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COMPARATIVE ANALYSIS OF DS AND IDS ALGORITHMS IN SUPER-SPATIAL STRUCTURE PREDICTION FOR MEDICAL IMAGE SEQUENCES

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Abstract

With the rapid growth of digital technology the demand to preserve raw image data for further processing is increasing. In medical industry the images are generally in the form of sequences which are much correlated. These images are very important and hence lossless image compression is needed to reproduce the original quality of the image without any loss of information. The correlation among the image sequences is exploited by interframe coding. Interframe coding includes Motion Estimation and Motion Compensation process supported by the Block Matching Algorithm. There are various block matching algorithms. The proposed method has taken Diamond Search and Inverse Diamond Search for comparison. The algorithms are used in Super-Spatial Structure Prediction to achieve high compression ratio. Results are compared in terms of compression ratio and search points to the prior arts.

Keywords:

Diamond Search, Inverse Diamond Search, Losssless Compression, MEMC, Super-Spatial Structure Prediction

1. INTRODUCTION

Various medical organizations need to store high volume of digital medical image sequences that includes Computed Tomography (CT), Magnetic Resonance Image (MRI), Ultrasound and Capsule Endoscope (CE) images. As a result hospitals and medical organizations have huge volume of images with them and require large disk space and transmission bandwidth to store these image sequences [1]. The solution to this problem could be the application of compression. Image compression techniques reduce the number of bits required to represent an image by taking advantage of coding, interpixel and psycho visual redundancies. Coding Redundancy occurs when less optimal code words are used. Interpixel Redundancy is the correlation between pixels. Psycho visual Redundancy is the data that is ignored by the human visual system. Medical image compression is very important in the present world for efficient archiving and transmission of images [2]. Image compression can be classified as lossy and lossless. Medical imaging does not require lossy compression due to the following reason. The first reason is the incorrect diagnosis due to the loss of useful information. The second reason is the operations like image enhancement may emphasize the degradations caused by lossy compression. Lossy scheme seems to be irreversible. But lossless scheme is reversible and this represents an image signed with the smallest possible number of bits without loss of any information thereby speeding up transmission and minimizing storage requirement. Lossless compression reproduces the exact replica of the original image without any quality loss. Hence efficient lossless compression methods are required for medical images [2] [3]. Lossless compression includes Discrete Cosine Transform, Wavelet Compression, Fractal Compression, Vector Quantization and Linear Predictive Coding. Lossless consist of two distinct and independent components called modeling and coding. The modeling generates a statistical model for the input data. The coding maps the input data to bit strings [4].

Several Lossless image compression algorithms were evaluated for compressing medical images. There are several lossless image compression algorithms like Lossless JPEG, JPEG 2000, PNG, CALIC and JPEG-LS. JPEG-LS has excellent coding and best possible compression efficiency [1]. But the Super-Spatial Structure Prediction algorithm proposed in [5] has outperformed the JPEG-LS algorithm. This algorithm divides the image into two regions, structure regions (SRs) and non-structure regions (NSRs). The structure regions are encoded with Super-Spatial Structure Prediction technique and non-structure regions are encoded using CALIC. The idea of Super-Spatial Structure Prediction is taken from video coding. There are many structures in a single image. These include edges, pattern and textures. This has relatively high computational efficiency. No codebook is required in this compression scheme because the structure components are searched within the encoded image regions [6]. CALIC is a spatial prediction based scheme which uses both context and prediction of the pixel values [7] which accomplishes relatively low time and space complexities. A continuous tone mode of CALIC includes the four components, prediction, context selection and quantization, context modeling of prediction errors and entropy coding of prediction error [8]. Most of the lossless image compression algorithms take only a single image independently without utilizing the correlation among the sequence of frames of MRI or CE images. Since there is too much correlation among the medical image sequences, we can achieve a higher compression ratio using interframe coding.

Interframe coding includes Motion Estimation and Motion Compensation (MEMC) to remove the temporal redundancy. Efficient motion estimation reduces the energy in the motion-compensated residual frame and can dramatically improve compression performance. Motion estimation can be very computationally intensive and so this compression performance may be at the expense of high computational complexity [9]. The idea of compressing sequence of images was first adopted in [10] for lossless image compression and was used in [11], [12], [13] for lossless video compression. The Compression Ratio (CR) was significantly low i.e., 2.5 which was not satisfactory. Hence in [1] they have combined JPEG-LS with Full Search to find the correlation among image sequences and the obtained ratio was 4.8. But this searching is a time consuming process and leads to computational complexity. Super-Spatial Structure

Prediction algorithm proposed in [14] has taken Binary Tree Search and produced ratio of 6.1. However this ratio can be enhanced by using Diamond Search and Inverse Diamond Search with Super-Spatial Structure Prediction technique and the comparison is done between the two searching techniques.

