DIRECTION BIASED SEARCH ALGORITHMS FOR FAST BLOCK MOTION ESTIMATION

Niranjan Mulay
Sasken Communication Technologies Ltd, Products Division, India

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Abstract: Motion estimation (ME) is computationally the most challenging part of the video encoding process. It has a direct impact on speed and qualitative performance of the encoder. Consequently, many sub-optimal but faster ME algorithms have been developed till date. In particular, the Three Step Search (TSS) and Four Step Search (FSS) algorithms have become popular because of their ease of implementation. The TSS algorithm is a uniformly spaced block matching algorithm, which performs better in case of large motion. On the other hand, the New Three Step Search (NTSS) and FSS are center-biased algorithms that outperform TSS in case of smooth correlated motion. Later, another center-biased search technique namely, the Diamond Search (DS) algorithm was introduced which was proved to deliver a faster convergence than FSS in case of smooth motion scenarios. However, the performance of the center-biased algorithms degrades in sequences having consistently large or uncorrelated motion as they become susceptible to getting trapped in local minima near the center. In this paper, two novel ME algorithms, namely, dual square search (DSS) and dual diamond search (DDS) are proposed in order to strike a balance between the center-biased and uniformly spaced search techniques. The proposed algorithms suggest that a decision to shift the search center should be delayed till the candidates on a coarse as well as fine grid are evaluated. Moreover, these algorithms are modeled to exploit motion vector distribution found in most of the real world video sequences by giving more precedence to candidates near the center, followed by the candidates in the horizontal and vertical directions than those in the diagonal direction. The performance of the proposed algorithms is compared with TSS and FSS algorithms in terms of computational speed, motion compensation error and the compression achieved for various kinds of video sequences. The tested sequences show that both these algorithms can be substantially faster than TSS and FSS. The proposed ME algorithms promise to achieve a balanced tradeoff amongst 'speed - bit rate - quality' for different kinds of motion sequences.

1 INTRODUCTION

The main objective of the Motion Estimation (ME) module is to exploit the temporal redundancy between successive frames of a video sequence in order to reduce the number of bits required for coding. In this paper, we focus on the block matching ME algorithms. In these block based coding schemes, the moving regions across the frames are analyzed by subdividing the frames into smaller units called blocks. The video standards such as H.26x and MPEG series (H263, 1998; MPEG4, 1999) specify block based coding techniques. The block based ME algorithms try to find the best matching block, the one giving the least Block Distortion Measure (BDM), in the reference frame for every block in the current frame. The idea is to encode the error data between the current block and the best matching block along with its displacement. The displacement is known as the motion vector (MV). The range of motion vectors is generally restricted to the certain region specified by the standard. This region is also known as search window. Most of the fast ME algorithms work under the assumption that the error surface is monotonic. The term error surface indicates a surface defined by the block distortion measured between the current block and every candidate block in the search window of a reference frame. The error surface is monotonic if there is a distinct trough at the global minimum and it increases monotonically as the checking point moves away from the global

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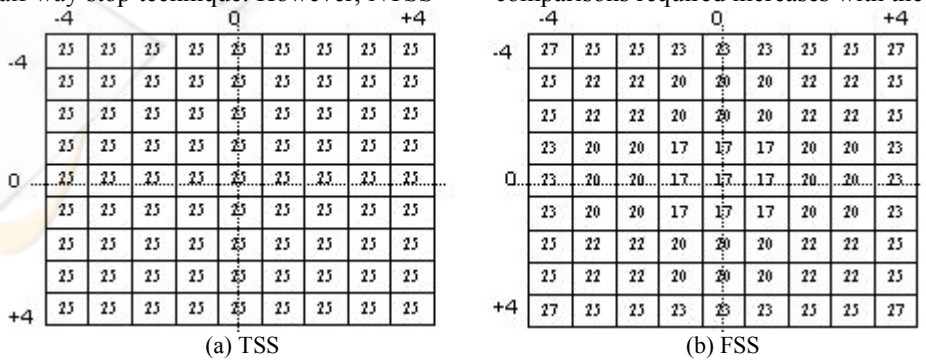
minimum. But for most of the real video applications or fast motion sequences, the error surface may not be always monotonic. Instead there could be multiple local minima in the search area. However, the assumption of monotonic surface facilitates the development of search patterns and hence most of the fast ME algorithms are developed under this assumption. The FS algorithm does an exhaustive search and evaluates each and every candidate in the search window to reach at the candidate with minimum BDM that may be called as the global minimum for that current block.

