Diamond Search Optimization-Based Technique for Motion Estimation in Video Compression

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ABSTRACT

In video compression procedure, movement estimation is one of the key segments due to its high computation unpredictability in finding the movement vectors between the frames. The purpose of movement estimation is to diminish the storage space, data transfer capacity, and transmission cost for transmission of video in numerous mixed media administration applications by decreasing the redundancies while preserving the better quality of the video. Each algorithm has its own benefits and culpabilities. Among these, block-based movement estimation calculations are most powerful and adaptable. In this paper, diamond search-hybrid teaching and learning-based optimization (DS-HTLBO) has been proposed for motion estimation. The performance of the proposed DS-HTLBO method is analyzed by considering different performance evaluation parameters such as peak signal-to-noise ratio, mean square error, and compression ratio. The comparative outcomes reveal that the proposed DS-HTLBO method outperformed in terms of PSNR of 41% and CR of 5.47% with other DS, 4SS, and NTSS methods.

KEYWORDS

Blocks Matching Algorithm, Diamond Search, Motion Estimation, NTSS, Video Compression

1. INTRODUCTION

In these days, the videos are in superior quality or top-notch characteristics, so it requires a huge transmission data transfer capacity and a measure of storage (Khalid, B et al, 2020). To lessen the excess information in the video, there are different systems to utilize that pack the data without contrarily influencing the nature of the frames (Madine, F et al, 2018). Video compression strategies are utilized to decrease repetition in video information without influencing visual quality (Yaakob, R et al, 2013).The key advance in the evacuation of temporal redundancy is the Motion Estimation (ME) where a Motion Vector (MV) is anticipated among the Current Frame (CF) and a Reference Frame (RF) (Díaz-Cortés et al, 2017). Block matching (BM) is one of the ME technique, where the frames of considered digital video is partitioned into number of macro blocks (Shiju, P et al, 2018).

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Every square in the CF, the best coordinating block is recognized in the hunting space of the past frame to limit the Mean-Square-Error (MSE) among macro blocks. The key test is the assessment of MSE is very tedious (Kwon et al 2020, Murthy et al 2016 and Mukherjee et al 2018). Thus, BM algorithm for ME is measured as an advancement issue and it has an objective to find the better coordinating macro square for an objective (Lee et al 2011). There exist different methodologies that were acquainted with accelerate BM through a settled subsection of the inquiry region at the expense of inadequate precision (Nalluri et al 2015).

The authors in (Al-Najdawi et al 2014) proposed DS algorithm which goes for further decreasing the computational multifaceted nature. It will be demonstrated that the proposed DS (Diamond Search) can additionally accelerate the other searching algorithms by a factor of two and keep up its consistency with great execution practically comparable (Yu et al 2017) with the New Three Step Search (NTSS), Four Step Search (4SS), Adaptive Rood Pattern Search (ARPS), and so on. These methodologies were discovered successful, however they unsuccessful to found the trade-off among precision and rapidity (Jianhua et al 1997). Following the motion estimation, a motion compensation is utilized for video compression in the encrypting of video information (Kim et al 2014). It is utilized to acquire the first frame with the assistance of a reference frame as well as the motion vector. The past frames are considered as the RF (Patnaik et al 2015). At the point, when CF could be precisely orchestrated from recently communicated or deposited frames, so that the compression proficiency can be enhanced.

The organization of the paper is listed as next to this introduction section, the prevailing literature survey is presented in section 2. Section 3 explains the motivation of the research work. The proposed method has been explained in section 4. Section 5 gives the simulation results and the conclusion part is described in section 6.

