

An Efficient Multifocus Image Fusion method using Curvelet Transform and Normalization

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Abstract:

Multi-focus imaging fusion is a technique that puts together a fully focused object from the partly focused regions of several objects from the same scene. For producing a high quality fused image, negligible aliasing and ability to separate positive from negative frequencies characteristics are important. The ringed artifacts, however, were inserted into a fused image because of a lack of negligible aliasing and ability to separate positive from negative frequencies properties. A multifocus image fusion algorithm is proposed to resolve these issues, in conjunction with curvelet transform and normalization. First, the source images are translated to the curvelet transform. It helps in the obtaining of the curvelet frequency components. Then the frequency components are combined with a fusion rule to transform the origin frames. curvelet transform has demonstrated that it provides an effective transformation for multi-resolution imaging fusion with its negligible aliasing and ability to separate positive from negative frequencies characteristics. In order to enlarge the effectiveness of the curvelet transform based method, the normalization technique is used. The proposed fusion approach has been tested on a numeral of multifocus images and compared to various popular methods of imaging fusion. The experimental results indicate that in subjective performance and objective assessment, the proposed fusion approach could deliver better fusion results.

Keywords: Image Fusion, Normalization, Curvelet Transform, Quality Evolution Metrics, Image Quality

1. Introduction

Because of the restricted focus range of optical lenses in CCD systems, it was impossible to derive an image that includes all of the required focal objects[1]. The method is a multifocus image fusion that combines multiple artifacts from the same scene into a more perceptible and observable composite image[2]. Several methods of image fusion are spatial, and they transform domain methods[3]. Transform domain algorithms, in particular, multi-resolution algorithms are best because the human visual system handles multi-resolution information in accordance with the computational principle of the transform domain method[4-8].

This paper focuses on the fusion of multi-focus images using curvelet transformation, and to increase the dynamic range of an image, normalization is applied. The extraction feature of the fused image is calculated using specific parametric methods. The proposed method is also compared to already authorized methods of fusion, such as LP, RP, DWT, DTCWT, and CVT. The result of CVT with normalization system shows that there is a much improvement in the statistical parameters than compared to other fusion methods.

2. Proposed Method

The proposed system structure is shown in Figure 1, which involves three processes: the curvelet transform - based image fusion process, and restoration process. The two steps are below. The CVT and normalization based image fusion is defined in Algorithm. 1.

Algorithm 1 : CVT and Normalization based image fusion

Input : Source Images

Output : Fused image (Noise reduction and recover the resolution loss)

Steps :

1. Start
2. Load the source multi-focus images
3. Perform Curvelet Transform on source images A & B to obtain array of curvelet coefficients of image A and image B
4. Fuse the curvelet coefficients using fusion rule to obtain composite curvelet coefficients.
5. Perform inverse curvelet transform on the composited curvelet coefficients to obtain the composited image i.e., fused image.
6. Perform normalization technique on fused image to reduce noise and recover the resolution loss.
7. Stop

