International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-2, December 2019

Advanced Multifocus Image Fusion algorithm using FPDCT with Modified PCA

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Abstract: ***Image fusion has been performed and reported in this paper for multi-focused images using Frequency Partition Discrete Cosine Transform (FP-DCT) with Modified Principal component analysis (MPCA) technique. The image fusion with decomposition at fixed levels may be treated as a very critical rule in the earlier image processing techniques. The frequency partitioning approach was used in this study to select the decomposition levels based on the pixel intensity and clarity. This paper also presents the modified PCA technique which provides dimensionality reduction. The wide range of quality evaluation metrics was computed to compare the fusion performance on the five images. Different techniques such as PCA, wavelet transforms with PCA, Multiresolution Singular Value Decomposition (MSVD) with PCA, Multiresolution DCT (MRDCT) with PCA, Frequency partitioning DCT (FP-DCT) with PCA were computed for comparison with the proposed FP-DCT Modified PCA (MPCA) technique. Images obtained after fusion process obtained by the method proposed shows enhanced visual quality, negligible information loss and discontinuities in the image than compared to other state of the art methods.***

Keywords: ***Frequency Partitioning, Image Fusion, Modified PCA, Multi-Focus Images, DCT, Quality Evaluation Metrics, Comparative Analysis, Image Quality***

I. INTRODUCTION

In the process of Image fusion two or more images are combines with different focus values of the same picture using different fusion rules. The composite image obtained after fusion called as all-in-focus image gives more information and is more convenient to visual perception which can be further processed for the object and target detection [1-5]. Generally the intention of the fusion process is to combine the redundant and complementary information from multiple images to create a composite fused image that contain better properties than individual input images in terms of visual perception and suitable for secondary processing. Complete information is obtained in the process of integrating differently focused images, since images with different principle characteristics are combined.

Revised Manuscript Received on December 30, 2019.
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The fused image also provides increased interpretation abilities and more consistent results. The performance of the secondary processing of the images such as feature extraction, object recognition and segmentation can be further improved at a greater level by using the images after image fusion. The main intention to design different algorithms in image fusion is to reduce the redundant data and also to retain important information of the visual characteristics of the multi source images. The images varying its spatial, temporal and spectral resolution characteristics may provide wide range information of the viewed objects [6]. Rapid innovative methodologies make it possible to produce fused images with high resolution containing spatial and spectral information. [7-8]. The fusion of images has vast number of applications which includes medical imaging, surveillance, military, microscopic imaging, remote sensing, computer vision, and robotic vision and navigation. Usually image fusion process is involved at one of the processing stages such as pixel, signal and feature based levels. The well known image fusion algorithms applied on the input images introduces serious effects such as decreasing the contrast of the image. At the later stages of the development, researchers are identified the importance to do the fusion process in the transform domain. With the development of wavelet theory, the multi-scale decomposition algorithm is used in the image fusion process [9]. The analysis of images using wavelet domain found many applications image processing such as image restoration, removal of noise, enrichments of image edges and feature extraction. However wavelet transforms are less efficient in acquiring information from two dimensional images [10]. Over the years many transform techniques have been recognized for the analysis of multi directional and multi-resolution images. However the proposed techniques failed to provide good fused image in terms of obtaining reasonable values of the statistical parameters such as PSNR, Normalized correlation (NC) and MSE. Variety of transformation techniques are available in the literature among which wavelet transformation and cosine transformation are generally used in image processing. In wavelet transformation algorithms, lifting wavelet and stationary wavelet transformation are majorly used. Discrete cosine transform (DCT) was frequently used by many researchers in group of cosine transforms.

Decomposition of multi-resolution images using variety of channels containing different frequency sub-bands in multi-scale. The decomposition operation applied on the image separates approximate and detailed component followed by 2-D DWT which converts the image from spatial domain to frequency domain.

DWT operation not only gives spatial component such as frequency content of the input at different scales and also temporal component such as at what times these frequency components are presented. On the other hand, a DCT represented by a finite sequence of data points using the sum of cosine functions fluctuates at different frequencies. DCT algorithms are used in number of applications in engineering and science from lossy compression of audio and images to spectral methods to find the solution to partial differential applications. Many algorithms were proposed with the combinations of DWT and PCA, Morphological processing and Combination of DWT with PCA and Morphological techniques [11-14]. These methods show the better performance than simple methods like averaging, minimum and maximum [15]. There is a lot of development in proposing pixel level based fusion algorithms. Majority of the fusion algorithms are based on wavelet transform [16-17], pyramid transform [18], statistical signal processing [19], principal component analysis [16, 19], fuzzy logic [20], DCT [15, 21-22] and frequency portioning [23]. DCT technique gives better results for image compression and also accepted as more suitable and time saving technique for many image preprocessing applications [16].

Recently Bin Yang et al [24] proposed both multi-focus image fusion and super-resolution algorithms via convolutional neural network (CNN). The main idea of this work is to learn the fusion weights using neural network technology to fuse the patches of multi-focus images. Then the non-linear mapping is used to project the fused image into patches of high resolution which on aggregate generate the final image. They observed that the processing of super resolution images shows less time consuming with better visual quality. Very recently Deepak Gambhir et al [25] reported the fusion algorithm in HSV color space based on fuzzy transform and spatial frequency. They observed superior results of the image fusion algorithms based on the best values of the quality evaluation metrics.