In this paper, we compare two searching techniques to be used with Super-Spatial Structure prediction for medical image sequences to achieve a high compression ratio and lower number of searches. The Compression Ratio (CR) can be calculated by Eq.(1).

$$\text{Compression Ratio} = \frac{\text{Original Image Size}}{\text{Compressed Image Size}} \qquad (1)$$

This paper is organized as follows: Section 2 explains the methodology used which includes Overview, Super-Spatial Structure Prediction, Motion Estimation and Motion Compensation, Motion Vector and Block Matching Algorithm (Inverse Diamond Search and Diamond Search). Section 3 discusses and compares the results obtained for the proposed methodology.

2. METHODOLOGY USED

2.1 OVERVIEW

The objective of the proposed method is to enhance the compression efficiency using Super-Spatial Structure Prediction (SSP) technique combined with Motion Estimation and Motion Compensation (MEMC). Fig.1 illustrates the complete encoding technique of the proposed method. The steps in the proposed method are discussed.

Step 1: Given an image sequence, input the first image to be compressed

Step 2: The image is classified as Structure Regions (SRs) and Non-Structure Regions (NSRs). SRs are encoded using SSP and NSRs are encoded using CALIC

Step 3: The first image will be compressed by Super-spatial Structure Prediction since there is no reference frame.

Step 4: Now the second frame becomes the current frame and the first frame becomes the reference frame for the second frame.

Step 5: Interframe coding includes MEMC process to remove temporal redundancy. Inter coded frame will be divided to blocks known as macro blocks.

Step 6: The encoder will try to find a similar block as the previously encoded frame. This process is done by a block matching algorithm called Diamond Search and Inverse Diamond Search.

Step 7: If the encoder succeeds on its search the block is directly encoded by a vector known as Motion Vector.

Step 8: After MEMC is done the difference of images is processed for compression. The difference is also compressed using SSP compression. MVs derived from MEMC is also compressed.

Step 9: Once the compression of the second frame is done it becomes the reference frame for the third frame and this process goes on until the last frame.

Step 10: Flag bits and the encoded bits are concatenated.

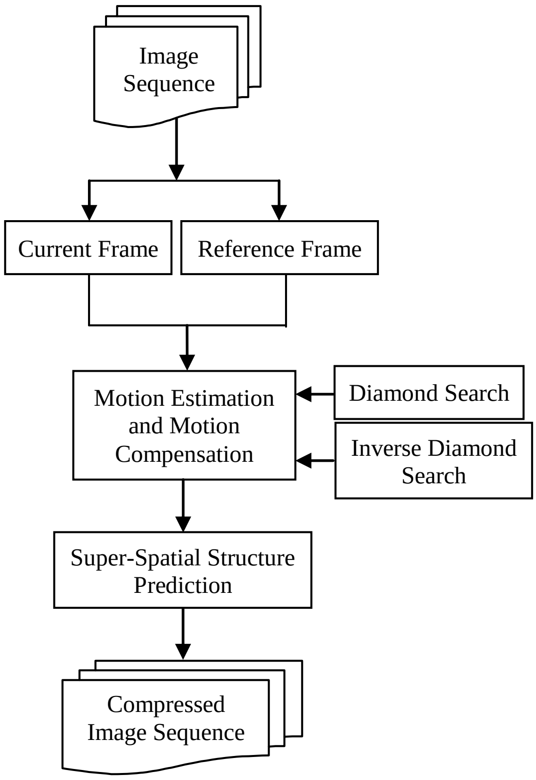


Fig.1. Encoding Technique of the Proposed Method

2.2 SUPER-SPATIAL STRUCTURE PREDICTION

Super-Spatial Structure Prediction borrows its idea from motion prediction [15]. In SSP an area is searched within the previously encoded image region to find the prediction of an image block. The reference block that results in the minimum block difference is selected as the optimal prediction. Sum of Absolute Difference (SAD) is used to measure the block difference. The size of the prediction unit is an important parameter. When the size is small the amount of prediction and coding overhead will become large. If larger prediction unit is used the overall prediction efficiency will decrease. In this paper, a good substitution between this two is proposed. The image is partitioned into blocks of 4×4 and classifies these blocks to structure and non-structure blocks. Structure blocks are encoded using SSP and non-structure blocks using CALIC.