2. SURVEY OF EXISTING LITERATURE

This area talks about the current research work being done utilizing H.265 video compression standard. Satpute, V. R., et al. (2017), two compression methods include 3D-Discrete Wavelet Transform (DWT) and 2D Embedded Zero Wavelet (EZW) are thought about relying upon the scientific parameters PSNR and CR. Mu et al. (2014) have exhibited a cascaded system for legacy protocols, for example, H.264/AVC and was exposed to H.265 encoding procedure to extricate the encoding coefficients. Belghith, F., et al. (2014) clarified a fast arrangement for ME is portrayed so as to diminish the elapsed time of the new High Efficient Video Coding (HEVC). Shen li et al (1999) proposed a BM algorithm dependent on an enhanced GA, where a target search, as well as random search, got from hereditary change is used to look through the worldwide ideal and a threshold determination administrator is connected to accelerate the estimation. Cuevasa et al. (2013) proposed an algorithm dependent on the ABC (Artificial Bee Colony) optimization so as to decrease the number of inquiry areas in the BM procedure. Cai, J., and David Pan, (2012) introduced a PSO-ZMP algorithm. It comprises of ZMP (Zero Moment Point), prescient image coding and Particle Swarm Optimization (PSO) coordinating daily practice. In spite of the fact that it produces positive outcomes regarding computational unpredictability when contrasted with the DS and ARPS, in the meantime it created negative patterns as far as quality. *Murugesan, K* et al (2020) discussed Three-layered feed forward back propagation neural network (TLFFBPNN). new three-step search (NTSS) algorithm proposed by Reoxiang Li wt al (1994).

From the above review, different examinations have concentrated on utilizing video compression algorithm. The procedures are related to favorable circumstances just as the restriction. The nature-roused algorithms have exhibited decent trade-off among precision and speed. Scientists have used Genetic Algorithm (GA), Particle Swarm Optimization (PSO), ABC and Harmony Search (HS) for ME, it is a key component utilized in vision as well as mechanical application. Here, HTLBO (Hybrid

Teaching and Learning Based Optimization) algorithm is implemented to suit the issue and executed them to enhance the BM algorithm.

3. THE MOTIVATION OF THE RESEARCH WORK

In day by day life, everyone manages various sorts of recordings like TV video signals, web recordings and etc. Since the original video have gigantic size, the capacity and transmission of video signals is a challengeable task in video processing. It requires a video compression technique that can pack the video with no loss of data. Over the most recent couple of decades, numerous researches have been done to develop a productive video codec that can pack the data with no misfortune. The uncompressed crude video contains a monstrous amount of information and memory limits are expensive and limited.

A video is an arrangement of video outlines in which each edge is a full shading still image. Consider the measure of information required to characterize a 2-hour(2-h) movie utilizing 720*480*24 bits pixel clusters. The video edges must be shown successively at a rate of 30 fps accordingly the movie must be retrieved to at 31,104,000 bytes/sec.

$$30\,\frac{frames}{sec}\times\left(720\times480\right)\frac{pixels}{frame}\times3\,\frac{bytes}{pixel}=31{,}104{,}000\,bytes\,/\,sec$$

There is a need of 27 number of 8.5 GB DVDs are expected to store2-h movie which comprises of 224 GB of information. To play a 2-h video on a single DVD, each edge must be compacted. In two successive video frames, there is a huge amount of redundancies in spatial and fleeting space. It can achieve a huge proportion of compaction by reducing these redundancies.

4. PROPOSED METHODOLOGY

The search patterns which are used in TSS method is not well coordinated to real time video sequences. This perception motivated the development of NTSS algorithm. It gives better movement estimation with less computational time when contrasted with the TSS and NTSS. Afterward, 4SS algorithm was developed to diminish the average search points from 21 to 19 by continuing similar performance of NTSS. Later, DS algorithm has been introduced to with minimum search points. In this paper, DS and HTLBO technique has been used together for improving the performance of PSNR and CR. Here, 13 video sequences have taken d for the experimental analysis. 14 search points (LDSP-9 and SDLP-4) has been used in the proposed method.

4.1 Parameter Optimization

The matching of one macro block with other block depends on the Mean Absolute Error (MAE). The macro block that outcomes at all expense are the one that coordinates the nearest to the current block. With the expectation of accomplishing least MAE, an optimization algorithm is developed called HTLBO.

4.1.1 Objective Function of Parameter Optimization

The objective function can be calculated based on the fitness function. The main purpose is to attain the best identical block by the minimization of MAE. The condition of MAE is expressed as in equation (1),

$$MAE=\frac{1}{m^2}\sum_{k=0}^{m-1}\sum_{l=0}^{m-1}\left|P_{kl}-S_{kl}\right| \tag{1}$$

$$MSE = \frac{1}{m^2}\sum_{k=0}^{m-1}\sum_{l=0}^{m-1}\left(P_{kl} - S_{kl}\right)^2 \quad (2)$$

Where, P indicates the search points and S represents the number of blocks.