Frequency portioning method is a basic approach in the fixed level approach. Each pixel can be decomposed uniformly and linearly in the fixed level based approach independent of the pixel intensity. On the other hand, the frequency partitioning based approach provides more specific and precise level for each pixel. This method provides range of the frequency values from 0.0 to 1.0 with an interval of 0.1 which create 10 distinct levels [26-29].

This paper focuses on the fusion of multi-focus images using discrete cosine transformation with frequency partitioning and feature extraction of the fused image using modified PCA. The feature extraction of the fused image is determined using different parametric analysis. The proposed method is also compared with already approved fusion methods like PCA, DWT with PCA, SWT with PCA and MSVD with PCA, MRDCT with PCA, FP-DCT with PCA. The result of FP-DCT with Modified PCA system shows that there is a much improvement in the statistical parameters than compared to other PCA based wavelet methods.

II. DISCRETE COSINE TRANSFORM (DCT)

DCT is widely used and accepted transform technique in the field of image processing. The coefficients of DCT concentrate on low frequency region. DCT uses cosine waves which decorrelates the image data. After decorrelation process, DCT coefficients are encoded independently not to lose the efficiency of the compression. Comparing to DFT, DCT is purely real and having numerous applications with respect to science and engineering.

Limitations of Discrete Cosine Transform

- The higher spectral coefficients causes for blurring in DCT transformation.
- In case of quantization some low spectral coefficients causes for graininess in smooth parts of image.
- Block boundaries are consisting series blocking artifacts in DCT because each block is encoded with different strategies and external quantization.

III. PROPOSED METHOD

The proposed method framework is depicted in Figure 1 which includes two processes: the FPDCT based image fusion process and MPCA process. The two processes are described as follows.

A. Image Fusion Based On DCT with Frequency Partitioning

The image fusion approach is applied with different fusion rules for high and low frequency components having partition factor (‘f’). The algorithm 1 describes the different steps involved in the implementation of the proposed method.

Algorithm 1: FPDCT based Image Fusion

Step1: Provide the Input images with multifocus resolution to the algorithm

Step2: Obtain high and low frequency components by applying FPDCT algorithm

Step3: Performed image fusion for the low and high frequency components separately using the fusion rules

Step4: Apply inverse DCT algorithm to the composite high and low frequency components to get the fused image.

The 2-D Lyapunov inequality becomes more critical option to apply for the entire frequency domain. To alleviate this it is necessary to use a matrix function varies with the frequency domain. Hence, in order to get the advantage of 2-D Lyapunov inequality, a group of discrete intervals of constant matrix functions can be considered using the frequency partitioning approach. Frequency is a periodic motion undergone for one cycle after passing through series of values. Frequency partition refers to identification of LF and HF in given set of data. Further apply frequency function f which divides LF and HF values separately. Here LF indicates low frequency and HF indicates high frequency.

In case of digital image, low frequency components are perceptually important. Generally, background components are considered as low frequency values. Whereas in case of high frequency components sharp image edges are identified which represents foreground components of image.

The frequency partitioning is very useful in identification of periodic texture pattern or extraction of features of image. In case of matching procedure, high frequency components are considered to identify texture pattern.