CALIC is a spatial prediction based scheme in which GAP (Gradient Adjusted Predictor) is used for adaptive image prediction. The image is classified to SRs and NSRs and then SSP is applied to SRs since its prediction gain in the non structure smooth regions will be very limited. This will reduce the overall computational complexity [5].

2.3 MOTION ESTIMATION AND MOTION COMPENSATION

Motion estimation is the estimation of the displacement of image structures from one frame to another in a time sequence of 2D images.

The steps in MEMC is stated as

- Find displacement vector of a pixel or a set of pixels between frame

- Via displacement vector, predict counterpart in present frame
- Prediction error, positions, motion vectors are coded & transmitted

The Fig.2 illustrates the block diagram of motion compensated coding.

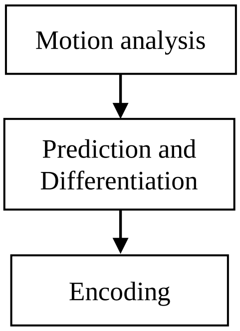


Fig.2 Block diagram of motion compensated coding

Motion estimation can be very computationally intensive and so this compression performance may be at the expense of high computational complexity. The motion estimation creates a model by modifying one or more reference frames to match the current frame as closely as possible. The current frame is motion compensated by subtracting the model from the frame to produce a motion-compensated residual frame. This is coded and transmitted, along with the information required for the decoder to recreate the model (typically a set of motion vectors). At the same time, the encoded residual is decoded and added to the model to reconstruct a decoded copy of the current frame (which may not be identical to the original frame because of coding losses). This reconstructed frame is stored to be used as reference frame for further predictions. The interframe coding should include MEMC process to remove temporal redundancy. Difference coding or conditional replenishment is a very simple interframe compression process during which each frame of a sequence is compared with its predecessor and only pixels that have changes are updated. Only a fraction of pixel values are transmitted. An intercoded frame will finitely be divided into blocks known as macro blocks. After that, instead of directly encoding the raw pixel values for each block, as it would be done for an intraframe, the encoder will try to find a similar block to the one it is encoding on a previously encoded frame, referred to as reference frame. This process is done by a block matching algorithm [15][16]. If the encoder succeeds on its search, the block could be directly encoded by a vector known as motion vector, which points to the position of the matching block at the reference frame.

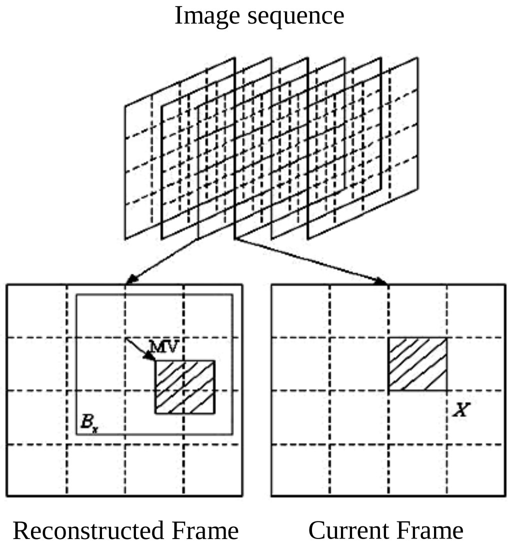
2.4 MOTION VECTOR

Motion estimation is using a reference frame in a video, dividing it in blocks and figuring out where the blocks have moved in the next frame using motion vectors pointing from the initial block location in the reference frame to the final block location in the next frame. For MV calculation we use Block matching algorithm as it is simple and effective. It uses Mean Square Error (MSE) for finding the best possible match for the reference frame block in the target frame. Motion vector is the key element in motion estimation process. It is used to represent a macro block in a picture based on the position of this macro block in another picture called the reference picture. In video editing, motion vectors are used to compress video by storing the changes to an image from one frame to next. When motion vector is applied to an image, we can synthesize the next image called motion compensation [11] [15] [16]. This is used to compress video by storing the changes to an image from one frame to next frame. To improve the quality of the compressed medical image sequence, motion vector sharing is used [13].