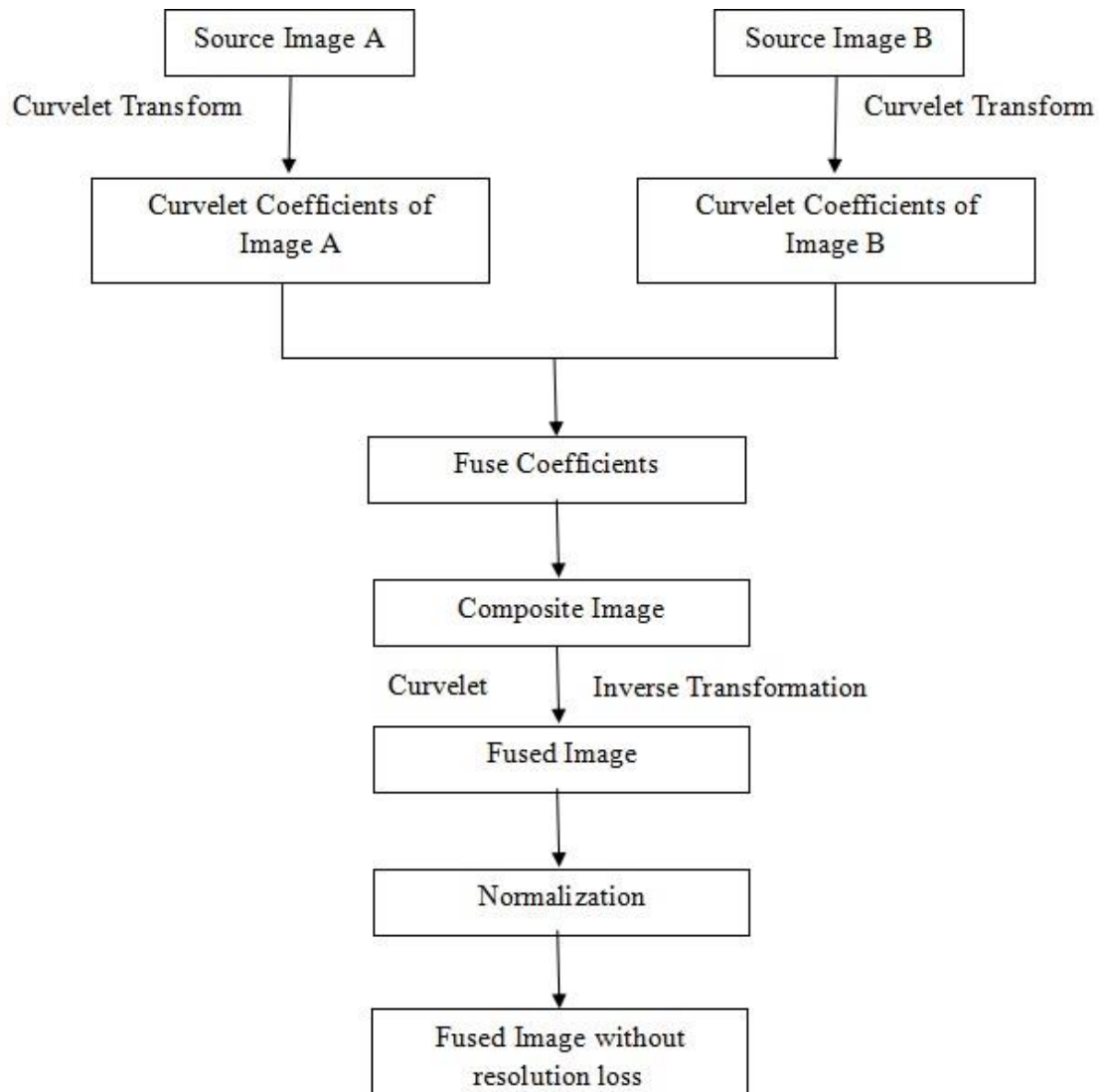


Figure 1 : The flow diagram of proposed method

2. 1. Curvelet Transform (CVT)

In the field of image processing, various system models may be used in specific areas like Denoising, Compression, Face Recognition, Biomedical Application etc. The study of images is based on the various forms of transform: Fourier transform, Wavelet transform, Curvelet transform[9], Now-a-days Curvelet transform is used in all fields of image processing. To address the disadvantage of Wavelet Transform, curve let Transform is created, Curve let Transform is a very effective modal that not only takes into account a local multi-scale Time– Frequency portion but also makes use of function direction.

It was introduced by Candes and Donoho in 1999, there are two types of Curvelet transform is unequally spaced Fast Fourier Transform and wrapping-based Fast Curvelet Transform, in Curvelet transforming the width and length are associated with the relation width length 2 described as parabolic or anisotropic scaling. Compared to wavelets where the elements have only scale and location, frame elements in the curvelet are indexed by parameters of scale, location and orientation. The transform can be used with both the physical world and the continuous world.

The Curvelet transform was first reconstructed by Candes in 2006 as a quick discrete Curve let transform (FDCT). In this angle, trapezoid windows of the polar wedge or angle are used in frequency domain. This transforming curve is intended for better comprehension and use in second generation. DCT can be performed at a given scale by wrapping a strong discrete curve. In a given scale and orientation the image and the curvelet are both translated into the Fourier domain. The product for curvelet and image is obtained in the Fourier domain.

To obtain a set of curvelet coefficients Inverse FFT refers to the product mentioned above. To attain IFT, the trapezoidal wedge obtained by the frequency response of the curve is enveloped in a rectangular base. The spectra is regularly tilted inside the wedge. As per regular tilting the rectangular region gathers broken parts of the wedge.

2. 2. Normalization Process

To increase the dynamic range of gray levels in the image, normalization is used. For example, the image display can display up to 256 gray levels in an 8-bit system. If the number of gray levels spread over a smaller range in the recorded image, the images can be enhanced by extending the number of gray levels to a wider range. This process is known as normalization. The resulting image shows increased contrast between interest characteristics. The unnormalized office image, for example, is shown in Figure 2(a). The normalized image is shown in Figure 2(b). The simplest kind of normalization scans the image to identify the lowest and highest pixel values in the image.



Figure 2 : Office image before and after normalization

3. Result and Discussion

The standard image test pairs (cameraman, lena, boat, clock, and pepsi) with multi focus were chosen by online resources such as www.imagefusion.org and www.mathworks.com. These images were given as inputs for different standard fusion algorithms such as LP, RP, DWT, DTCWT, CVT, and CVT + Normalization (proposed method). The performance of these algorithms was analyzed using different visual and quantitative measures. The proposed algorithm fuse source images with CVT process and also reduce the noise and recover the losses occurred due to normalization.

Different statistical measures [10 -14] such as RMSE, MAE, PSNR, SSIM, SC, QTE used to quantify the performance of the fusion algorithms mentioned. The computed values of the statistical measures for different standard image test pairs using the mentioned fusion algorithms are specified in the table 1- 5. Based on the nature of these statistical measures, the values of PSNR, SSIM, SC, QTE should be of higher value and the other measures should be lower value to show the enhanced performance of the fusion algorithm. The images obtained after fusion process should be in such a way that it provide more necessary information based on people's perceptions, visual and quantitative analysis. The visual analysis of the fused image should reveal the significant improvement in the transfer of information from the source images, information lost from the source images and less artifacts.

Figure 3 describes the standard cameraman images obtained by different image fusion algorithms. The image (figure 3(h)) obtained from the proposed fusion algorithm shows better visual quality and less information loss. The statistical metrics evaluated for standard cameraman images using different fusion algorithms are specified in the table 1. After the comparison of the statistical measures obtained by different fusion algorithms, the proposed method shows good performance over other standard fusion methods.

