International Journal of Emerging Trends & Technology in Computer Science (IJETTCS)
Web Site: www.ijettcs.org Email: editor@ijettcs.org
Volume 6, Issue 6, November- December 2017 ISSN 2278-6856

A NOVEL VIDEO CODING FRAMEWORK BASED ON COMPRESSED SENSING AND DISCRETE WAVELET CODING APPROACH FOR EDGE PRESEVING

[1]KAVITHA.P , [2]DR. ANNA SARO VIJENDRAN

[1]Research Scholar , Sri Ramakrishna College Of Arts Science , India

[2]Dean, School Of Coputing , Sri Ramakrishna College Of Arts Science , India

Abstract

Nowadays people have to handle a large amount of data at every time which is even highly not easy with the increasing development of technology and the opening into the new trend of digital age. So there is a necessity to store and retrieve the digital information in a scalable and better way which is highly useful for practical use. With this motivation wavelets used to provide a mathematical way of encoding the data recently in such a way that according the level of details it is layered. This layering helps approximations at various intermediate stages and these approximations can be accumulated with a lot less space when compared to the original information.In this research work, an efficient video compression framework is proposed based on compressed sensing in the wavelet domain. The new framework contains four stages in which the source images are signified with their sparse coefficients by using the Discrete Wavelet Transform (DWT) initially. In the next stage, usingthe random Gaussian matrix the measurements are attained from their sparse coefficients. Thirdly novel Fast Continuous Linearised Augmented Lagrangian Method (FCLALM) is utilized to reconstruct the sparse coefficients that will be transformed by the Inverse DWT (IDWT) to the fused image. Finally Local Linear Stein's Unbiased Risk Surface Estimator (LLSURE) filter is proposed for edge-preserving surface estimator. The proposed estimator is used to leave some noise in the vicinity of edges and improve those edges during denoising process. The experimental results demonstrate that the LLSURE with FCLALM has a provides higherPeak-Signal-To-Noise Ratio(PSNR), Lesser Mean Square Error(MSE), and a faster convergence rate when compared with other some other existing edge preserving methods such as LLSURE, SURE and Optimal Compression Plane (OCP).

Keywords:-Discrete Wavelet Transform, Fast Continuous Linearised Augmented Lagrangian Method (FCLALM), Gaussian Matrix, Inverse DWT, video compression, edge preserving.

1.INTRODUCTON

In general, the main aim of video compression is highly motivated to remove redundancies in both spatial and temporal domains. The video compression is a two-stage process such as inter-frame coding techniques and intra-frame coding techniques. To diminish the temporary redundancies between successive frames of a video sequence, the inter-frame coding techniquesare utilized. On the other hand, the intra-frame coding techniques are utilized to condense the spatial redundancies within the difference frame attained via inter-frame coding. Normally, it is attained via orthogonal transforms that make use of intra-image correlation.

Some of the orthogonal transforms are Discrete Cosine Transform (DCT) [1] utilized in image compression standards for example JPEG [2], MPEG.1 which is the video compression standards [3] and MPEG.2 [4], or the Discrete Wavelet Transform (DWT) [5] for instance JPEG2000 [6], thatafford an well-organized framework of multi-resolution space-frequency representation and used in many promising applications due to its flexibility in representing non-stationary signals for example images and video sequences. In numerous fields for example biomedical imaging, remote sensing and computer vision, image fusion plays an important role. In addition to that the multi-focus image fusion [7] is a sub-field of image fusion.
Nowadays wavelet based image compression is used in many researches, with the results showing that wavelet-based approaches perform better than DCT-based techniques for still images [8]. However, the major difficulty in video sequence is motion management that constitutes a challenge in DWT-based video compression. Compared to block-based DCT algorithm, DWT algorithm decomposes the image or video frame in its full size and then the sub-sampling of the filtering production cannot make certain the translation invariance. In [9], a scheme for image compression based on Embedded Zerotree Wavelet (EZW) algorithm [10] named Separated Sign Coding (SSC) has been proposed.

Based on objective and subjective qualities, this scheme gives better results compared to JPEG.2000 standard. Because of its better performance, this scheme is utilized in the video coding field. In [11], the dissimilarity between the image in the coder and the reconstructed image in the decoder is considered as a technique to facilitate remove temporal redundancies. There are many image fusion methods has been proposed based on the integration criteria that are divided into individual pixels and integration criteria based on regional characteristics. A convergence criterion which is based on a single pixel is a simple criterion compared to fusion and it is based on regional characteristics, but it has edge-sensitive as a disadvantage.