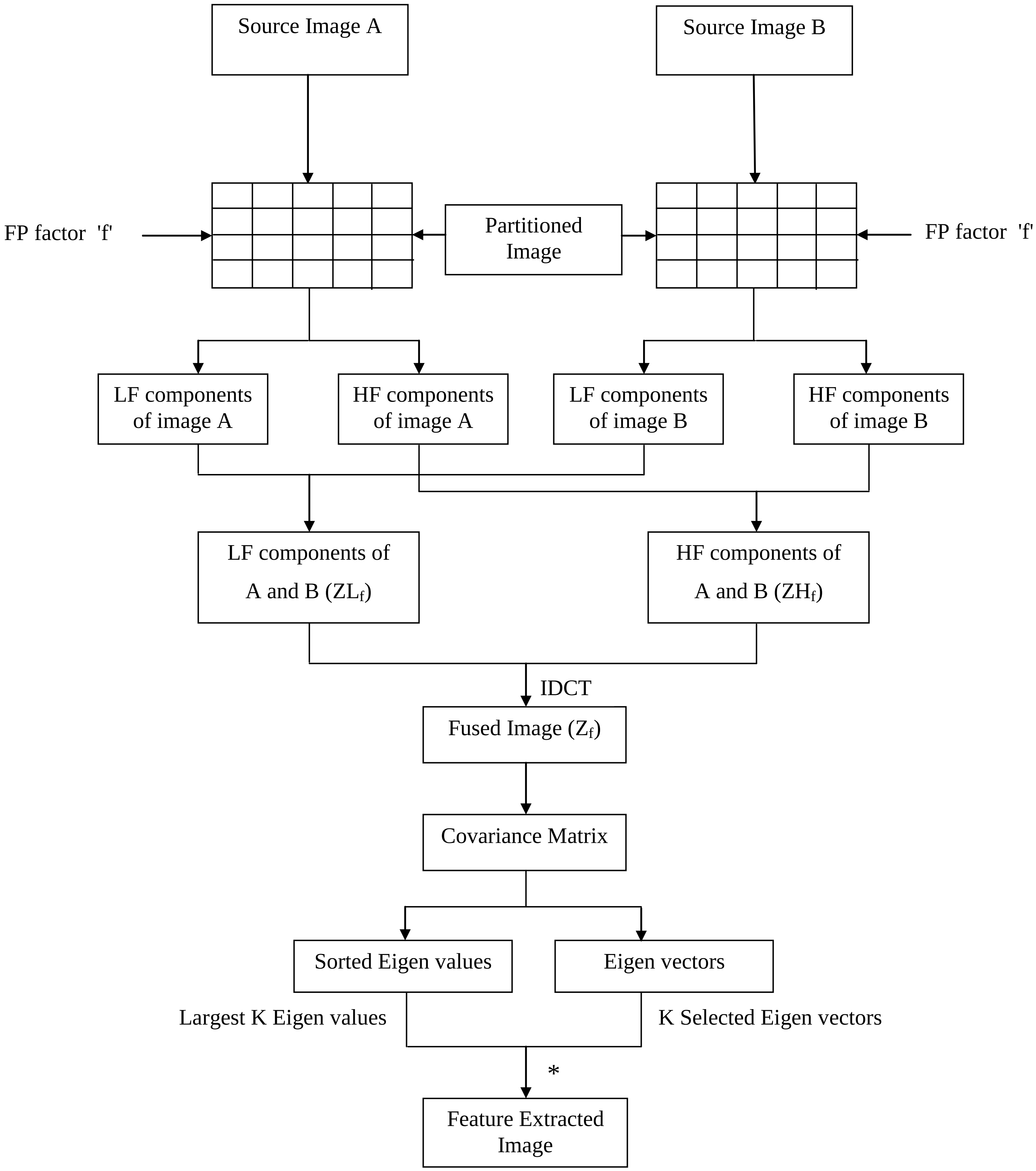

Figure 1: The flow diagram of the proposed method

Vector data has been generated with the help of 1D DCT, DCT function Z(x). Further, DCT coefficients are identified for the given vector. A partition factor 'f' is applied for energy compaction DCT coefficients (high and low frequency) which separates DCT coefficients as low frequency and high frequency separately as shown in below figure1.

$$A(p) = DCT\big(a(p)\big),\ p, v = 0,1,2,\dots,XY-1 \quad (1)$$
$$AL(v) = A(v), v = 0,1,2,\dots,XYf-1 \quad (2)$$
$$A(v) = A(v), v = XYf, XYf+1,\dots,XY-1 \quad (3)$$

Let the images to be fused are $a_1(p,q)\&a_2(p,q)$ and the image fusion process is as follows:

$$a_1(p) = c2dt1d(a_1(p,q), X, Y) \quad (4)$$
$$a_2(p) = c2dt1d(a_2(p,q), X, Y) \quad (5)$$
$$A_1(v) = DCT(a_1(p)) \quad (6)$$
$$A_2(v) = DCT(2(p)) \quad (7)$$

With the help of eq. 3, the fused coefficients are represented as:

$$AL_f(v) = 0.5\big(AL_1(v) + AL_2(v)\big),\quad v = 0,1,\dots,XYf-1 \quad (8)$$
$$AH_f(v) = \begin{cases} AH_1(v)\ if\ |AH_1(v)| \geq |AH_2(v)| \\ AH_2(v) if\ |AH_1(v)| < |AH_2(v)|' \\ v = XYf, XYf+1,\dots,XY-1 \end{cases} \quad (9)$$
$$A_f(v) = \big[AL_f(v)AH_f(v)\big] \quad (10)$$
$$a_f(p) = idct\left(A_f(v)\right),\ p, v = 0,1,2,\dots,XY-1 \quad (11)$$

The fused image is: $I_f = c1dt2d(A_f(p), X, Y)$ (12)

B. Implementation of MPCA algorithm

The fused image obtained after applying FPDCT algorithm is given as an input to MPCA algorithm. The purpose of using MPCA algorithm is to reduce the dimensionality of the images [16, 19, 32-33]. The detailed description of some key steps involved in the MPCA algorithm is given in algorithm 2.

Algorithm 2: MPCA
Input : Fused image by FPDCT
Step 1 : Load the fused image
Step 2 : Compute C = cov([im1(:)])
Step 3 : [V, D] = eig(C)
Step 4 : [max, ind] = sort(diag(D), 'descend')
Step 5 : a = V(: , ind(1) . / sum(V(: , ind(1)))
Step 6 : F_E_img = a(1)*im1
Output : Features extracted image

The MPCA involves as mathematical procedure to transform correlated variables into number of uncorrelated principle components. It computes optimal description for a given data set with compact operation. The first principal of MPCA is to estimate covariance values for given set of data. Maximum variance is computed from the first principle component.

Let the source image is arranged as one column vector. The following steps are needed to project the data in 1D subspace.

- Arrange the data in a vector.
- Compute the covariance matrix for the given vector.
- Compute Eigen values for given covariance matrix.
- Find out V, D from the Eigen function.
- Sort the D in order of decreasing eigenvalue.
- Compute first column of V corresponds to larger Eigen value. To compute P as
  P = V(: , ind(1))./sum(V(: , ind(1))) (13)
- Finally to get the features extracted image as
  PCA = P(1) * Img (14)

IV. QUALITY METRICS OF THE IMAGE FUSION ALGORITHM

The quality measure of the image fusion process is categorized into subjective and objective metrics. The subjective metrics usually depends on visual features and observer's professional knowledge. Further, the computation time of this process is time-consuming with poor readability.