Table 1 : Statistical measures of multifocus images (Cameraman) using different fusion algorithms

Algorithm	RMSE	MAE	PSNR	SSIM	SC	QTE
LP	5.322045097	2.77526368	40.9040138	0.99043248	1.017269183	0.444539568
RP	6.133392515	2.911394009	40.28779172	0.988812996	1.019961364	0.428084449
DWT	8.884714	4.69291306	38.6783648	0.97894538	1.02333663	0.43413078
DTCWT	8.519343615	4.448908374	38.86073795	0.977586199	1.025059048	0.453060834
CVT	3.689963679	2.168729355	42.49457839	0.991456952	1.01071427	0.436977977
Proposed Method	0.240813108	0.20408862	54.34799809	0.999517228	3.371895778	0.562610151

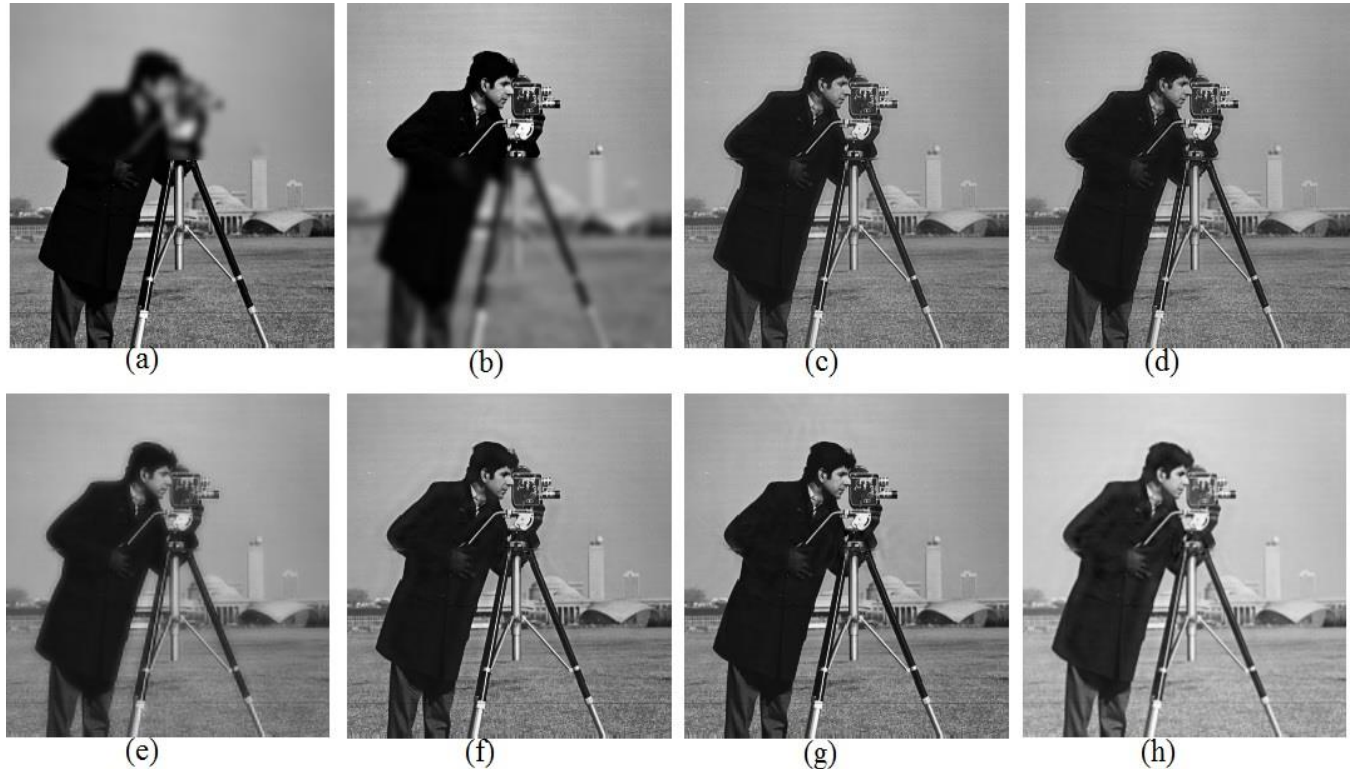


Figure 3 : Multifocus Images (Cameraman): (a) Input Image (X), (b) Input Image (Y), (c) LP, (d) RP, (e) DWT (f) DTCWT, (g) CVT, (h) Proposed Method

The standard lena images and images after various image fusion methods can be visualized in Figure 4. After the visual analysis of these images, the image obtained using the proposed method shows better quality and less information loss. Table 2 shows the statistical measures of the different fusion algorithms and the metrics obtained for the proposed algorithm shows better values than compared to other algorithms.

Table 2 : Statistical measures of multifocus images (Lena) using different fusion algorithms

Algorithm	RMSE	MAE	PSNR	SSIM	SC	QTE
LP	3.376611227	1.828758488	42.8799887	0.99392641	1.00614014	0.413980834
RP	4.044798257	1.971692369	42.09583066	0.991923169	1.005883634	0.413160256
DWT	5.22811853	2.8254137	40.9813451	0.98709633	1.00810699	0.41305479
DTCWT	5.189588322	2.767607294	41.01347023	0.985702127	1.008768266	0.415906181
CVT	2.240548775	1.411533557	44.66125528	0.996162505	1.00399734	0.40866229
Proposed Method	0.23796225	0.20614424	54.3997186	0.99906449	3.26074392	0.47723959



Figure 4 : Multifocus Images (Lena): (a) Input Image (X), (b) Input Image (Y), (c) LP, (d) RP, (e) DWT (f) DTCWT, (g) CVT, (h) Proposed Method

Standard multifocus boat images obtained after applying to different fusion algorithms are shown in figure 4. The boat image (figure 5(h)) obtained using the proposed method shows the better visual appearance and appreciably more image quality. Table 3 shows the quality metrics of the boat image using different fusion algorithms. From the visual appearance and quality metrics the proposed algorithm shows better performance than other algorithms.