2.5 BLOCK MATCHING

In the block-matching technique, each current frame is divided into equal-size blocks, called source blocks. Each source block is associated with a search region in the reference frame. The objective of block-matching is to find a candidate block in the search region best matched to the source block. The relative distances between a source block and its candidate blocks are called motion vectors. Fig.3 illustrates the Block-Matching technique.

The block-matching process during the function MEMC taken from [1] takes much time hence we need a fast searching method and we have taken Diamond Search (DS) method [15] which is best among accuracy, speed and Inverse Diamond Search (IDS) method [16] which has lower number of searches and search points. In the matching process, it is assumed that pixels belonging to the block are displaced with the same amount. Matching is performed by either maximizing the cross correlation function or minimizing an error criterion.



X : Source block for block-matching

B_x : Search area associated with X

MV: Motion Vector

Fig.3. Block -Matching Technique

In the matching process, it is assumed that pixels belonging to the block are displaced with the same amount. Matching is performed by either maximizing the cross correlation function or minimizing an error criterion. The most commonly used error criteria are the Mean Square Error (MSE) as stated in Eq.(3) and the Minimum Absolute Difference (MAD) as stated in Eq.(4).

$$MSE = \frac{1}{M*N}\sum_{i=0}^{M}\sum_{j=0}^{N}\left[M1(m,n) - M2(m,n)\right]^2 \quad (3)$$

$$MAD = \frac{1}{M*N}\sum_{i=0}^{M}\sum_{j=0}^{N}\left[M1(m,n) - M2(m,n)\right] \quad (4)$$

2.5.1 Diamond Search (DS):

The DS algorithm is based on MV distribution of real world video sequences. It employs two search patterns, Large Diamond Shape Pattern (LDSP) and Small Diamond Shape Pattern (SDSP). The entire process is discussed here.

Step 1: It first uses large diamond search pattern (LDSP) and checks nine checking points to form a diamond shape.

Step 2: The second pattern consists of five checking points and forms a small diamond shape pattern (SDSP).

Step 3: The search starts with the LDSP and is used repeatedly until the Minimum Block Distortion Measure (MBD) point lies on the search centre.

Step 4: The search pattern is then switched to SDSP.

Step 5: The position yielding minimum error point is taken as the final MV.

2.5.2 Inverse Diamond Search (IDS):

The IDS algorithm is also based on MV distribution of real world video sequences. It employs two search patterns, Small Diamond Shape Pattern (SDSP) and Large Diamond Shape Pattern (LDSP) In order to reduce the number of search points, use Small Diamond Search Pattern (SDSP) as the primary shape. The entire process is discussed here.

Step 1: It first uses small diamond search pattern (SDSP) and checks five checking points to form a diamond shape.

Step 2: The second pattern consists of nine checking points and forms a large diamond shape pattern (LDSP).

Step 3: The search starts with the SDSP and is used repeatedly until the Minimum Block Distortion Measure (MBD) point lies on the search centre.

Step 4: The search pattern is then switched to LDSP.

Step 5: The position yielding minimum error point is taken as the final MV.

DS and IDS are an outstanding algorithm adopted by MPEG-4 verification model (VM) due to its superiority to other methods in the class of fixed search pattern algorithms.

3. RESULTS AND DISCUSSION

The proposed methodology has been simulated in MATLAB. The block size was set to 8 × 8. To evaluate the performance of the proposed methodology we have tested it on a sequence of MRI and CE images. Medical video is taken from MR-TIP database and Meds Cape. Input image sequences are taken from these videos. The image data for testing include few CT image sequences and few MRI sequence. The results are evaluated based on Compression Ratio and search points. Fig.4 shows sample MRI Image sequences and Fig.5 shows sample CT Image Sequences. The images in these CT sequences are of dimension 225 × 225 and the images in these MRI sequences are of dimension 225 × 225. Motion Estimation and Motion Compensation is applied to these image sequences using Diamond Search algorithm and Inverse Diamond Search with Super-Spatial Structure Compression individually. With Diamond Search method the accuracy is 90% and the time saved is 93%. With Inverse Diamond Search algorithm the accuracy is 92% and the time saved is 95%.

Table.1 gives the compression ratio and search points of MRI sequence for DS and IDS. It is seen that the IDS is better than DS. IDS are more efficient search compared to DS and all other searches. It also gives high PSNR than other searches. Fig.6 illustrates the compression ratio of MRI sequence compared to DS and IDS.