On the other hand, the objective metrics can easily be computed and calculates the similarity between the fused image and input images. The present paper evaluates twelve objective metrics to understand the performance of the proposed algorithm. [31, 33-43].

V. RESULTS AND DISCUSSION

Various standard multifocus images are analyzed using the proposed algorithm to understand the quality, important characteristics and features of the fused image. Standard test images namely multifocus Flowerpot, Clock, Pepsi, Cameraman and Disk images was chosen as source images. Image fusion carriedout by the proposed method (i.e., FPDCT+MPCA) is compared with different methods: PCA, DWT with PCA, SWT with PCA, MSVD with PCA, MRDCT with PCA, and FPDCT with PCA. Comparison of performance evaluation is based on visual quality and quantitative performance measures. All the source images are fused using FPDCT followed by dimensionality reduction using MPCA.

Performance measures such as En(Entropy), API(Average Pixel Intensity), SD(Standard Deviation), SF(Spatial Frequency), RMSE(Root Mean Square Error), PFE(Percentage Fit Error), NK(Normalized Cross Correlation), SNR(Signal to Noise Ratio), PSNR(Peak Signal to Noise Ratio), FL(Fusion Loss), Q_W(Weighted Fusion Quality) and $Q^{AB/F}$ (Total Fusion Performance) were evaluated for fused images of five sets of multifocus images. Table 1 gives the statistical details such as Weighted Fusion Quality (Q_W) and Total Fusion Performance ($Q^{AB/F}$) for the multifocus fused images. The remaining performance measures were tabulated for Flowerpot, Clock, Pepsi, Cameraman and Disk images and shown in table 2, 3, 4, 5 and 6 respectively. As the goal of image fusion process is to enhance the comprehensive, accurate and stable information such that the fused image is more suitable for human perception, visual and quantitative analysis. The performance of image fusion algorithms with respect to visual analysis can be decided based on widely accepted criteria such information transfer from input image to fused image, loss of information from input images, introduction of artifacts in fused images.

Figure 2 describes the output images of multifocus flowerpot obtained by different PCA based techniques. From the figure it is evidenced that, the quality of the fused flowerpot images by the proposed method (Fig. 2(h)) shows better improvement than the other PCA based methods. The output results also reveals that no loss of information, higher visual quality and further avoided artifacts.

Hence the proposed algorithm able to fuse much of the information from both the multifocal input images when compared with other fused images obtained by other techniques. The statistical parameters are provided in the table 2 can be considered to compare the quality of the fused multifocal flowerpot images quantitatively. From the observed statistical parameters of multifocal flowerpot image, it is evidenced that, the FPDCT-MPCA algorithm has shown good performance over other techniques.

Visual quality of fused clock images is shown in Fig. 3 for different image fusion algorithms. This figure reveals that the fused image by proposed algorithm (Fig. 3(h)) could be capable to acquire much of information from the input multifocal images (Fig. 3(a) and 3(b)) than compared with other image fusion algorithms. From the Table 2 it is observed that, the performance of the proposed method is improved than compared with other methods.

Fig. 4 shows the comparison of the fused images of multifocus pepsi by different PCA based image fusion methods. It is observed that, the image quality of fused image by proposed method (Fig. 4(h)) contains more information than the source images and shows best visual effects. The performance metrics have been tabulated in table 3. It was evident from the table that the proposed method is better than the other methods in terms of all of the statistical parameters.

PCA based fusion of multifocus cameraman images was presented in fig. 6. Among the considered fusion methods, the proposed method (Fig. 5(h)) has shown very good image quality in terms of all statistical parameters which was shown in table 5. The statistical parameters obtained by the proposed method provide promising objective than other algorithms.

Figure 5 shows the multifocus images of disk and the results of various PCA based techniques. The output image generated from the FPDCT with modified PCA method shows better image quality than comparing to other PCA based methods. The statistical parameters obtained for this multifocus image is presented in the table 6. According to the table, the statistical parameters show better numerical values for the proposed method than comparing to other techniques.

It is concluded from the results shown in the table 1 to table 6 that the proposed