In addition, Nyquist sampling theorem is applied for all the samples for sampling, which is bound to increase the data storage, calculation and processing load. Therefore, image fusion method that is proposed recently is completely based on Compressed Sensing(CS) [12] that will reduce the loss calculation and transmission, so it is considered as an effective method for image fusion. Nowadays, number of CS-based image fusion method has been proposed. Li et al [13] proposed a two-dimensional Fourier matrix with observations and linear weighted average fusion observation vector.

Fourier-domain sparse matrix is used in narrow range of applications only when the signal is irrelevant. Luo [14] shows ideological similarities in the proposed integration of the observation vector classification, but this method is complex due to its computation. Zebhi[15] explained DCT sparse image fusion based on sampling methods, but sampling matrix is not an orthogonal matrix, the calculation of this method is complex. In [16], at first images are decomposed via wavelet transform and during maximum selection rule bands with low and high frequency are fused and by means of windowing technique the empty is exploited.

Based on directionlets, compressive sensing fusion method projectedwith the fusing sparse matrices through coefficient absolute value maximum scheme in which sparse matrix attained from the directionlet coefficient sparse representation [17]. Form image fusion, the Dual Tree Complex Wavelet Transform (DT-CWT) method is projected to defeat the shift variance problem through the use of a reversible and discrete complex wavelet transforms [18]. By means of fuzzy logic approach, the pixel level image fusion has been examined together with quality assessment evaluation measure and it provides significantdevelopment on the quality of the fused image [19].

The all problems discussed above have been solved by a video compression method that is based on compressed sensing, and fully belongs to the field of image and signal processing. The proposed method consists of the following steps: First, the source images are represented by their sparse coefficients that are generated by DWT. The random Gaussian matrix of their sparse coefficients is used to calculate these measurements. Finally, the Fast Continuous Linearized Augmented Lagrangian Method is projected to sparse coefficient reconstructionfrom the combined measurement, which is converted into an integrated image by using Inverse Discrete Wavelet Transform (IDWT).
The rest of the work is organized as follows: Section 2 explains an overview of basics of DWT based video compression techniques. Also presents the basics of the proposed technique and the extensions selected to get better the compression ratio. This is the main contribution of this work. Section 3 presents the results of a comparative study between earlier compression methods with the proposed technique. The last section concludes this work with a short summary.

2.PROPOSED METHODOLOGY

Initially, the source images are represented as $x_1 \in R_{n \times n}$ and $x_2 \in R_{n \times n}$ in sampling phase, respectively, by sparse coefficients Θ_1 and Θ_2 using the DWT, each written as a column vector of length$N = n^2$.The measurements y_1 and y_2 are calculated by the random Gaussian matrix A from Θ_1 and Θ_2, respectively. The measurements y_1 and y_2 are integrated to generate combined measurement y through the novel FCLALM scheme in the integrations phase. The reconstructed coefficient vector Θ is first obtained from the combined measurement y, and its IDWT will be applied to restructure the integrated image in the image reconstruction phase. The overall diagram is illustrated in Fig.1.

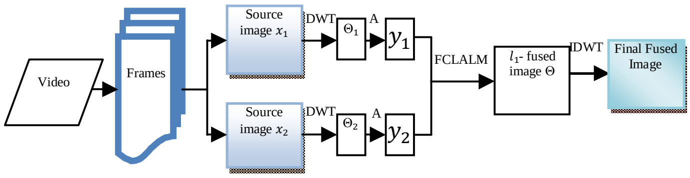

Fig 1: Overall flow diagram of the proposed method

2.1 SPARSE REPRESENTATION

In sparse representation theory, small number of elementary signals is combined to reconstruct sparse signals. Sparse representations become an invaluable tool, when compared to through time domain and transform domain signal processing methods. A natural signal can be called as sparse signal when it can be efficiently stated as a linear combination of the minority number of basis vectors. A signal which has a small number of non-zero entries relative to its dimension named as sparse signal. A large number of real world signals are either sparse in their natural form or represented as a sparse signal in a transform domain.