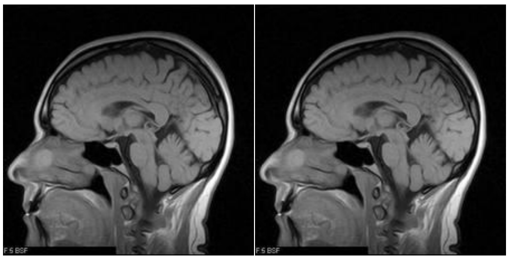


Fig. 4 MRI Image Sequences

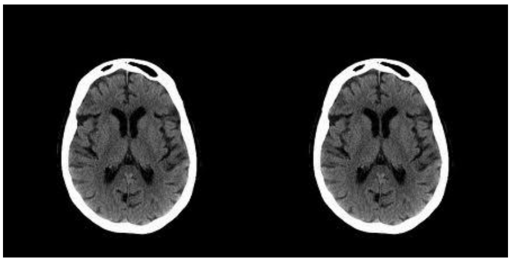


Fig. 5 CT Image Sequences

Table.1 CR and search points of MRI Sequence

Image Sequences	**MRI Sequence**			
	CR		**Search Points**	
	DS	**IDS**	**DS**	**IDS**
F1	5.53	5.59	21.34	20.11
F2	5.72	5.79	21.56	20.35
F3	5.62	5.68	21.43	20.15
F4	5.34	5.40	21.23	20.07
F5	5.56	5.63	21.31	20.10
AVG	**5.55**	**5.62**	**21.37**	**20.16**

From Table.1 MRI sequence has an average CR of 5.55 for DS, 5.62 for IDS and average search point of 21.37 for DS and 20.16 for IDS. Comparatively IDS has lower search points than DS for MRI sequence. Fig.7 shows the search points of MRI image sequences.

Table.2 gives the compression ratio and search points of CT sequence for DS and IDS. It is seen that the inverse DS is better than DS. Fig.8 illustrates the compression ratio of CT sequence compared to DS and IDS. From Table.2 CT sequence has an average CR of 6.63 for DS, 6.67 for IDS and average search point of 22.23 for DS and 19.72 for IDS. IDS have lower search points than DS for CT sequence also. Fig.9 shows the search points of CT image sequences.