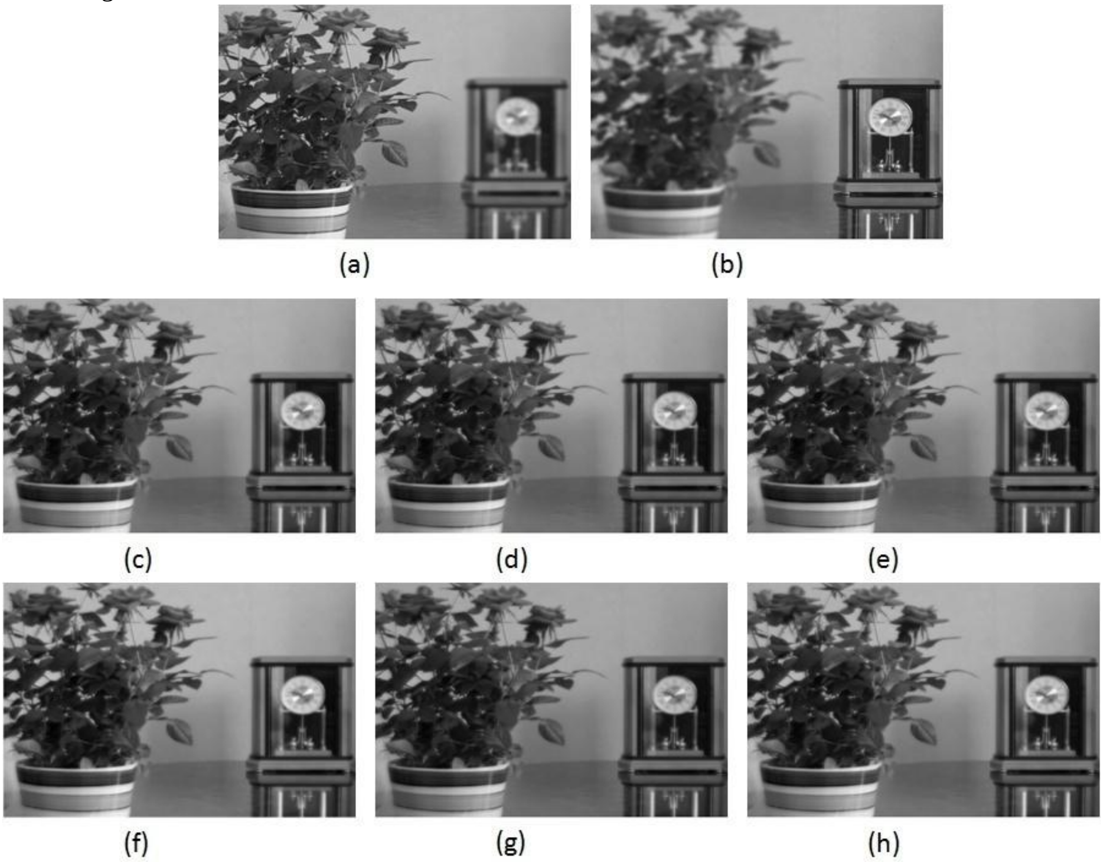

Figure 2: PCA based fusion results of first pair of multifocus images (Flowerpot): (a) Input image (X), (b) input image (Y), (c) PCA, (d) DWT+PCA, (e) SWT+PCA, (f) MSVD+PCA, (g) MRDCT+PCA, (h) proposed method.

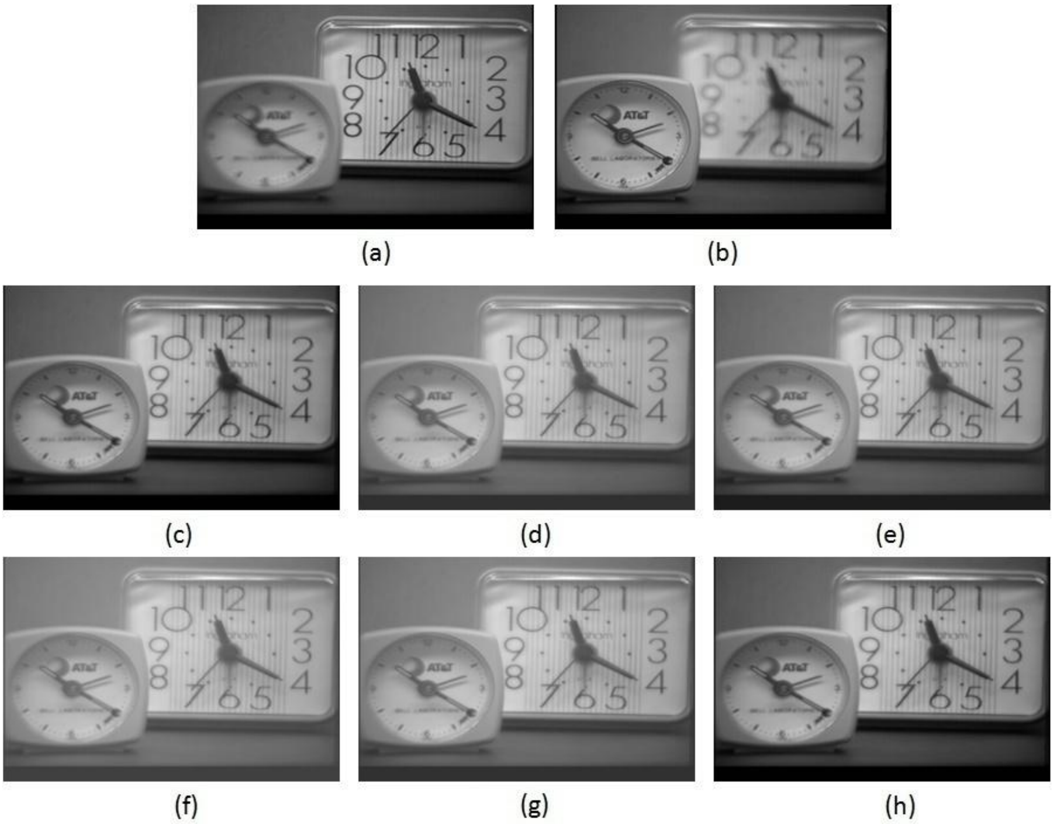

Figure 3: PCA based fusion results of second pair of multifocus images (Clock): (a) Input image (X), (b) input image (Y), (c) PCA, (d) DWT+PCA, (e) SWT+PCA, (f) MSVD+PCA, (g) MRDCT+PCA, (h) proposed method