The large number of applications of sparse signal representations are image compression and restoration, channel equalization, echo cancellation, source separation, and so on. Signal which consists of spikes and low frequency components may not have sparsity in time domain or frequency domain. In order to improve sparsity of such signals, large dictionary matrix needs to be constructed. It can be classified into three types such as overcomplete, undercomplete and complete dictionary. Depending upon coherent values, there are different dictionaries such as random Gaussian matrix, random DFT matrix,random Bernoulli matrix, etc. In this work, random Gaussian matrix is used to generate the sparse coefficients.

2.2 PROPOSED VIDEO COMPRESSION METHOD

Step by step process of the proposed video compression method is given as follows

1. A **image fusion method** based on compressed sensing, the two original images $x_1 \in R_{n \times n}$ and $x_2 \in R_{n \times n}$ were compressed into samples to obtain the observation vector of the two images; To fuse two images, observation vector of two images are fused; Fused observation vector of two images is used to

reconstruct the fused image the observation vector of two images to be fused, is expressed in the following way: First, the two images to be fused has the observation vector as $y_1 = (u_i, u_2, \ldots, u_M)$,$y_2 = (v_1, v_2, \ldots, v_m)$ and then its segment is expressed as $y_1 = (u_i, u_2, \ldots, u_M)^T$ and $y_2 = (v_1, v_2, \ldots, v_m)^T$; wherein, $u_j = \left(u_{(j-1)\cdot q+1}, u_{(j-1)\cdot q+2}, \ldots, u_j.q\right)^T$; then segmented according to the following formula to calculate the vector $u_j$and v_j . Energy Match D_j is calculated as :

$$D_j = \frac{2E_{12j}}{E_{1j} + E_{2j}} \tag{1}$$

where, E_{1j}, E_{2j} were local energy measure of u_j, v_j's, E_{12j} for u_j and v_j mixing energy measure, obtained according to the following formula:

$$E_{12j} = \sum_{(j-1)\cdot q+1}^{fq} \frac{|u_j v_j|}{q} \tag{2}$$

Based on the energy matching with a preset threshold value $T \in (0.5, 1)$ of the comparison result calculated by the following method fusion observation vector $y = (w_1, w_2, \ldots, w_P)^T$segment vector w_j, $j = l, 2, \ldots, P$: If$d_j < t$, then:

$$w_j = \begin{cases} u_j & if\ E_{1j} \geq E_{2j} \\ v_j & if\ E_{1j} < E_{2j} \end{cases} \forall j = 1,2, \ldots, P\ \& D_j \geq T \tag{3}$$

$$w_j = \omega u_j + (1-\omega) v_j (j = 1,2, \ldots, P) \tag{4}$$

whereinω is an adaptive weighting factor that is calculated according to the following formula:

$$\omega = \frac{E_{1j}}{E_{1j} + E_{2j}} \tag{5}$$

Finally fused observation vector $y = (w_1, \ldots, w_P)^T$.

2. Further, the **image reconstruction module** through rapid and sustained linear augmented Lagrangian method (hereinafter referred to as FCLALM) is solving the following minimization problem of l_1- fused image that is obtained from sparse coefficients Θ $\min_\Theta \|\Theta\|_1$st $y = A\Theta$

Where, y is the integrated observation vector, A is compressed measurement matrix sampling that is solved by FCLALM method which includes the following steps:

Step 1: Initialization: Set the initial penalty parameter $\mu_0 > 0$, The maximum penalty parameter $\mu_{max} > \mu_0$, the parameter $\alpha > 0$, the initial variable$t_0 = 1$, amplification factor $\eta > 1$, the initial sparse coefficient Θ_0, initial auxiliary variables $\overline{\Theta}_0$, initial multiplierd_0, initial iterations k = 0;

Step 2: Update auxiliary variables

$$\overline{\Theta} = \overline{\Theta}_{k+1} = soft(\Theta_k - \alpha A^t(A\Theta_k - d_k), \frac{\alpha}{\mu_k} \tag{6}$$

Step 3: Update the variable t, $t_{k+1} = \frac{1+\sqrt{1+4t_k^2}}{2}$

Step 4: The coefficient of updating sparse Θ

$$\Theta_{k+1} = \overline{\Theta}_{k+1} + \left(\frac{t_k - 1}{t_{k+1}}\right)(\overline{\Theta}_{k+1} - \overline{\Theta}_k) \tag{7}$$

Step5: Update the penalty parameter μ: $\mu_{k+1} = \min\{\eta\mu_k, \mu_{max}\}$;