Table 3 : Statistical measures of multifocus images (Boat) using different fusion algorithms

Algorithm	RMSE	MAE	PSNR	SSIM	SC	QTE
LP	3.794494724	2.026576476	42.37325977	0.992936934	1.006425869	0.35146039
RP	4.635525096	2.190544	41.50380994	0.991267344	1.00622992	0.346156768
DWT	6.453207574	3.500684738	40.06704296	0.982749748	1.008903317	0.361763054
DTCWT	6.294285032	3.372536756	40.17533525	0.981066115	1.009785986	0.344574716
CVT	2.010742344	1.211702743	45.13123507	0.99713951	1.002711752	0.340243186
Proposed Method	0.247635823	0.222003112	54.22666461	0.998985558	3.327980544	0.553058322

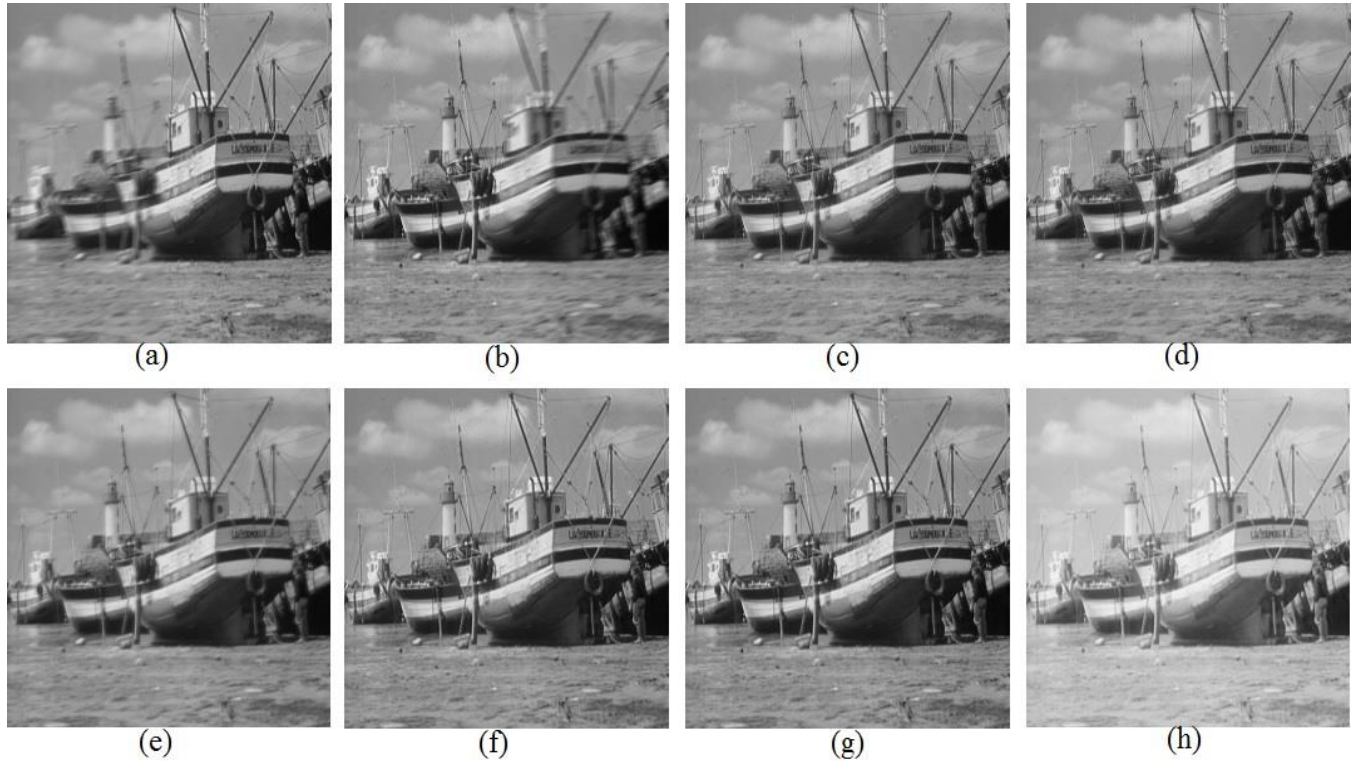


Figure 5 : Multifocus Images (Boat): (a) Input Image (X), (b) Input Image (Y), (c) LP, (d) RP, (e) DWT (f) DTCWT, (g) CVT, (h) Proposed Method

The visual information of clock images both input and output of various image fusion algorithms are shown in figure 6. Table 4 gives the statistical measures of the fusion algorithms of the multifocus clock image. After comparing the performance of the fusion methods, the proposed method shows good image quality and better statistical measures.

Table 4 : Statistical measures of multifocus images (Clock) using different fusion algorithms

Algorithm	RMSE	MAE	PSNR	SSIM	SC	QTE
LP	4.040135512	2.482776204	42.10083998	0.993677079	1.011527869	0.43056011
RP	5.009549836	2.709151509	41.16681229	0.99234258	1.008374994	0.421872135
DWT	5.97567675	3.5465126	40.4009283	0.98699939	1.01528684	0.43163249
DTCWT	5.719931345	3.412534118	40.59089115	0.986245242	1.016611554	0.432140415
CVT	3.694164593	2.206414973	42.48963689	0.995175673	1.007321273	0.419858145
Proposed Method	0.182389925	0.147872991	55.55479087	0.998844712	2.893775312	0.507809226