Let [-W, +W] be the maximum range allowed for motion vectors in horizontal and vertical direction [i.e. search window size = (2W+1)]. We have done the comparative analysis for some of the popular ME algorithms for W = 7, i.e. for search area of 15 x 15 pixels around the center. The FS algorithm does an exhaustive search demanding $(2W+1)^2 = 225$ BDM computations per block. Hence, various sub-optimal and fast ME algorithms are developed in an attempt to devise a mechanism of choosing the suitable subset of these 225 candidates. The TSS algorithm starts with the 8 search points at large step size, typically half the search range. At every stage, the search center is moved to the best match in the previous step and the stepsize is reduced by half. Therefore, TSS always demands fixed 25 search points to trace any point within W = 7 window. For most of the real world video sequences, the motion vector distribution is observed to be prominently biased towards the zero motion. The various center-biased algorithms such as NTSS (Zeng et al., 1994, pp.438-442), FSS (Po and Ma, 1996, pp.313-317) and DS (Tham et al., 1996, pp.369-377) were developed to exploit this fact in order to efficiently detect small motions appearing in stationary or quasi-stationary (within a region of +/- 2 pixels) blocks. As compared to TSS, the NTSS algorithm ensures the fast detection of quasi-stationary blocks by using a half way stop technique. However, NTSS demands worst case 33 search points for large motion blocks, 8 more than TSS. The FSS algorithm is a center-biased algorithm as it typically starts on a fine grid of step size 2. The center-biased strategy of FSS makes it far more efficient than NTSS while providing the same quality as that of NTSS. Later, another center-biased algorithm, namely, the diamond search [DS] was proposed to speed up the motion estimation of stationary and quasi-stationary blocks. Even though, both the algorithms - FSS and DS, perform their best for slow motion sequences, DS is proved to be faster in terms of required number of search points. However, the work done by Tham et al. (1996) mentions that FSS can be more efficient than DS beyond +/- 3 region. Moreover, this best-case analysis assumes that the error surface is monotonic. But in practice, FSS and DS might take larger number of block comparisons than the best possible theoretical numbers. In general, it is observed that the performance of center-biased algorithms degrades as compared to that of TSS if the majority of motion vectors lie beyond +/- 3 region. With these observations mentioned here and with the due consideration to the space constraints, we have limited the comparison of the proposed algorithms in our simulation experiments to TSS and FSS algorithms.

The figure 1 illustrates the best-case number of search points required to be evaluated for TSS and FSS algorithms in order to converge at a particular location. The comparative numbers are shown only for the motion vectors restricted within a region of +/- 4 pixels around the center [i.e. |MV| <= 4 region]. As mentioned earlier, for the given window size W = 7, TSS always requires fixed 25 number of search points to trace any location. In case of FSS, the number of search points required to reach at a particular location varies with its distance from the center. Compared to TSS, FSS is faster for near center locations, but the number of block comparisons required increases with the increase in



(a) TSS (b) FSS

Figure 1: Best-case analysis for TSS and FSS.

distance from the center. It can be perceived that within |MV| <= 4 region, FSS outperforms TSS but beyond that, TSS is the clear winner.