Step 6: Update multiplier d

$$d_{k+1} = y - \frac{\mu_k}{\mu_{k+1}}(A\Theta_{k+1} - d_k) \tag{8}$$

Step7: If the termination condition is met then the algorithm is terminated, otherwise, let k = k + l go to step 2. From the above algorithm it is clear that in order to reconstruct the fused image, sparse coefficient Θ, and Inverse Discrete Wavelet Transform (IDWT) should be used. Complexity of FCLALM algorithm mainly is in steps 2 and 5, which calculates the amount of $O(MN)$, and in step 3, 4, 6 that calculates volume and $O(1)$. Advantages of FCLALM algorithm is that it directly solves the image quality problem, while the other algorithms solve the problem approximately only. In addition, linearization, sustained, rapid thoughts can fully accelerate the convergence speed. Therefore, FCLALM algorithm has better reconstructed image than other algorithms and more rapid convergence speed. Finally the system propose an edge preserving image filtering method which is an adaptive local linear model and the principle of Stein's unbiased risk estimate (SURE) known as LLSURE[20].

3. EXPERIMENTAL RESULTS AND DISCUSSION

In this section, the occasional experimental results are offered to evaluate the performance of the proposed FCLALM and the proposed fusion and reconstruction framework.To begin with, the test image of size $n \times n$ is arranged into a column vector of length $N = n^2$. Subsequently, this vector is divided into n frames of size n and solves one frame at a time. The sampling rate of the test image is defined as follows,

$$r = m / n \tag{9}$$

where n is the frame size and m is the dimension of the measurement of each frame. Here, the comparison is done between FCLALM reconstruction algorithm, LLSURE and OCP. Further, alsoprovide the results of a proof-of-concept experiment showing the effectiveness of the FCLALM over LLSURE and OCP.

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Volume 6, Issue 6, November- December 2017 ISSN 2278-6856

Figure 2: Sample Input Image

The figure 2 shows the input video frame image.

3.1Performance Metrics

Peak Signal to Noise Ratio (PSNR) and Mean SquareError (MSE) are the mostly used performance metrics for measuring the quality of compressed images. These metrics are also used for measuring the results of quality of edge preserving methods. The final compressed image is given as input to edge preserving algorithm and the compressed image results are measured by using edge preserving methods.

3.1.1Peak Signal to Noise Ratio (PSNR) and Mean Square Error (MSE)

Two of the error metrics utilized to compare the various edge preserving methods are Mean Square Error (MSE) and the Peak Signal to Noise Ratio (PSNR). The MSE is calculated based on the cumulative squared error between the compressed and the original image, whereas PSNR is a measure of the peak error. The mathematical formulae for the two are

$$\text{MSE} = \frac{1}{MN}\sum_{y=1}^{M}\sum_{x=1}^{N}[I(x,y)-I'(x,y)]^2 \quad (10)$$

$$PSNR = 20 * \log_{10}\left(\frac{255}{\sqrt{MSE}}\right) \quad (11)$$

where I(x,y) is the original image, I'(x,y) is the decompressed image and the dimensions of the images is represented as M and N. Reasonably, a higher value of PSNR is high-quality because it represents that the ratio of Signal to Noise is high.

Maximum difference is defined as follows:

$$MD = \max|x(i,j)-y(i,j)| \quad (12)$$

3.1.2Maximum Error

Figure 3 shows the Maximum Error (ME) results for the corresponding frames values. With the increase in frame size, the ME value increases linearly. The ME value of the proposed LLSURE with FCLALM is observed to be lesser when compared with the existing compression techniques like SURE and OCP. This is mainly due to the fact that for the FCLALM, smaller tolerance values are determined (e.g., $\varepsilon = 10^{-4}$) which do not consistently improve the relative error. The numerical values are shown in Table 1.

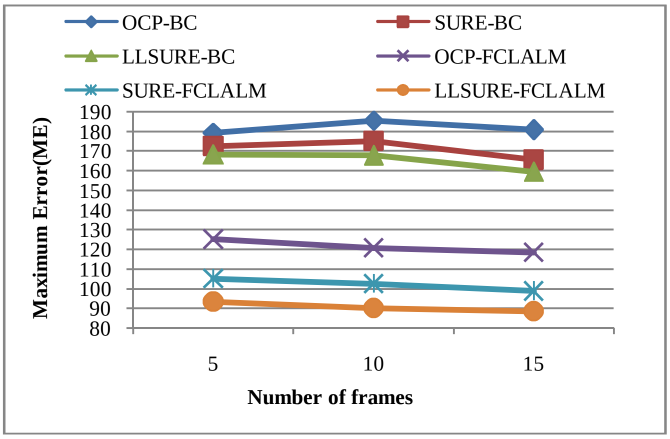

Figure 3: Maximum Error Comparison

Table 1: ME comparison values

No. of frames	Before compression			After compression		
	OCP	SURE	LLSURE	OCP	SURE	LLSURE
5	179.4	172.56	168.2	125.2	105.3	93.56
10	185.6	175.23	167.8	120.8	102.69	90.21
15	180.8	165.51	159.4	118.5	98.81	88.52