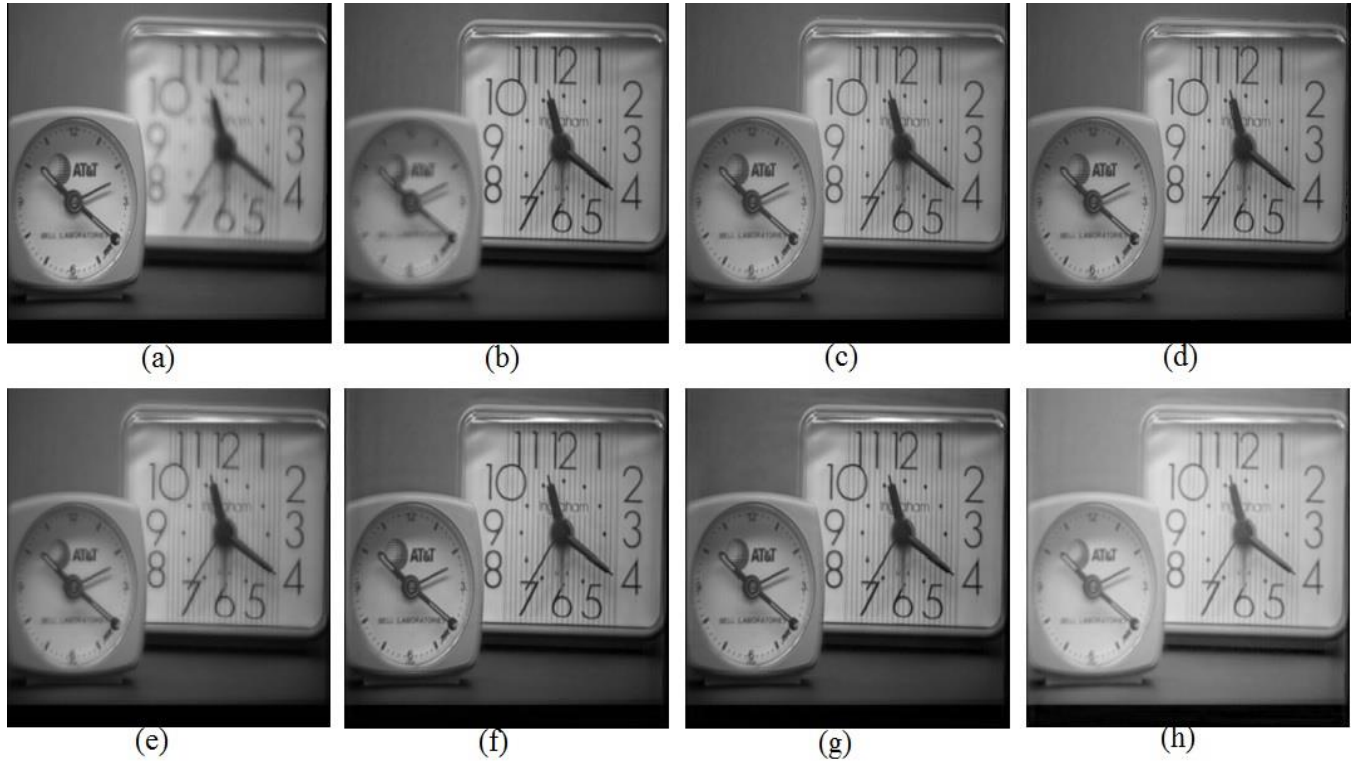


Figure 6 : Multifocus Images (Clock): (a) Input Image (X), (b) Input Image (Y), (c) LP, (d) RP, (e) DWT (f) DTCWT, (g) CVT, (h) Proposed Method

Figure 7 shows the multifocus pepsi images of various fusion algorithms. The fusion image obtained using proposed method shows better visual quality and appreciably no loss of information. Table 5 gives the information about statistical measures of the pepsi image processed with different image fusion algorithms. The comparison of the processed fusion images and statistical measures reveals that the proposed method shows better performance than other algorithms.

Table 5 : Statistical measures of multifocus images (Pepsi) using different fusion algorithms

Algorithm	RMSE	MAE	PSNR	SSIM	SC	QTE
LP	3.394757308	1.869426938	42.85671199	0.99096639	1.006055084	0.439282128
RP	3.784052373	1.965768303	42.38522792	0.988352009	1.005153342	0.434663491
DWT	5.208042559	2.684242249	40.99805406	0.98388609	1.008697636	0.440732943
DTCWT	5.111583838	2.570903428	41.07924442	0.982539251	1.009623427	0.443727215
CVT	2.66399212	1.599630071	43.90946995	0.992733538	1.00322768	0.436414845
Proposed Method	0.176365	0.141943	55.70067	0.999283	2.806225	0.494514