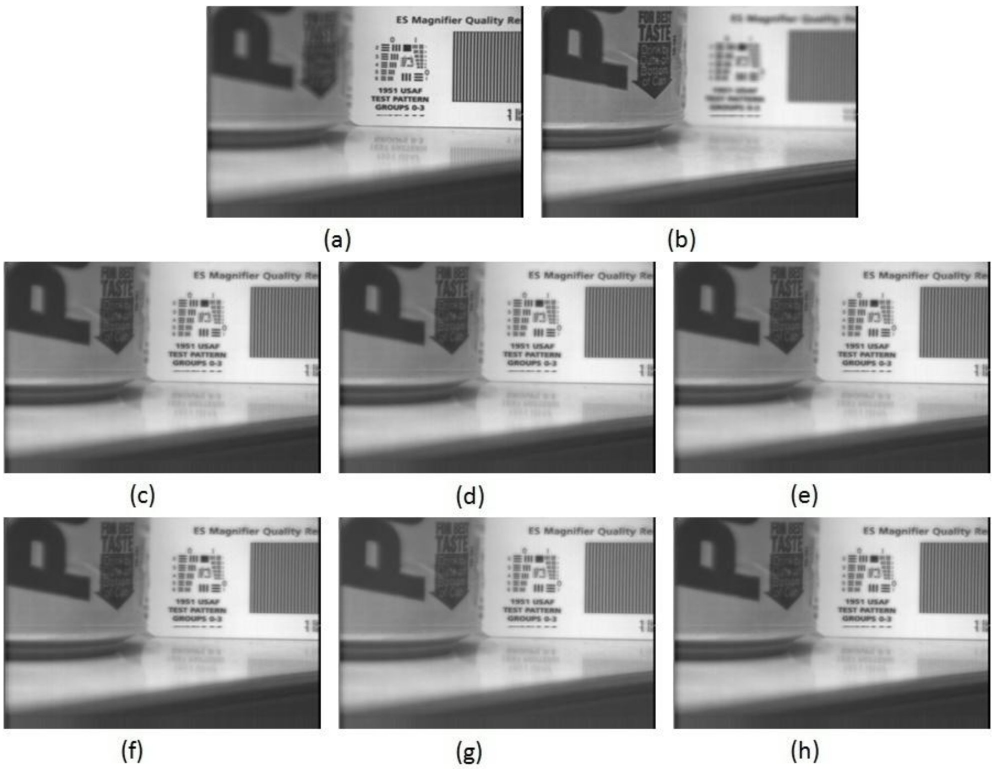

Figure 4: PCA based fusion results of third pair of multifocus images (Pepsi): (a) Input image (X), (b) input image (Y), (c) PCA, (d) DWT+PCA, (e) SWT+PCA, (f) MSVD+PCA, (g) MRDCT+PCA, (h) proposed method.

International Journal of Innovative Technology and Exploring Engineering (IJITEE)
ISSN: 2278-3075 (Online), Volume-9 Issue-2, December 2019

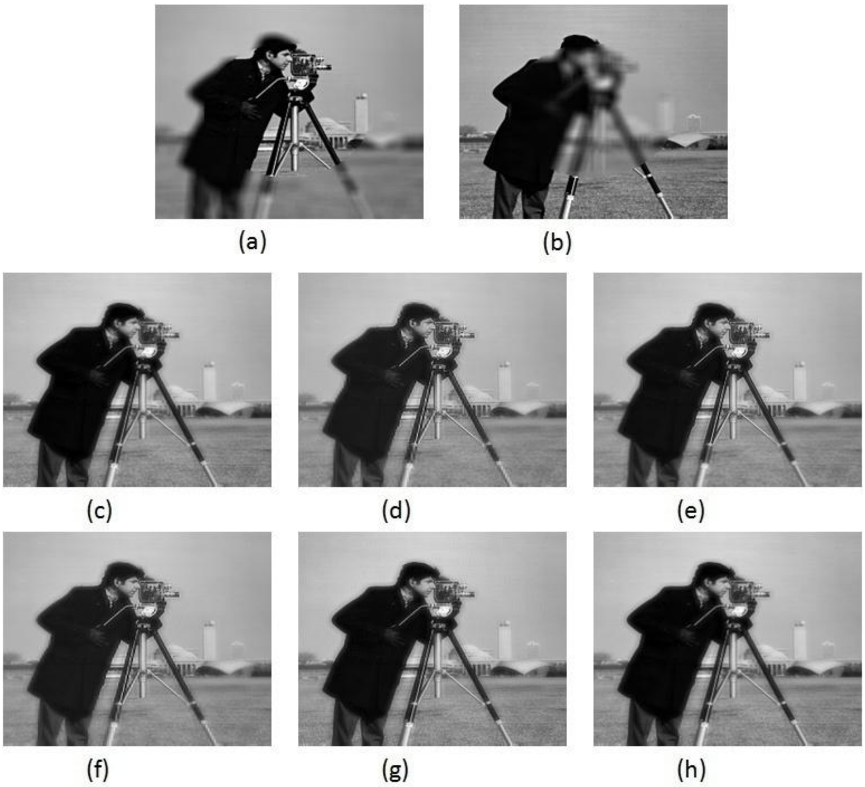

Figure 5: PCA based fusion results of fourth pair of multifocus images (Cameraman): (a) Input image (X), (b) input image (Y), (c) PCA, (d) DWT+PCA, (e) SWT+PCA, (f) MSVD+PCA, (g) MRDCT+PCA, (h) proposed method.