The best-case analysis of the above-mentioned popular algorithms helps to evaluate the performance of the proposed algorithms. This paper is organized as follows. In section 2 of the paper, two ME algorithms are proposed and their performance is theoretically analyzed in terms of computational requirement. The section 3 presents the simulation results in order to evaluate the performance of the proposed ME algorithms in comparison with TSS and FSS. The conclusions are drawn in section 4.

2 ME ALGORITHMS

As discussed earlier, the TSS is a coarse to fine search algorithm that performs better in cases where the best match is located far from the center whereas FSS and DS are center-biased search algorithms which yields faster convergence when the best match is located near the center of the search. For the sequences having consistent large or uncorrelated motion, the center-biased algorithms might maintain faster convergence than TSS but they seem to get trapped in nearby local minima, thereby giving a high speed but poor compression, affecting the quality (Alkanhal et al., 1999).

The interesting observation in TSS, FSS and DS algorithms is that the center is immediately moved after all the candidates at the same step size (might be coarse or fine) gets evaluated in stage1. This is critical to these algorithms as they can get trapped in local minima (Turaga and Chen, 2001). To minimize this intricacy, the proposed algorithms suggest that a decision to shift the search center should be delayed till the candidates on a coarse as well as fine grid are evaluated. This makes the proposed algorithms more robust giving a better starting point for the succeeding stage and hence promises to enhance the chances of reaching global minima quickly. The work presented by Cheung and Po (2002, pp.1168-1177) mentions that the majority percentage of motion vectors are typically enclosed within the central 5x5 area, i.e. a region of +/-2 pixels around the zero motion position. Also it is known that even though the block displacement of real world video sequences can be in any direction, the motion is predominant in the horizontal or vertical direction. The algorithms proposed in this section exploit these two facts giving less priority to candidates in a diagonal direction. The proposed algorithms can trace the maximum motion displacement of +/- 7 pixels (i.e. W=7).

2.1 Algorithm I: Dual Square Search

As the probability of finding the best match within an area of +/-2 pixels around the zero motion vector is very high, the number of search points required to converge at these points becomes an important issue. Hence, the proposed algorithm aims to maintain the advantage of the center-biased algorithms by ensuring fast convergence within this area. The basic square search configuration used in dual square search (DSS) algorithm is indicated in figure 2. This configuration is used to localize the search within 5x5 window (or +/2 region) of the selected center.

Let, 'C' be the block in a current frame whose best match is to be found in the reference frame. The figure 3 indicates the candidates from a reference frame chosen for searching the best match. The algorithm involves two square shaped patterns, a short square at step size 1 and a long square at step size 5. The algorithm starts with BDM calculation of 5 candidates in step 1 using basic square search configuration at the center. If the minimum BDM point is found at the center, only 4 additional block comparisons are needed to stop the search. If the minimum BDM point is found on the short square then the center is not immediately moved to this point. The key is to evaluate 4 candidates on a distant grid, 2 in horizontal direction and 2 in

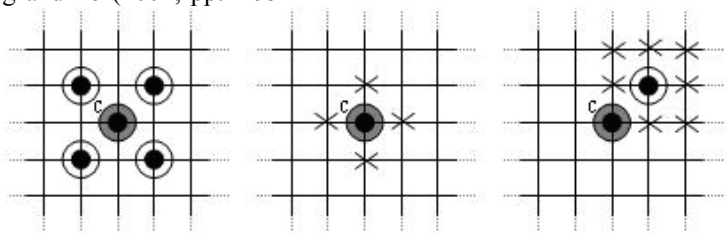
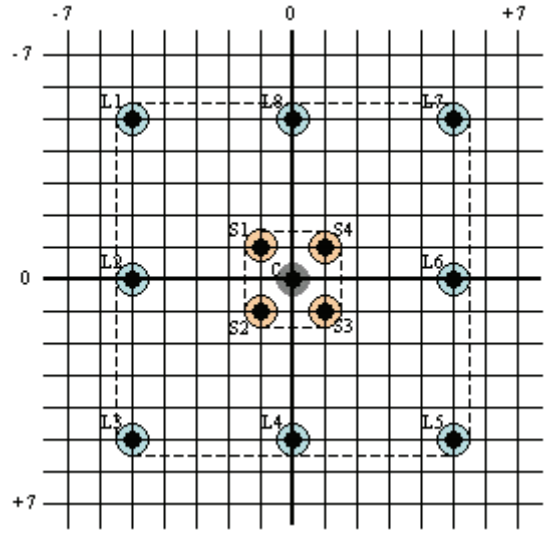