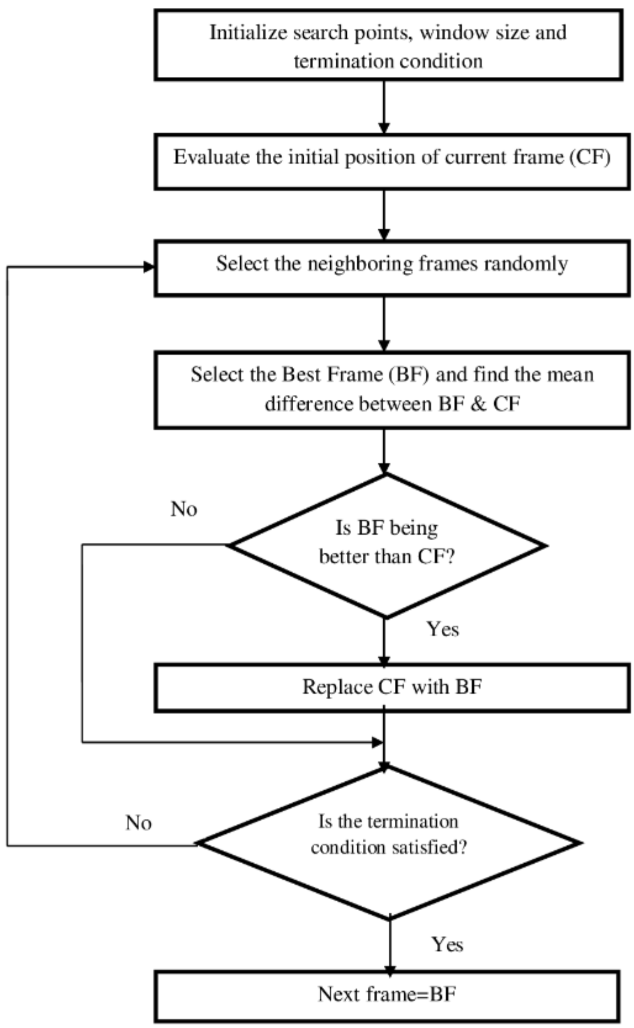
4.1.2 Hybrid Teaching and Learning Based Optimization (HTLBO) Algorithm

The block diagram of proposed DS-HTLBO algorithm is given in fig.1. HTLBO involves the updating procedure, there will be specific updating characteristics of metaheuristic algorithms. The procedure of DS-HTLBO is partitioned into two phases namely teaching phase and learning phase.

4.1.2.1 Teaching Phase

The teaching phase means taking of the students from the instructor. The educator attempts to expand the learning dimension of understudies and make the students to get extraordinary engravings.

Figure 1. Flow diagram of DS-HTLBO method



However, students gain information and acquire imprints as per the nature of instructing conveyed by the instructor and the nature of understudies pre-sent in the class. Let M_j^i be the mean of all students and X_T^i be the most possible arrangement of the population at i^{th} teaching-learning cycle. The distinction between the consequence of the instructor and the mean aftereffect of the understudies in subjects given by,

$$D_j^i - r(X_{T,j}^i - T_F M_j^i$$

Where, T_F is a training factor and *r* is a discretionary number in the range [0 1]. The feasible solutions are upgraded by moving their situations towards the situation of the best attainable arrangement by thinking about the present mean estimation of the practical arrangements. The i^{th} attainable arrangement in the populace at k^{th} educating learning cycle is refreshed by the accompanying articulation which is given by,

$$X_{new,ij}^i - X_{old,ij}^i + D_j^i$$

If X_{new} is better than X_{old}, then X_{new} is accepted; Otherwise it is rejected. All the recognized feasible solutions are preserved and it is given to the input of student phase.

4.1.2.2 Learning Phase

Here, the students gain information through shared correspondence. An understudy (student) coordinates randomly with various understudies of the class to improve the familiarities. A student (S_1) discovers some information from other student (S_2) of the class if S_2 has more knowledge than S_1. Thusly, if S_2 is superior toS_1, then S_1 is moved towards S_2. Otherwise, S_1 is stimulated far from S_2. The learning rationality of this stage is recreated as beneath:

Two students are haphazardly chosen from the class, whereS_1, $S_2$are the two arbitrary numbers belong to [1, Np] and $S_1 \neq S_2$.