3.1.3. Maximum Difference

Figure 4 shows the comparison result of MD on frames. The MD value of the proposed LLSURE with FCLALM algorithm is observed to be lesser than the existing algorithm such as SURE and OCP. The MD value increases linearly for all the approaches taken for consideration. Since the warm starting of LLSURE with FCLALM from the previous solutions leads to a better performance, the proposed method outperforms other methods in terms of the MD at the same frame rate. The numerical values are shown in Table 2.

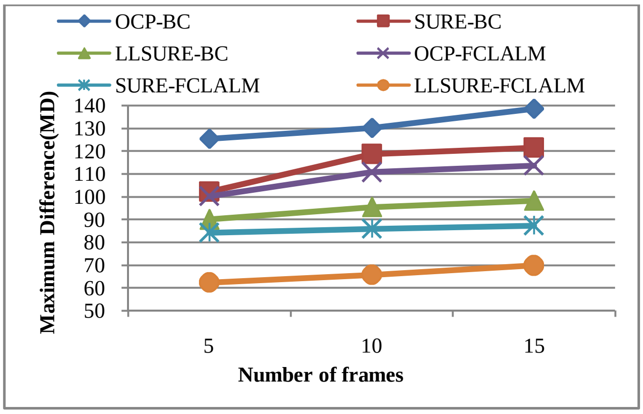

Figure 4: Maximum Difference Comparison

Table 2: MD comparison values

No. of frames	Before compression			After compression		
	OCP	SURE	LLSURE	OCP	SURE	LLSURE
5	125.4	102.25	90.04	104.21	84.21	62.34
10	130.2	118.87	95.6	110.78	85.93	65.82
15	138.6	121.58	98.2	113.81	87.41	69.87

3.1.4. Mean Square Error (MSE)

Figure 5 shows the Mean Square Error (MSE) performance comparison of the proposed LLSURE with FCLALM approach against the frames values. MSE values attained for the proposed method is lesser when compared with the other existing techniques. This performance significance is mainly due to the fast convergence rate of the LLSURE with FCLALM when compared to existing SURE and OCP techniques. The numerical values are shown in Table 3.

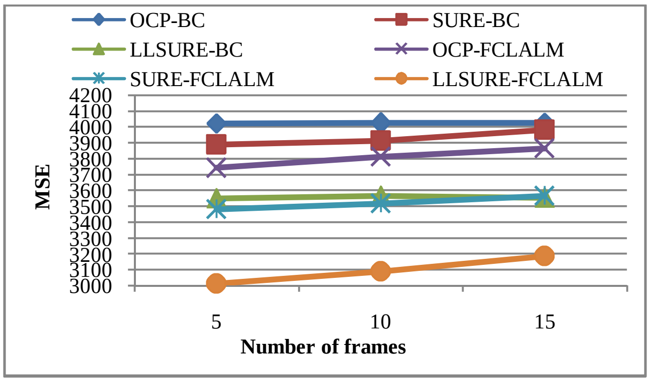

Figure 5: MSE comparison

Table 3: MSE comparison values

No. of frames	Before compression			After compression		
	OCP	SURE	LLSURE	OCP	SURE	LLSURE
5	4020.32	3889.21	3550.2	3741	3481	3015
10	4023.43	3912.52	3567.3	3812	3518	3089
15	4025.4	3981.23	3552.2	3863	3567	3187

3.1.5. Peak Signal Noise Ratio (PSNR)

Figure 7 shows the PSNR results of LLSURE, SURE and OCP with different frames. It is observed from the figure that PSNR of the FCLALM with LLSURE approach is higher PSNR for different frames. It is also obvious that, with increasing the sampling rate, the PSNR becomes higher for all the methods, that is, a better quality fused image can be obtained by taking more measurements. Clearly, the proposed method has the best performance and the fastest convergence rate regardless of the frame rate. The numerical values are shown in Table 4.