Figure 2: (a) Basic square search configuration. (b) Next step if center is the best match. (c) Next step if the candidate of a square is the best match.



L: Long Square S: Short Square

Figure 3: Dual Square Search.

vertical direction and only then take a decision to move the center of the search in a direction of the best match. This is the center corrective step to make the algorithm more robust minimizing the chances of being trapped in local minima. The further convergence path will be clearer with the following explanatory steps.

Step 1: Use basic square search to evaluate 4 candidates of a short square along with the co-located block. If the center C is the point of minimum BDM, evaluate just 4 candidates on a '+' sign of stepsize 1 and the best match amongst these candidates will be the final integer motion vector.

Step 2: If the best match in step 1 is found at the short square candidate, evaluate L2, L4, L6 and L8 as a center corrective measure. Even after these comparisons, the short square candidate is proved to be the minimum BDM point then move the center to this point for the next stage and calculate the block distortion for the 7 valid points of a square of stepsize one around this newly shifted center to find the final best match candidate.

Step 3: If step 2 delivers minimum BDM at one of the long square candidates (amongst L2, L4, L6, L8), then evaluate two points in a diagonal direction lying in the relevant zone of the motion field. For e.g. if step 2 yields L2 as the best match, then evaluate L1, L3 and only then take a decision to shift the search center. Once the center is shifted to the minimum BDM point, the final best match is found out by doing a basic square search at that point.

From the algorithm, it can be perceived that the search technique uses two-tier strategy each time before shifting the center. It tries to exploit the features of both, the center-biased and non center-biased search algorithms.

Computational Complexity:

With the DSS algorithm, any candidate within 15 x 15 window is traceable. The total number of search points is varied from (5 + 4) = 9 in the best-case to (5+4+2+4+7) = 22 in the worst case. The figure 4 depicts the number of search points required to reach a particular location within |MV| <= 4 area.

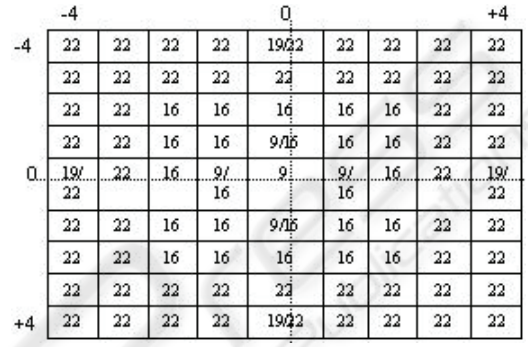


Figure: 4 Best-case analysis for DSS.

It can be clearly seen that the algorithm promises faster convergence than TSS and FSS to converge at any point within W=7 region. The ability to detect stationary and quasi-stationary blocks with just 9 or 16 search points and to detect large motion blocks with maximum of 22 search points makes DSS a far more efficient algorithm than the previous search techniques.

2.2 Algorithm II: Dual Diamond Search

As mentioned earlier, the motion in real video scenarios is predominant in the vertical and horizontal directions. The fact that the motion in the diagonal direction is very rare is evident by the 'probability matrix of MV distribution' presented in the work of Cheung and Po (2002). This fact has inspired the direction biased – dual diamond search (DDS) algorithm to achieve faster convergence along the horizontal and vertical directions at the expense of higher computational cost to converge in the diagonal direction. The search pattern of the proposed algorithm involves a combination of both the techniques, center-biased as well as uniformly spaced search technique. The algorithm still maintains the two-tier strategy to evaluate candidates on finer as well as coarser grid before shifting the search center.