If $F\left(X_{s_1}^i\right) > F\left(X_{s_2}^i\right)$

$$X_{new\,Sp,S_1,j}^i = X_{S_1,j}^i + r\left(X_{S_1,j}^i - X_{S_2,j}^i\right)$$

Else

$$X_{new\,Sp,S_1,j}^i = X_{S_1,j}^i + r\left(X_{S_2,j}^i - X_{S_1,j}^i\right)$$

EndWhere, F(X) is a fitness function. After the evaluation of fitness function, the best solution can be obtained by using below conditions,

If $F\left(X_{new\,Sp,S_1}^i\right) > F\left(X_{new,S_1}^i\right)$

$$X_{new,S_1}^i = X_{new\,Sp,S_1}^i$$

Else

$$X^{i}_{new,S_1} = X^{i}_{new\ ,S_1}$$

End

The DS-HTLBO algorithm has the following steps,

Step 1. The number of search points, block size and the termination conditions are initialized.

The fitness function value for each block is calculated using equation (3).

$$Fitnessfunction = Min\_MAE \tag{3}$$

Step 2. Evaluate the initial position of current frame and generate the neighboring frames randomly.

Step 3.[Teacher phase] Find the best frame among the randomly generated frames and find the mean difference among the CF and BF.

Step 4. [Learning Phase]If the best frame is better than the current frame, then replace the current frame with the best frame.

Step 5: The algorithm stops its execution, if the most extreme number of iterations is accomplished and the solution which is holding the minimum MAE as optimal.

5. SIMULATION RESULTS AND EVALUATION OF DS-HTLBO

The proposed video compression analysis is implemented in MATLAB 2017a system configuration, i5 processors with 4GB RAM. There are 13 video sequences have taken for motion estimation and compensation which includes coat image,akiyo image etc. Initially, the input video sequences have been converted into 34 input frames and these frames have been used for compression. The compressed image using DS-HTLBO method is given in fig.2. Fig.2 (a) represents the compressed coat image and fig.2 (b) represents the compressed image of Akiyo image.

5.1 Performance Evaluation

The performance evaluation measure is an efficient way to analyze the performance of DS-HTLBO with other existing methods. Before one gets to know the performance of DS-HTLBO method, knowing comprehensively the definitions of metrices are inevitable. The performance of DS-HTLBO method is analyzed in terms of some performance measures such as PSNR, search points, compression ratio and MSE with some existing BM algorithms.

Figure 2. Compressed Image Using DS-HTLBO

(a) Coat Image (b) Akiyo Image

5.1.1 PSNR

PSNR is utilized to quantify the nature of reconstructed compressed image. Higher value of PSNR indicates better quality of recreated image. PSNR is most effectively characterized by means of MSE [22]. The PSNR and MSE values of DS-HTLBO method is calculated by using the following equations,

$$MSE = \frac{1}{mn}\sum_{i=0}^{m-1}\sum_{j=0}^{n-1}\left[I\left(i,j\right) - K\left(i,j\right)\right]^2 \tag{4}$$

$$PSNR = 10log_{10}\left(\frac{MAX_I^2}{MSE}\right) \tag{5}$$

$$= 20log_{10}\left(\frac{MAX_I}{\sqrt{MSE}}\right) \tag{6}$$

5.1.2 Compression Ratio

CR is the ratio among the total number of bits in compressed image and in the original image. Higher values of CR indicate better compression of the original image. It is defined as,

$$CR = \frac{Number\, of\, bits\, in\, Compressed\, Image}{Number\, of\, bits\, in\, original\, image} \tag{7}$$

The PSNR values of DS-HTLBO with other existing methods are listed in table 1. From the table it can be noticed that, DS-HTLBO methodology gives better PSNR values when compared with other methods. NTSS produces very poor PSNR values, so that the quality of the compressed image will be very poor by using that method.

The MSE values of DS-HTLBO, DS, 4SS and NTSS methods are given in table 2. PSNR and MSE values are associated with each other. Higher value of MSE yields poor PSNR value, so that the quality of the compressed image will be poor. The proposed DS-HTLBO method gives least MSE when compared with other existing methods.

The Compression ratio of DS-HTLBO, DS, 4SS and NTSS methods are tabled in table 3. The lower value of CR yields poor compressed image. The compression ratio must be high for better compression. Here, DS-HTLBO method produces highest compression ratio when compared with other DS, 4SS and NTSS methods.