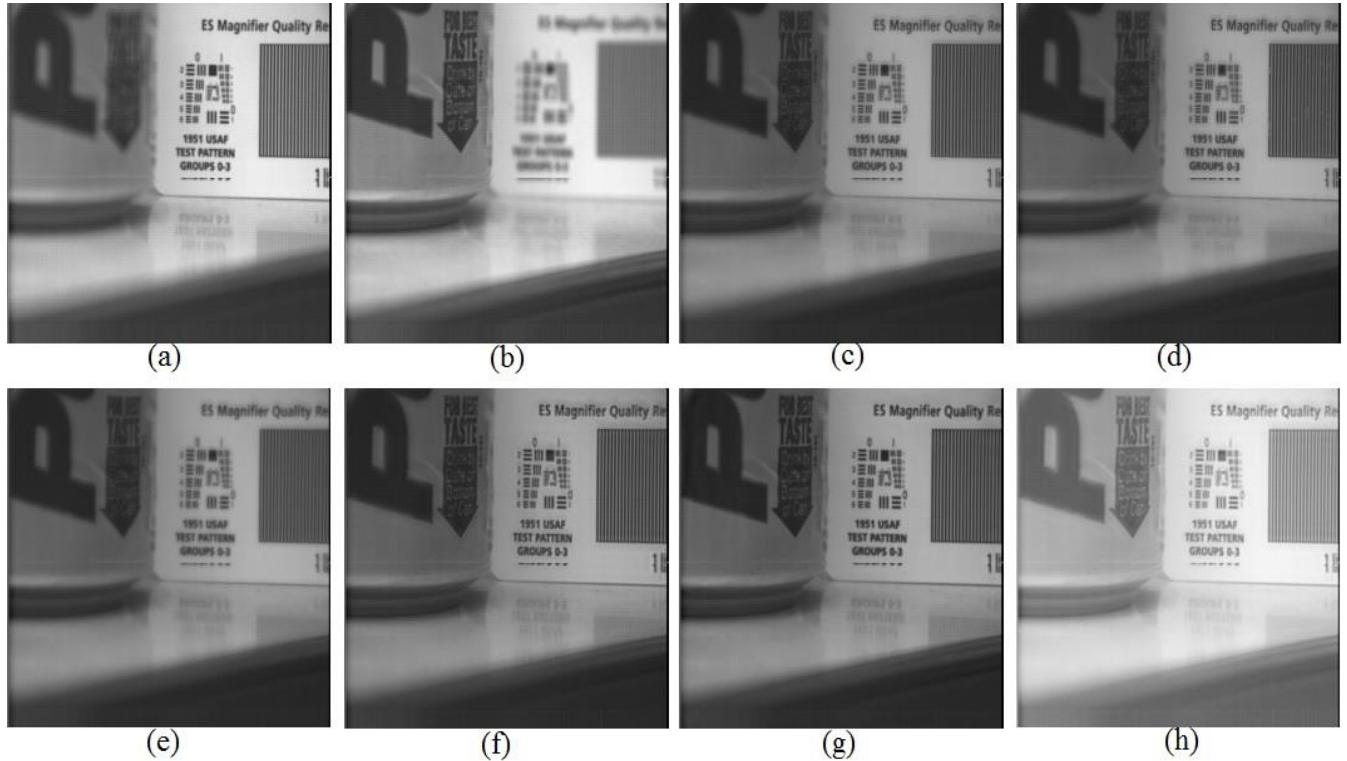
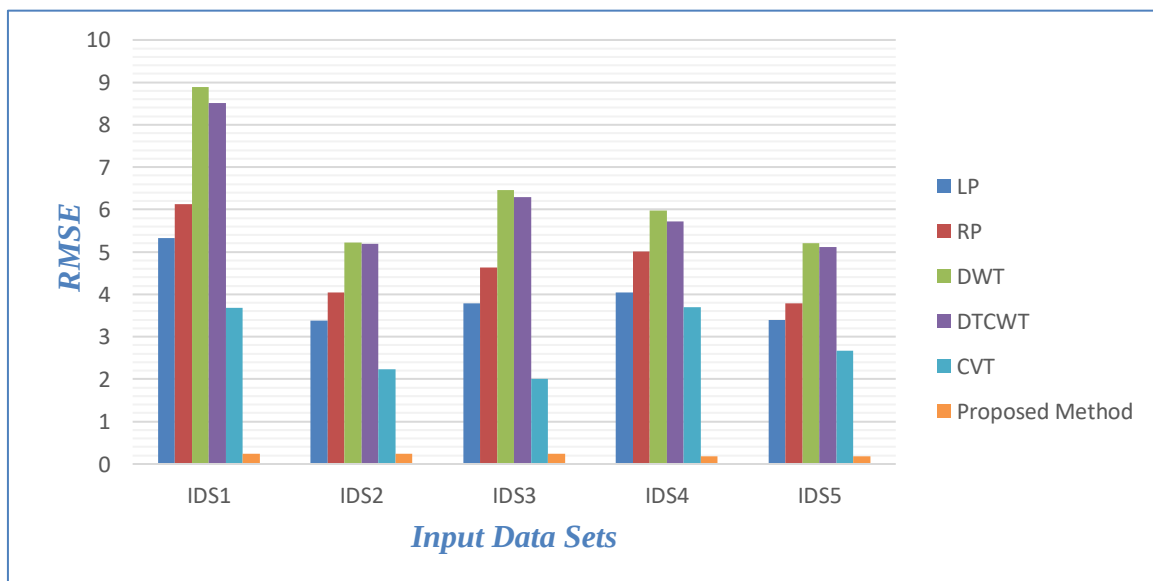
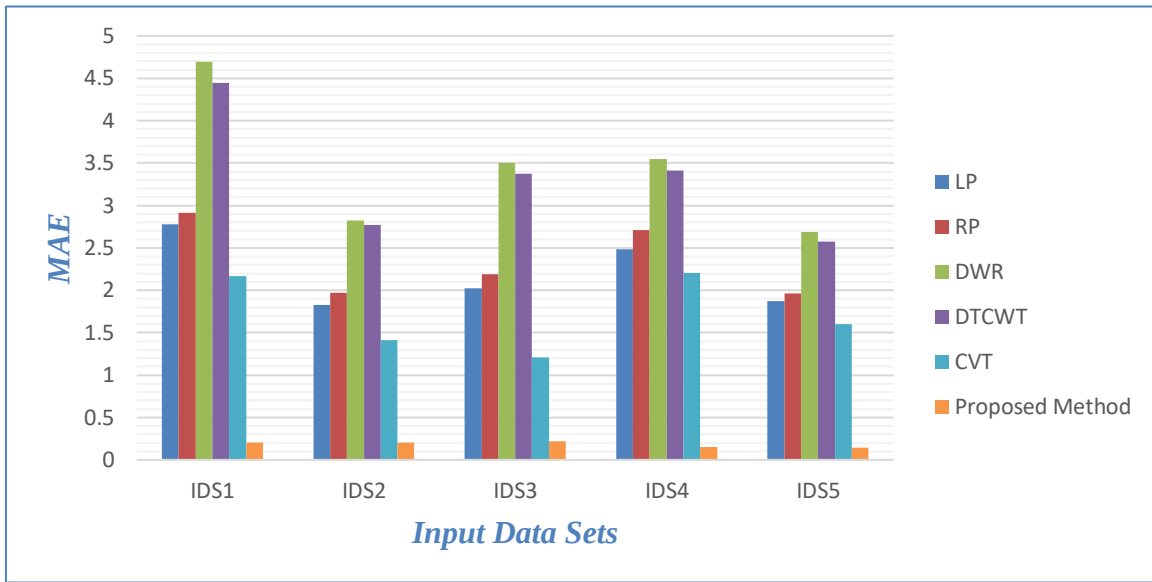