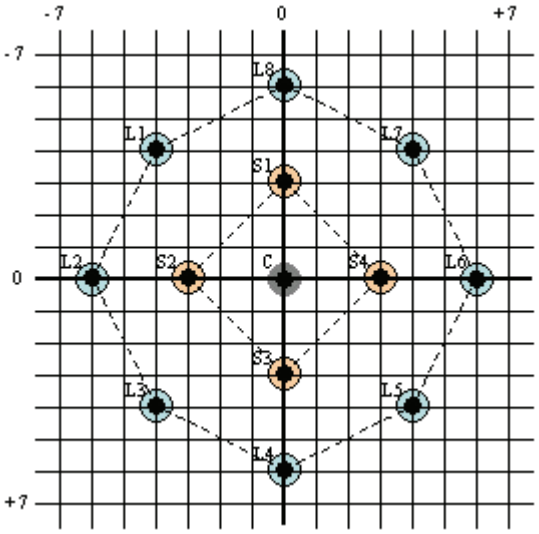


Figure 5: Dual Diamond Search.

The search pattern used in the DDS algorithm involves two shapes: small diamond shaped pattern and long diamond shaped pattern. In true sense, the outer shape is octagonal, but it will be referred as a long diamond in this text. In the very first step, the DDS algorithm evaluates 4 candidates of a short diamond at stepsize 3 along with the co-located block. If the center C is the best match, evaluate 8 candidates of a square of stepsize 1 around the center. The minimum BDM point will indicate the final integer MV. Let this process of evaluating 8 candidates of a square of stepsize 1 around the selected center be designated as 'short square search'. If step 1 yields the best match on the short diamond then take a center corrective step like in DSS to evaluate 4 candidates on a distant grid, namely, L2, L6 in the horizontal direction and L4, L8 in the vertical direction. If a short diamond point still holds to be the point of minimum BDM, move the search center at this point and do a short square search to find the final best match. Otherwise if the minimum BDM point is found on the long diamond then evaluate the two diagonal candidates in the probable zone of the motion field. If the best match is amongst L2, L4, L6 and L8 then the final best candidate is traced by a short square search technique at that point. In case of the minimum BDM point being found in a diagonal direction, a technique similar to TSS is employed to search the best matching candidate. The DDS algorithm is summarized as follows.

Step 1: Compute block distortion for co-located block and 4 candidates of a short diamond. If the center C is the point of minimum BDM, apply short square search technique at the center to find the final integer motion vector.

Step 2: If the best match in step 1 is amongst the short diamond candidates, evaluate L2, L4, L6 and L8 as a center corrective measure. After these comparisons, if the short diamond candidate is proved to be the point of minimum BDM then the decision to move the search center to this point is taken. This shift of a search center is then followed by a short square search to find the final best match candidate.

Step 3: If step 2 delivers minimum BDM at one of the long diamond candidates (amongst L2, L4, L6, L8), then evaluate two points in a diagonal direction lying in the relevant zone of a motion field. For e.g. if step 2 yields L8 as the best match, then evaluate L1, L7 and only then take a decision to shift the search center. After evaluation of two relevant diagonal candidates, if minimum BDM point is still found at the previously shortlisted horizontal/vertical candidate then the center of the search is shifted to this point. The final best match is found out by doing a short square search at that point.

Step 4: If the diagonal candidate proves to be the best match in step 3 then the center is moved to this point and a search pattern similar to TSS is employed to finalize the integer MV. Here, 8 candidates at a stepsize of 2 from the center are evaluated and in the next step, center is moved to the minimum BDM point and step size is halved to 1. In the last step, 8 candidates around this new center are evaluated to deliver the final MV location.