The analysis of PSNR measure for the thirteen video sequences is depicted in fig.3. The results conclude that the maximum PSNR value is attained in the proposed DS-HTLBO algorithm. Also, the values are compared with some existing BM algorithms like 4SS, NTSS and DS. Fig.4 shows the error rate (MSE) analysis of proposed algorithm DS-HTLBO and existing techniques such as 4SS, NTSS and DS. From fig.4, it can be easily observed that, the DS-HTLO method gives lowest value of MSE and NTSS method produces highest values of MSE.

The graphical representation of comparative analysis of another important parameter, compression ratio is depicted in fig.5. Form the graph, it can be visually noticed that, DS-HTLBO method gives higher compression ratio when compared with all other existing methods which includes DS, 4SS and NTSS.

6. CONCLUSION

In this paper, Diamond Search based HTLBO (DS-HTLBO) method has been proposed for motion estimation and compensation. Here 13 video sequences have been used, initially these video sequences

Table 1. Comparison of PSNR of DS-HTLBO, DS (Ismail 2011), 4SS (Lai-Man 1996) and NTSS (Reoxiang 1994) methods

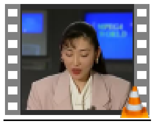
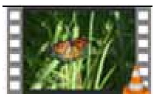
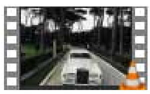
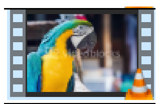
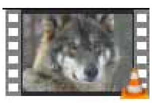
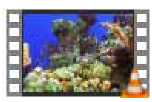
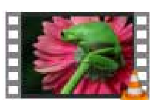
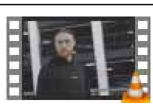
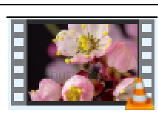
Video Sequences	DS-HTLBO	DS	4SS	NTSS
	41.06	40.22	40.04	38.03
	40.46	40.18	40.17	37.94
	40.76	40.62	40.25	38.03
	40.62	40.76	40.29	37.93
	41.89	40.14	40.26	37.93
	41.13	40.25	39.88	38.04
	41.16	40.86	40.21	38.08
	40.83	39.91	39.85	37.82
	41.10	39.94	39.98	37.81
	41.03	40.26	39.79	37.99
	40.87	40.42	40.18	37.96
	40.92	40.27	40.13	37.93
	40.85	40.38	40.34	37.99

Table 2. Comparison of MSE of DS-HTLBO, DS [23], 4SS [24] and NTSS [25] methods

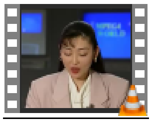
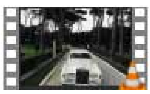
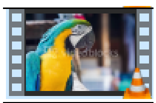
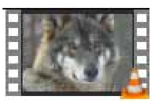
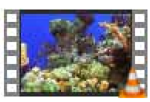
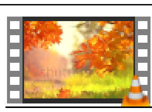
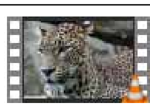
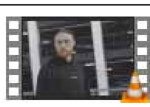
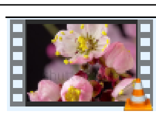
Video Sequences	DS-HTLBO	DS	4SS	NTSS
	5.13	6.18	6.43	10.23
	5.37	6.23	6.25	10.44
	5.45	5.64	6.13	10.23
	5.63	5.45	6.08	10.45
	4.2	6.43	6.12	10.46
	5.01	6.13	6.68	10.21
	4.97	5.33	6.19	10.10
	5.36	6.63	6.72	10.72
	5.04	6.59	6.53	10.75
	5.12	6.12	6.82	10.32
	5.32	5.89	6.23	10.41
	5.25	6.11	6.31	10.45
	5.34	5.95	6.01	10.32

Table 3. Comparison of CR of DS-HTLBO, DS [23], 4SS [24] and NTSS [25] methods

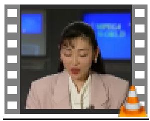
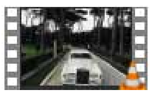
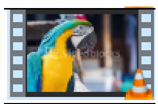
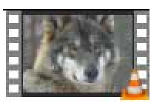
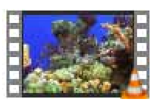
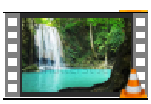
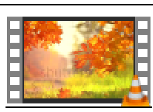
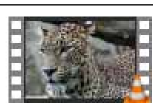
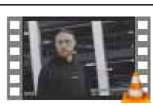
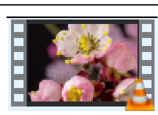
Video Sequences	DS-HTLBO	DS	4SS	NTSS
	5.96	4.16	4.02	3.96
	5.53	5.45	4.69	3.56
	5.68	4.32	4.5	3.87
	4.23	4.98	3.84	3.68
	5.61	4.52	3.84	3.87
	5.98	4.65	4.10	3.82
	5.99	4.87	4.23	3.92
	5.41	4.82	4.11	3.74
	4.25	4.11	4.12	3.65
	6.24	5.23	4.21	3.94
	4.89	4.78	4.11	3.92
	5.75	5.01	4.01	3.64
	5.66	4.56	4.23	3.84