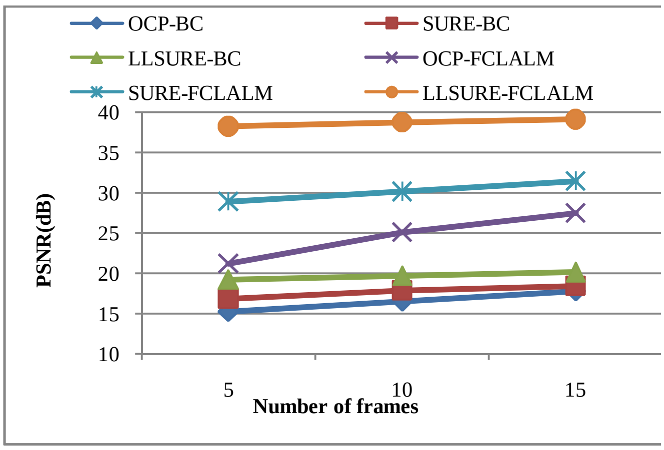

Figure 6: PSNR comparison

Table 4: PSNR comparison values

No. of frames	Before compression(dB)			After compression(dB)		
	OCP	SURE	LLSURE	OCP	SURE	LLSURE
5	15.23	16.81	19.25	21.23	28.93	38.25
10	16.51	17.88	19.68	25.12	30.14	38.78
15	17.78	18.42	20.14	27.51	31.48	39.12

Following are some measurements used to evaluate the performances of edge preserving algorithms. Compression Ratio (CR) is the ratio between the size of the compressed file and the size of the source file.

$$CR = \frac{Size\ After\ Compression}{Size\ Befor\ Compression} \tag{13}$$

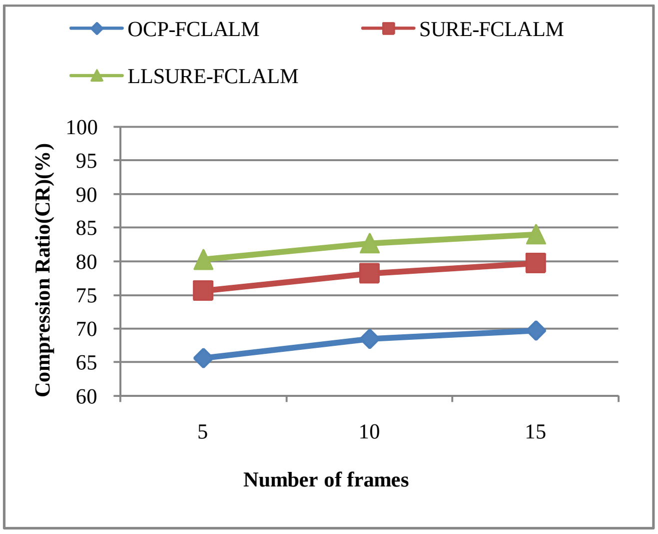

Figure 6: CR results comparison

Figure 6 shows the Compression Ratio (CR) performance comparison of the proposed LLSURE with FCLALM approach against the frames values. CR values attained for the proposed method is higherfor all three edge preserving methods. It becomes very higher for proposed LLSURE based edge preserving algorithm. This performance significance is mainly due to the higher compressed rate of the LLSURE with FCLALM when compared to existing SURE and OCP techniques. The numerical values are shown in Table 5.

Table 5: CR comparison values

No of frames	Compression Ratio (CR)(%)		
	OCP-FCLALM	SURE-FCLALM	LLSURE-FCLALM
5	65.63	75.63	80.25
10	68.52	78.23	82.69
15	69.72	79.69	83.97

4.CONCLUSION AND FUTURE WORK

An effective image fusion technique based on wavelet method and its reconstruction framework is presented in this work. DWT based new fusion scheme attains anenhanced performance to LLSURE, SURE and OCPfusion methods in fusing the measurements of images. In order to reconstruct the sparse coefficients from the fused measurement a fast convergent algorithm, referred to as FCLALM, has been proposed, and thereby the fused image is reconstructed through the IDWT. From the experimental results it is clear that the proposed image fusion scheme provides better fusion quality than the existing image fusion methods. FCLALM gives a high PSNR and a better convergence rate compared to traditional methods. Finally, the proposed framework provides better computation, communication and storage space. In the future work improved compression methods such Discrete Cosine Transform (DCT), Improved DCT and hybrid DCT algorithms are introduced to increase the compression results.