From the above explanations, it is apparent that the algorithm is well modeled to exploit the probability distribution of motion vectors. The details about the probability distribution of motion vectors can be found in the work of Cheung and Po (2002). The DDS algorithm is direction biased as it gives the highest preference to the candidates near zero motion location followed by the candidates in the horizontal and vertical directions. The algorithm takes longer time to converge in a diagonal direction, as the motion in this direction is rare in practical scenarios. Like DSS, the DDS algorithm attempts to combine the features of both the center-biased and uniformly spaced search strategies. The center corrective approach in DDS helps to maintain the robustness by minimizing the chances of getting seized in the local minima. Unlike DSS, DDS speeds up the motion estimation of blocks moving largely in the horizontal and vertical directions. This might be crucial for the CIF sequences compared to QCIF sequences as the CIF sequences typically manifests larger motion due to scale up effect.

Computational Complexity:
The DDS algorithm can trace any candidate within 15x15 search window. The total number of search points in the best-case are (5 + 8) = 13. The DDS algorithm exhibits a noticeable faster convergence along the horizontal and vertical directions by demanding maximum of 17 BDM computations for |MV| <= 4 and 19 BDM computations for |MV| > 4. However, if the best match lies in a diagonal direction then the algorithm demands worst case 27 search points, two more than TSS. The fig. 6 depicts the number of search points required to reach a particular location within |MV| <= 4 area.

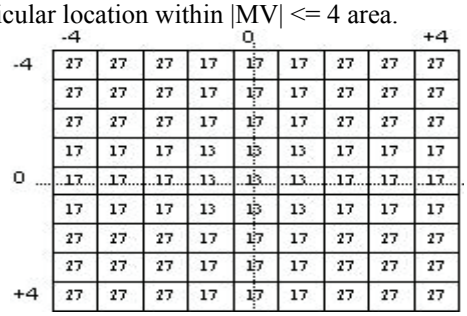


Figure 6: Best-case analysis for DDS.

The analysis shown in fig. 6 indicates that the DDS algorithm exploits the MV distribution found in the real world sequences. For the blocks having motion within +/- 1 region, the DDS algorithm performance is better than that of TSS, NTSS, FSS and more or less the same (if not better) as that of DS. The point to be noted is that any candidate in horizontal and vertical direction beyond +/- 1 region can be traced with just 17 or 19 BDM computations. The algorithm is more efficient than other algorithms in case the best match consistently lies in near center region or in the horizontal/vertical direction. Nevertheless, the 27 BDM computations required to reach a location in the diagonal direction seems like an expensive penalty. But given the fact that it is very unlikely to find consistent motion in a diagonal direction for real world scenarios, the DDS algorithm maintains its performance across various kinds of motion sequences.

3 EXPERIMENTAL RESULTS

We have summarized the results of our simulation experiments in this section. The algorithms have been analyzed in MPEG4 framework for a large number of QCIF/CIF test sequences. However, with due regards to the space limitations, the results are tabulated only for five CIF sequences representing different types of motion content. These are the YUV420 sequences captured at 15 fps. The algorithms have been analyzed for the block size, N = 16 and search window, W = 7. The error measure namely, 'Sum of absolute difference' (SAD) is used as a BDM for a block matching criterion. For block size = N, One SAD computation demands [$2N^2$ Load, N^2 Sub, N^2 Abs, (N^2 - 1) Add] operations. The tools like - unrestricted motion vectors and macroblock skipping are disabled.

The performance is analyzed based on the following three parameters:

1. Speed: Average number of search points per block.
2. Quality: The quality of the motion estimation is analyzed in terms of mean square error (MSE) between the original frames and the motion estimated frames.
3. Compression: The number of bits required to code a particular sequence conveys practically the most significant information. This is analyzed in terms of the average number of bits required per block. The rate control module is disabled, rather kept as VBR (variable bit-rate) in order to see the direct impact of motion estimation algorithms on the size of the bit streams.