Figure 7 : Multifocus Images (Pepsi): (a) Input Image (X), (b) Input Image (Y), (c) LP, (d) RP, (e) DWT (f) DTCWT, (g) CVT, (h) Proposed Method

The standard images are mentioned with notation IDS1 to IDS 5. The statistical measures obtained with different fusion methods for different standard images are plotted for analysis. Figure 8 shows the variation of the metrics RMSE and MAE for the different images processed with fusion algorithms. The lowest values of these metrics indicate the better performance of the image fusion algorithm. The proposed method shows lowest values among the other fusion methods and in turn shows good efficiency.



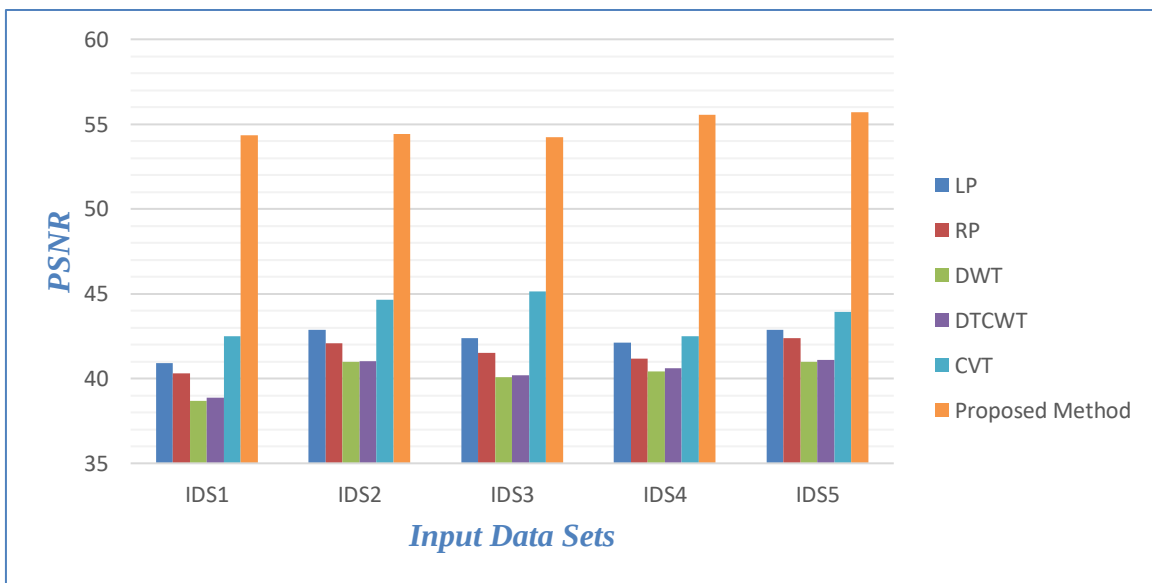
(a)



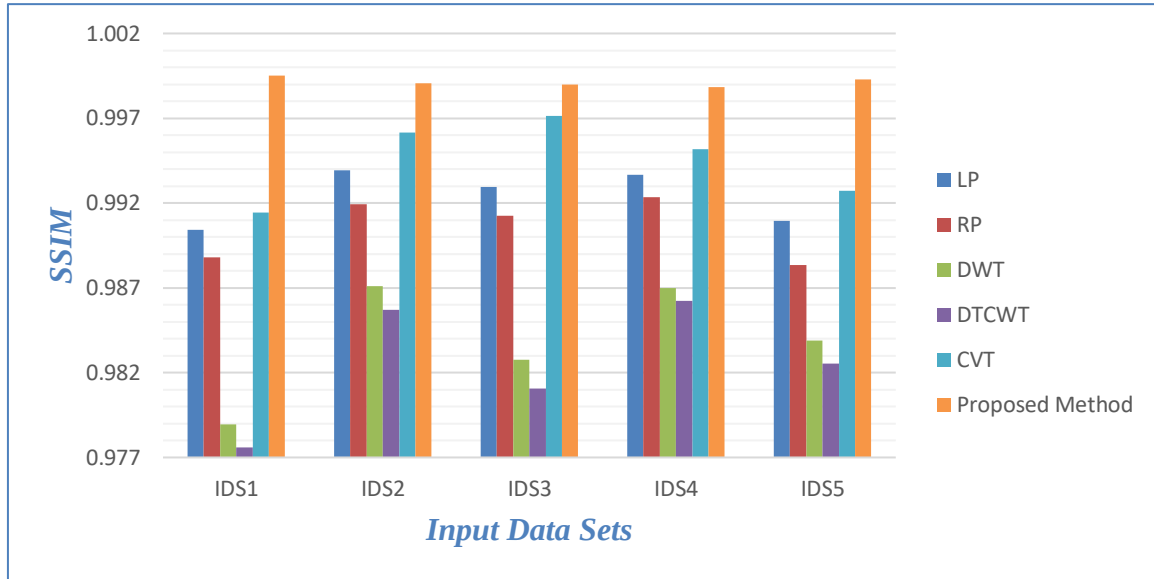
(b)

Figure 8 : Quality metrics (RMSE and MAE) comparison for multifocus image sets.

Similarly, figure 9 shows the variation of PSNR and SSIM quality metrics. The proposed method shows better high value of PSNR and high value of SSIM than comparing to other fusion methods for all the image sets. In view of this results the proposed fusion algorithm outperforms and shows best performance than comparing to other algorithms.