Figure 3. Comparative Analysis of PSNR

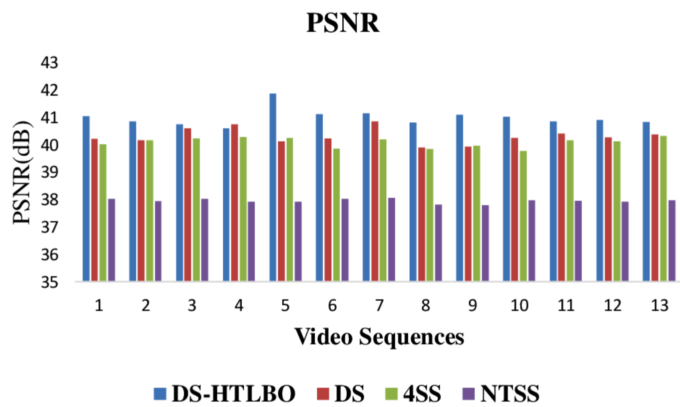


Figure 4. Error Rate Analysis

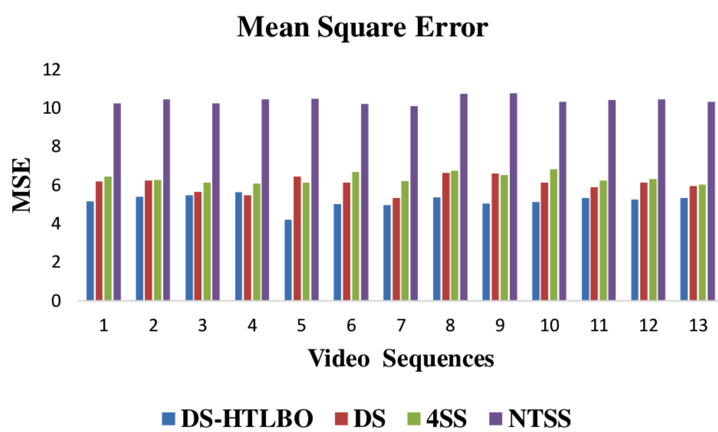
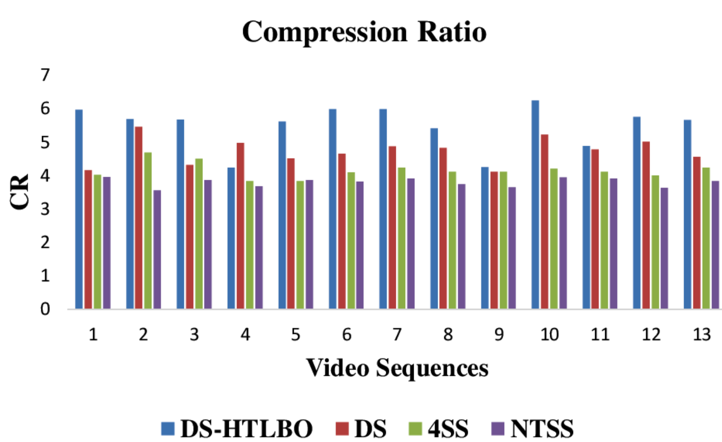


Figure 5. Comparative Analysis of Compression Ratio



are converted to number of frames and it is used for motion estimation. This paper implements BM algorithms for motion estimation by matching search blocks of the considered images. For matching purpose, meta-heuristic algorithm named as HTLBO has been utilized. The matching of one macro block with another depends on MAE. The minimum MAE is achieved by the proposed BM i.e. DS based HTLBO method. Followed by a motion compensation process was done, where the two images are presently detracted and the differentiation is directed to the recipient along with the motion vectors. From the simulation results and performance evaluations it be clearly concluded that, the presented DS-HTLBO accomplishes desired PSNR of 41%, CR of 5.47% with minimum MSE.

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