From the table 1, it can be seen that for the low motion sequences like Akiyo and Hall, all the algorithms perform equally good in terms of quality and compression. However, in terms of speed, DSS clearly out-shadows the other algorithms, as it demands nearly half the BDM computations as compared to that of FSS. For the selected sequences, FSS is observed to be always faster than the TSS algorithm. However, when compared for the sequences with greater motion content like coastguard, foreman, and football the FSS fails to find good matches and thereby it shows degradation in terms of MSE and the number of bits needed. For these fast motion sequences, the DSS algorithm maintains its significant speed efficiency at the cost of some more quality degradation compared to that of FSS. This is where the DDS algorithm outperforms the other algorithms by exhibiting a good 'speed-quality' tradeoff. Compared to DSS, the DDS algorithm takes slightly more number of search points, still less than FSS and tries to achieve the qualitative solution as close as that of TSS. Most of the center-biased algorithms show considerable degradation in their performance for large motion sequences. Our simulation results show that, DDS can offer a better solution to counteract this problem common to most of the center-biased algorithms.

Table 1: Performance Analysis for CIF Test cases.

Test Sequence	Algorithm	Avg. no. of search points per block.	Average MSE	Average number of bits per block
Akiyo [Slow motion]	FS	225	19.64	14.547
	TSS	25	19.92	14.485
	FSS	15.86	19.9	14.458
	DSS	8.51	20.11	14.413
	DDS	12.22	20.03	14.512
Hall [Moderate & correlated motion]	FS	225	42.69	36.495
	TSS	25	43.36	35.151
	FSS	16.02	44.09	35.062
	DSS	8.68	45.33	35.000
	DDS	12.39	43.84	35.268
Coastguard [Large & correlated motion]	FS	225	129.95	154.738
	TSS	25	138.68	160.515
	FSS	18.94	148.95	166.596
	DSS	11.2	163.92	186.681
	DDS	14.98	138.07	160.105
Foreman [Moderate & uncorrelated motion]	FS	225	222.05	123.412
	TSS	25	230.94	126.467
	FSS	19.53	243.08	129.055
	DSS	13.72	252.43	131.806
	DDS	15.39	240.88	127.503
Football [Fast Motion]	FS	225	335.67	209.184
	TSS	25	353.58	216.811
	FSS	20.76	385.58	229.513
	DSS	15.36	393.5	231.831
	DDS	17.15	377.7	220.6

