Avg. SPT | Speedup | PSNR |
| FS | 961.000 | 1.000 | 35.837 | 3969.000 | 1.000 | 36.278 |
| 3SS | 33.000 | 29.121 | 34.502 | 41.000 | 96.805 | 34.115 |
| N3SS | 23.706 | 40.538 | 34.754 | 23.771 | 166.968 | 34.307 |
| DS | 20.464 | 46.961 | 34.659 | 20.626 | 192.427 | 34.842 |
| EHS | 16.590 | 57.926 | 34.886 | 16.718 | 237.409 | 35.156 |
| E3SS | 20.822 | 46.153 | 34.788 | 21.237 | 186.891 | 34.585 |
| ESDS | 19.529 | 49.209 | 34.936 | 20.402 | 194.540 | 35.047 |

Table 6. Performance comparisons for CCIR601 “Garden”

| BMA | Max. Displacement $W=\pm 15$ | | | Max. Displacement $W=\pm 31$ | | |
|------|------------------------------|---------|--------|------------------------------|---------|--------|
| | Avg. SPT | Speedup | PSNR | Avg. SPT | Speedup | PSNR |
| FS | 961.000 | 1.000 | 28.171 | 3969.000 | 1.000 | 28.262 |
| 3SS | 33.000 | 29.121 | 25.250 | 41.000 | 96.805 | 22.188 |
| N3SS | 27.486 | 34.963 | 24.486 | 26.463 | 149.983 | 21.268 |
| DS | 22.329 | 43.038 | 26.252 | 22.339 | 177.671 | 26.255 |
| EHS | 17.606 | 54.584 | 26.155 | 17.612 | 225.358 | 26.158 |
| E3SS | 26.098 | 36.823 | 26.983 | 26.739 | 148.435 | 24.059 |
| ESDS | 25.907 | 37.094 | 27.532 | 26.898 | 147.557 | 26.887 |



(a)



(b)

Fig. 6. Frame by frame performance comparisons for CCIR601 “Stefan” sequence with $W=\pm 31$. (a) The average PSNR per frame. (b) The average number of search points per block.

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