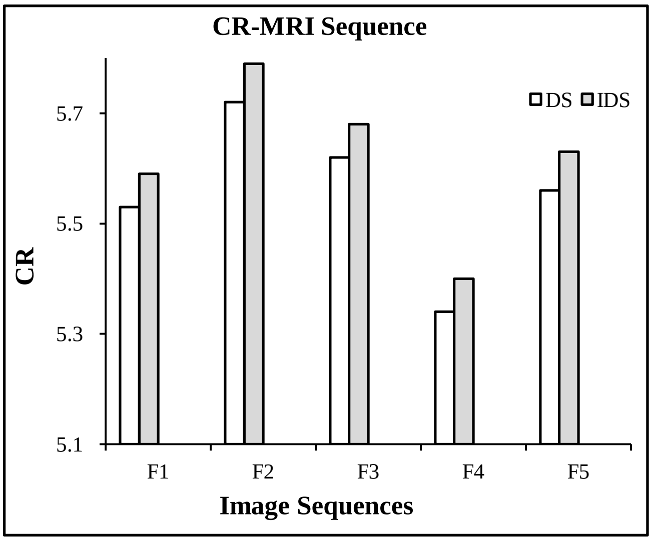


Fig.6. Compression ratio of MRI image sequences

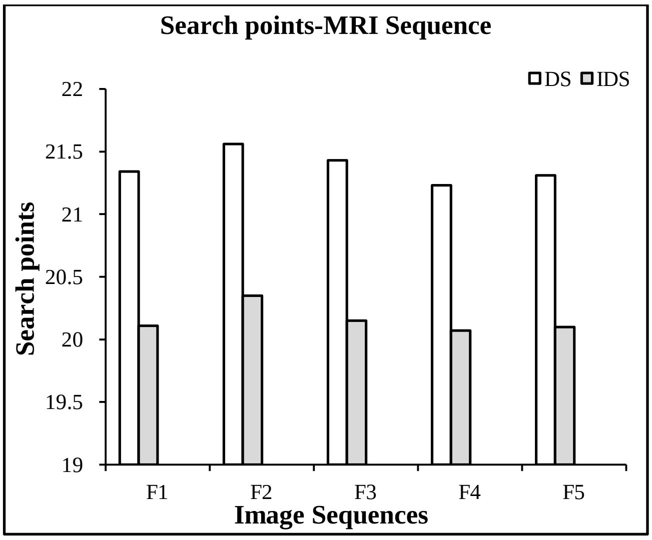


Fig.7. Search points of MRI image sequences

The first frame is decompressed using Super-Spatial Structure Prediction decoder. After the reproduction of the first frame the difference of the rest of the frames are decompressed. The first frame becomes the reference frame for the next frame. After the reproduction of the second frame it becomes the reference frame for the next frame and the process continues until all the frames are decompressed. After decompression original image sequences are recovered without any quality loss.

Table.2. CR and search points of CT Sequence

Image Sequences	**CT Sequence**			
	CR		**Search Points**	
	DS	**IDS**	**DS**	**IDS**
F1	6.34	6.39	22.13	19.48
F2	6.75	6.81	22.23	19.76
F3	6.62	6.67	22.32	19.95
F4	6.76	6.79	22.21	19.56
F5	6.66	6.71	22.26	19.83
AVG	**6.63**	**6.67**	**22.23**	**19.72**

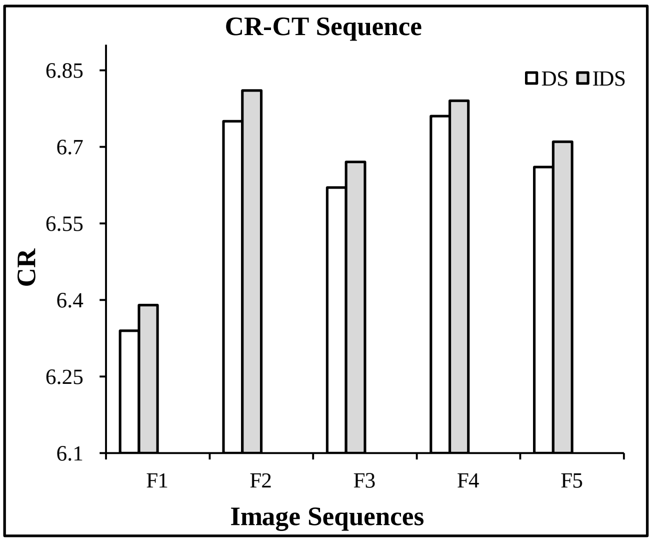


Fig.8. Compression ratio of CT image sequences

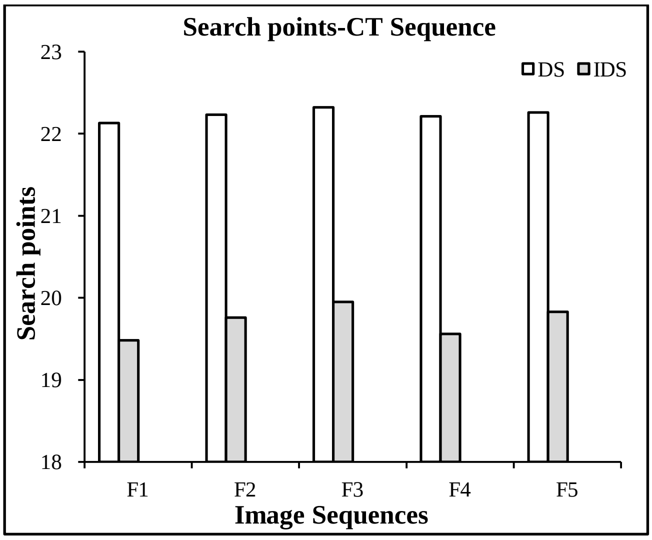


Fig.9. Search points of CT image sequences

4. CONCLUSION

The algorithm given in this paper makes use of the lossless image compression technique and video compression to achieve higher CR. To achieve high CR the proposed method combines Super-Spatial Structure Prediction (SSP) with two fast block matching algorithms DS and IDS individually. DS and IDS are compared in terms of compression ratio and search points. IDS is faster than Diamond Search(DS) as the number of searches and search points are low.CR for IDS is little higher than DS.

From Table.1 and Table.2 it is analyzed that proposed IDS has better CR and lower searches compared to DS.

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