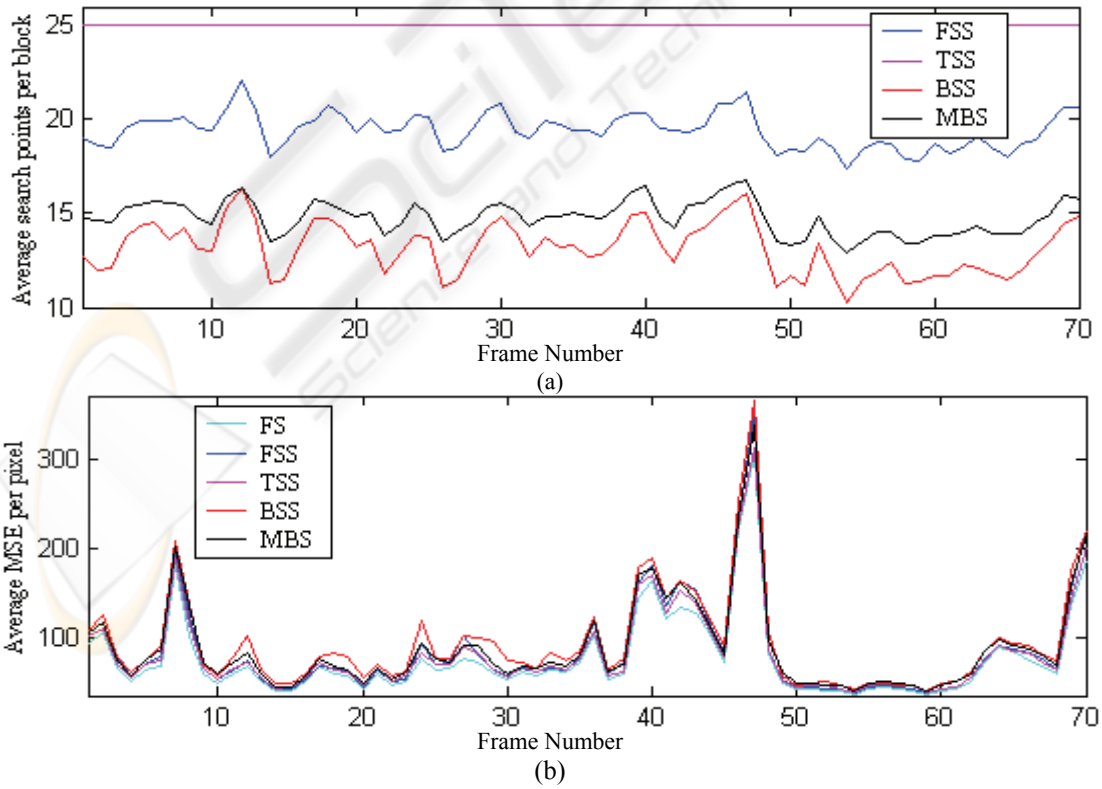


Figure 7: Comparison of TSS, FSS, DSS and DDS in terms of average search points and MSE for the foreman sequence.

It can be seen that, especially for the fast motion sequences, the performance of DDS algorithm is better than FSS with regards to all the three parameters - speed, quality and compression.

The figure 7 shows the performance of each of the search techniques for the foreman sequence on a frame-by-frame basis. The foreman sequence is selected because it has some fast, uncorrelated motion and it doesn't favor center-biased or non-center-biased search pattern in particular. It can be seen that the DSS algorithm substantially improves the speed efficiency at the cost of marginal increase in the distortion. Thus, the DSS can be justified as the natural choice for many time critical applications. Otherwise, DDS gives an option of trading off some speed compared to DSS for the improvement in quality.

4 CONCLUSIONS

The two sub-optimal block matching algorithms, namely, Dual Square Search (DSS) and Dual Diamond Search (DDS) are proposed in this paper. The number of search points required to trace a particular position varies depending on the direction of the position with respect to the center. The algorithms give the highest preference to the candidates near the center and the least preference to the candidates in the diagonal direction. Both the algorithms are based on the principle that the candidates on a finer grid and those on a coarser grid should be evaluated before taking a decision to move the search center. This center corrective approach makes these algorithms more robust minimizing the chances of getting trapped in local minima. The DDS algorithm goes one step further to model its search strategy in order to exploit the MV distribution of most of the real world video sequences. With regards to the computational speed, both the proposed algorithms, DSS and DDS clearly outperform TSS and FSS algorithms. For large or uncorrelated motion sequences, DSS may suffer from more degradation in terms of quality. Nevertheless, DSS enjoys the privilege of being the fastest algorithm amongst these algorithms. Between the two proposed algorithms, DSS is more effective than DDS algorithm for smooth and small motion sequences thereby promising to work at its best in videoconference kind of applications. Moreover, the DSS algorithm possesses the features like regularity and simplicity that might be helpful for hardware implementations. However, DDS is the one that combines the efficient center-biased nature of FSS with the advantage of TSS to find good matches for large motion sequences. Compared to DSS, the DDS algorithm has an ability to tradeoff some speed in order to maintain its performance in terms of quality and compression regardless of the motion content. Clearly, the proposed algorithms try to blend the best features of the center-biased and uniform search strategies so as to provide good performance in terms of 'speed-quality-bit rate tradeoff' when considered across different kinds of motion sequences including panning, zooming, smooth, correlated, uncorrelated and fast motions.

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