REFERENCES

[1] N. Ahmed, T. Natrajan, and K. R. Rao, "Discrete cosine transform," IEEE Trans. Comput., vol. C-23, no. 1, pp. 90–93, Dec. 1984.
[2] G. K. Wallace, "JPEG still picture compression standard," in Commun. ACM, vol. 34, Apr. 1991, pp. 30–44.
[3] ISO, "MPEG : generic coding of moving pictures and associated audio", Recommendation H.262, ISO/IEC, 13818-2, 1995
[4] B. G. Haskell, A. Puri, and A. N. Netravali, Digital Video: An Introduction to MPEG-2. London, U.K.: Chapman & Hall, 1997, Digital Multimedia Standards Series.
[5] S. G.Mallat, "A theory formultiresolution signal decomposition: the wavelet representation," IEEE Trans. Pattern Anal. Machine Intell., vol. PAMI-11, pp. 674–693, July 1989.
[6] D. Taubman, M. Marcellin, JPEG2000: Image Compression Fundamentals, Standards, and Practice, Kluwer Academic Publishers, 2001.
[7] Li, H.F., Chai, Y., Yin, H.P., Liu, G.Q.: 'Multifocus image fusion and denoising scheme based on homogeneity similarity', Opt. Commun., 2012, 285, (2), pp. 91–100
[8] J.Mbainaibeye and N. Ellouze, "Optimal Image Compression Based on Sign and Magnitude Coding of Wavelet Coefficients", International Journal of Signal Processing, Vol. 3, No 4, pp.243-251, 2007.
[9] J. Wu, C. Olivier and C. Chatellier, "Embedded Zerotreerunlength wavelet image coding", 8th ICIP-Signal Processing, Thessaloniki, Greece, pp.784-787, Oct. 2001.
[10] J. M. Shapiro,, "Embedded Image Coding Using Zerotrees of Wavelet Coefficients", IEEE trans. on Signal Processing,Vol.41, No.12, pp.3445-3462, Dec. 1993.
[11] M.Jérôme, and N.Ellouze, "Embedded Zerotree Wavelet Coding of Image Sequence", Proc. International Conference on Wavelet Analysis and Its Applications, Springer Publisher, Lecture Notes in Computer Science, vol.2251, ISBN 3-540-43034-2, pp.65-75, Hong Kong, Dec.18-20, 2001.
[12] Wan, T., Qin, Z.C.: 'An application of compressive sensing for image fusion'. 2010 ACM Int. Conf. Image and Video Retrieval, 2010, pp. 3–9
[13] Li, X., Qin, S.Y.: 'Efficient fusion for infrared and visible images based on compressive sensing principle', IET Image Process., 2011, 5, (2), pp. 141–147
[14] Luo, X.Y., Zhang, J., Yang, J.Y., Dai, Q.H.: 'Classification-based image-fusion framework for compressive imaging', J. Electron. Imaging, 2010, 19, (3), pp. 1–14
[15] Zebhi, S., Aghabozorgi, S., Masoud, R., Sadeghi, M.: 'Improvement of compressive sampling based approaches in images fusion'. ICEE 2012 –20th Iranian Conf. Electrical Engineering, 2012, pp. 1088–1092
[16] Sahoo M. Biomedical Image Fusion & Segmentation using GLCM. IJCA Special Issue on 2ndNational Conference on Computing, Communication and Sensor Network, Vol. 1, pp. 34-39, 2011.
[17] Zhou X, Wang W, Liu RA, Compressive sensing image fusion algorithm based on directionlets. Journal on Wireless Communications and Networking 2014.
[18] Pratap R, Dwivedi R, Negi S. Comparative Evaluation of DWT and DT-CWT for Image Fusion and De-noising. International Journal of Applied Information Systems, Vol. 4, pp. 40-45, 2012.
[19] Dammavalam S, Maddala S, Krishna Prasad MHM. Quality Assessment Of Pixel-Level Image Fusion Using Fuzzy Logic. International Journal on Soft Computing,Vol.3, No.1, pp.13-25,2012.
[20] Kavitha, P. and Vijendran, A.S., 2016. A Novel Edge Preserving Local Linear Stein's Unbiased Risk Surface Estimator Approach for High Dynamic Range Image. Indian Journal of Science and Technology, 9(6),pp.1-7.