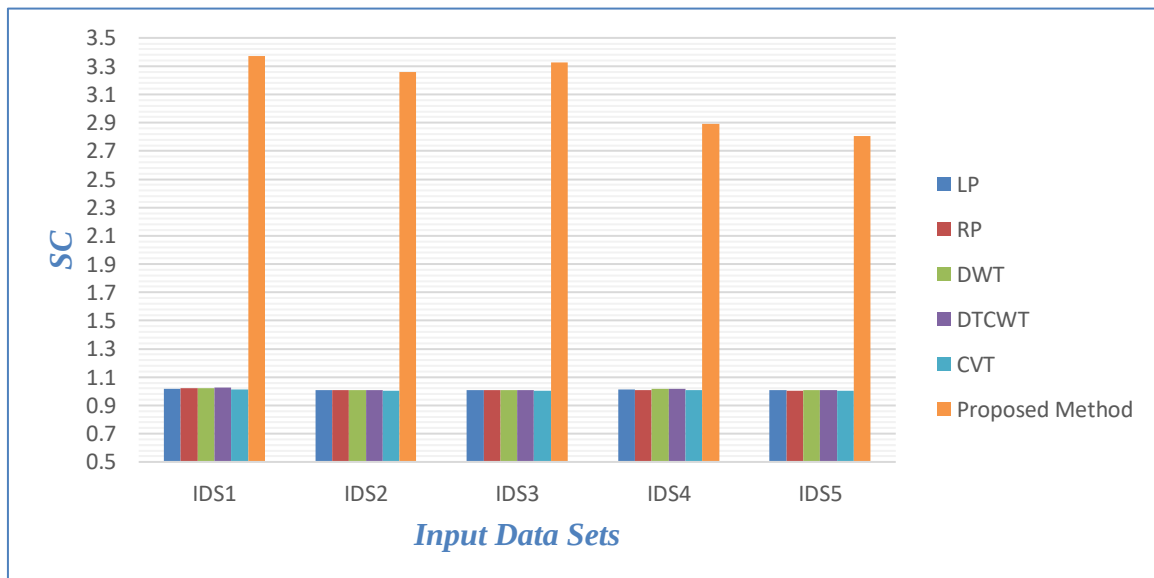
(a)



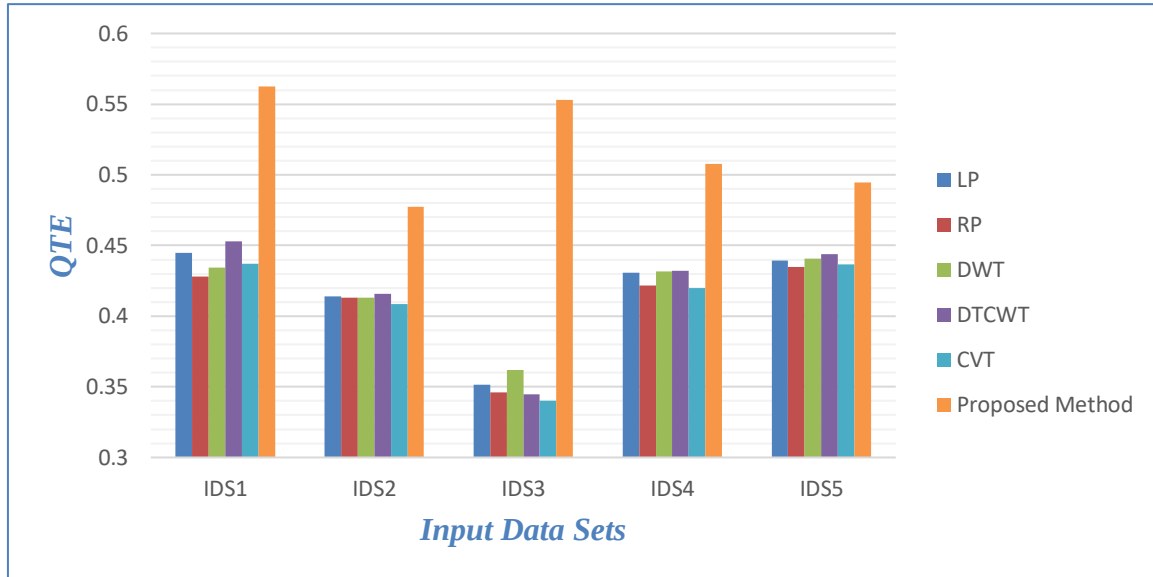
(b)

Figure 9 : Quality metrics (PSNR and SSIM) comparison for multifocus image sets.

Figure 10 depicts the comparison on quantitative metrics of different methods; it is easy to find that the SC value of the proposed method is the largest. It is the optimal value. That is to say, compared with other methods, the fused image of the proposed method is better than other methods. In addition, the QTE values of the proposed method results also outperform the other methods.



(a)



(b)

Figure 10: Quality metrics (SC and QTE) comparison for multifocus image sets.

The results illustrates that not only the proposed fusion algorithm applied to all six multifocus image sets shows better visual performance but also the statistical measures proved the same than compared to other fusion methods. It is also evidenced that the proposed algorithm shows better visual appearance and also exhibits better statistical measures than compared to other methods published recently [25].

4. Conclusion

CVT (Curvelet Transform) and Normalization technique was proposed and applied to image fusion. Many more methods have been developed using LP, RP, DWT, DTCWT, CVT, CVT + Normalization and compared. In order to check the reliability of the images, different quality assurance approaches are evaluated. The proposed CVT with Normalization shows better performance assessment metrics, which in turn has better image quality without any information loss or objects, among the various techniques applied to different pairs of multifocus images.

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