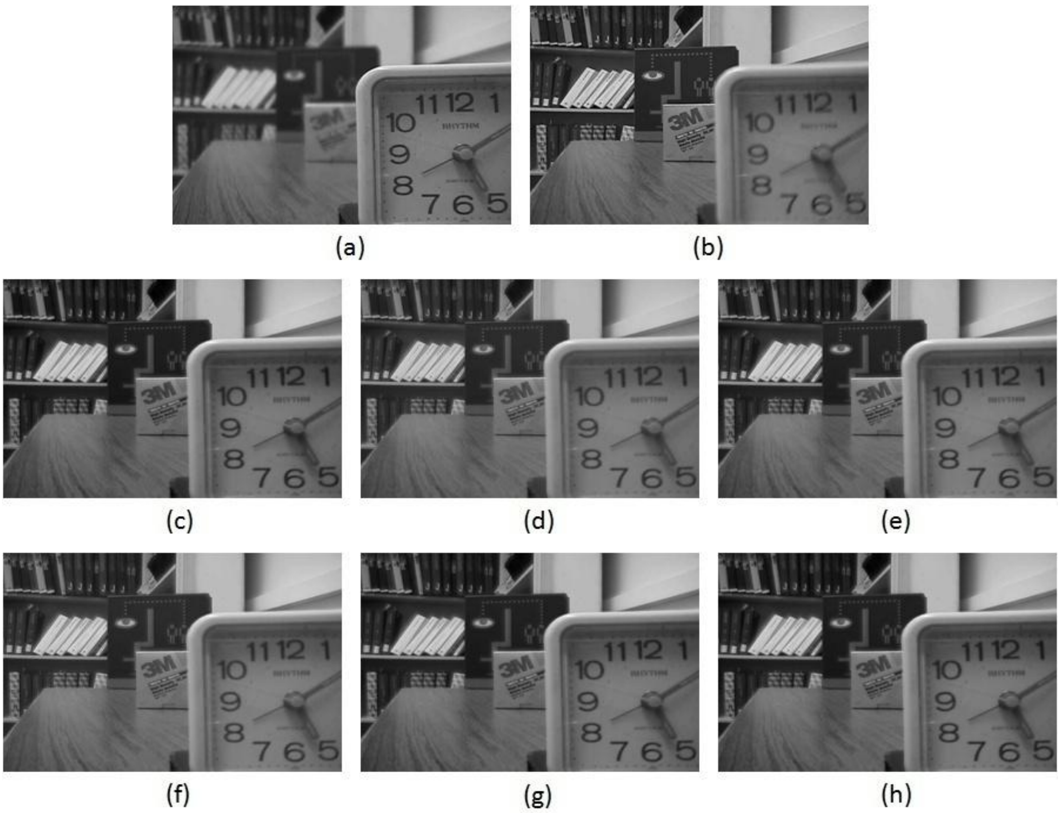

Figure 6: PCA based fusion results of fifth pair of multifocus images (Disk): (a) Input image (X), (b) input image (Y), (c) PCA, (d) DWT+PCA, (e) SWT+PCA, (f) MSVD+PCA, (g) MRDCT+PCA, (h) proposed method.

Table 1: Objective performances of different PCA based fusion algorithms.

Source Images	Evaluation Criteria	PCA	DWT+ PCA	SWT+ PCA	MSVD+ PCA	MRDCT+ PCA	**Proposed Method**
Flowerpot	Q_W	0.860571	0.860804	0.861131	0.794400	0.860235	**0.933416**
	$Q^{AB/F}$	0.862571	0.864158	0.865277	0.646634	0.861240	**0.963229**
Clock	Q_W	0.866725	0.860984	0.866448	0.840766	0.867720	**0.941447**
	$Q^{AB/F}$	0.866055	0.838268	0.87289	0.825380	0.871926	**0.952022**
Pepsi	Q_W	0.854098	0.858916	0.859607	0.755039	0.851632	**0.944694**
	$Q^{AB/F}$	0.805360	0.827116	0.831849	0.600928	0.797171	**0.978838**
Camera man	Q_W	0.836517	0.815159	0.833777	0.827224	0.849236	**0.940652**
	$Q^{AB/F}$	0.794417	0.733837	0.772308	0.754174	0.844893	**0.956441**
Disk	Q_W	0.849818	0.854224	0.859939	0.857094	0.848682	**0.976384**
	$Q^{AB/F}$	0.833182	0.838767	0.877333	0.855921	0.835644	**0.949319**

Table 2: Comparison of quality parameters for the first pair of multifocus images (Flowerpot)

Algorithm	En	API	SD	SF	RMSE	PFE	NK	SNR	PSNR	FL
PCA	7.35871	113.73529	49.90987	9.68369	8.40922	6.69977	0.98736	23.47879	38.91724	0.13572
DWT+PCA	7.35878	113.7344	49.91207	9.75061	8.40289	6.69473	0.98737	23.48533	38.9205	0.13413
SWT+PCA	7.35882	113.73491	49.91333	9.75308	8.39324	6.68704	0.98738	23.49531	38.92549	0.13302
MSVD+PCA	7.35487	113.73396	49.56489	8.53607	10.9664	8.73719	0.98469	21.17256	37.76412	0.348
MRDCT+PCA	7.36237	113.71013	49.90874	10.2582	8.44326	6.72689	0.98716	23.4437	38.89969	0.13678
Proposed Method	**7.55586**	**114.5534**	**53.71092**	**13.024**	**7.42749**	**5.9176**	**1.00628**	**24.55707**	**39.45637**	**0.03019**

Table 3: Comparison of quality parameters for the second pair of multifocus images (Clock)

Algorithm	En	API	SD	SF	RMSE	PFE	NK	SNR	PSNR	FL
PCA	6.96476	78.38025	39.67307	5.06392	5.35636	6.06461	0.99282	24.34394	40.87609	0.13282
DWT+PCA	6.99622	78.387	39.70469	5.86464	5.46653	6.18935	0.99297	24.16709	40.78767	0.15991
SWT+PCA	6.97634	78.38001	39.69822	5.32468	5.35406	6.06201	0.99294	24.34766	40.87796	0.12591
MSVD+PCA	6.97897	78.37973	39.67596	6.37107	5.88958	6.66833	0.99244	23.51965	40.46395	0.17283
MRDCT+PCA	7.01667	78.38131	39.68605	5.43774	**5.32952**	**6.03422**	0.99291	**24.38757**	**40.89791**	0.12692
Proposed Method	**7.15664**	**78.93378**	**41.76998**	**8.00297**	5.84666	6.61974	**1.00899**	23.58316	40.49571	**0.03972**

Table 4: Comparison of quality parameters for the third pair of multifocus images (Pepsi)

Algorithm	En	API	SD	SF	RMSE	PFE	NK	SNR	PSNR	FL
PCA	7.08946	97.57656	43.99289	10.60286	5.66472	5.26497	0.99344	25.57207	40.63301	0.19413
DWT+PCA	7.08938	97.57661	44.0067	10.69703	5.57749	5.18389	0.99354	25.70687	40.70041	0.17237
SWT+PCA	7.08951	97.57662	44.00633	10.68514	5.56461	5.17193	0.99354	25.72693	40.71044	0.16764
MSVD+PCA	7.06786	97.57675	43.65395	7.443489	8.45015	7.85384	0.99046	22.09835	38.89615	0.39411
MRDCT+PCA	7.09892	97.57704	44.00763	10.97629	5.73032	5.32594	0.99347	25.47205	40.583	0.20222
Proposed Method	**7.17966**	**97.64966**	**46.04247**	**14.24063**	**3.82537**	**3.55542**	**1.00278**	**28.98217**	**42.33806**	**0.0175**

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DOI: 10.35940/ijitee.A5312.129219
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Table 5: Comparison of quality parameters for the fourth pair of multifocus images (Cameraman)

Algorithm	En	API	SD	SF	RMSE	PFE	NK	SNR	PSNR	FL
PCA	7.01645	118.7175	57.40254	15.16215	11.82322	8.82756	0.98077	21.08317	37.43744	0.20399
DWT+PCA	7.02158	118.7179	57.93231	20.70814	12.76615	9.53159	0.98183	20.41668	37.10419	0.26099
SWT+PCA	7.01031	118.7177	57.74853	19.09884	11.96842	8.93597	0.98179	20.97715	37.38443	0.22464
MSVD+PCA	7.01128	118.7178	57.78185	19.07134	12.25526	9.15014	0.9817	20.77143	37.28157	0.24176
MRDCT+PCA	7.10591	118.7184	57.66759	18.88011	11.33094	8.46002	0.98195	21.45257	37.62213	0.15281
Proposed Method	**7.3177**	**118.8201**	**60.93475**	**26.04613**	**9.058552**	**6.76338**	**0.99471**	**23.39671**	**38.59421**	**0.03142**

Table 6: Comparison of quality parameters for the fifth pair of multifocus images (Disk)

Algorithm	En	API	SD	SF	RMSE	PFE	NK	SNR	PSNR	FL
PCA	7.19069	98.34998	44.09726	8.91577	8.61486	7.93879	0.99012	22.00491	38.81231	0.16489
DWT+PCA	7.20854	98.34781	44.33602	11.4522	8.43571	7.77369	0.99112	22.18744	38.90358	0.15777
SWT+PCA	7.20052	98.34815	44.22685	10.2959	8.25356	7.60583	0.99084	22.37705	38.99838	0.12041
MSVD+PCA	7.20461	98.34706	44.34168	11.1425	8.31958	7.66668	0.99122	22.30784	38.96378	0.1409
MRDCT+PCA	7.20685	98.33069	44.10162	9.59297	8.6928	8.0106	0.98991	21.92668	38.7732	0.16207
Proposed Method	**7.43678**	**98.90916**	**48.21908**	**15.1807**	**7.44114**	**6.85718**	**1.01176**	**23.27708**	**39.4484**	**0.039**

FPDCT with modified PCA method provides better objectives than other state of the art PCA based algorithms. The statistical results obtained for different multifocus images has shown that the FPDCT algorithm shows superior performance as compared to other methods [24-25].

VI. CONCLUSIONS

Frequency partitioning DCT (FP-DCT) with modified PCA technique was proposed and applied to image fusion. Many other techniques using DWT, DCT, etc were also developed and compared with the proposed technique. Various quality evaluation metrics were evaluated to check the quality of the images. Among the different techniques applied on various pairs of multifocus images, the proposed technique FPDCT with MPCA shows better quality evaluation metrics which in turn has the better quality of the images with no loss of information and artifacts.

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