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AN ENHANCEMENT PROCESS FOR GRAY-SCALE IMAGES RESULTED FROM IMAGE FUSION USING MULTIRESOLUTION AND LAPLACIAN PYRAMID

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Abstract

The main issue with the multi-focus images lies in obtaining the relative information about the identification of objects in the individual images with less resolution. Hence the image fusion methods have attracted attention to obtain high resolute image with a pair of multifocus images. An attempt has been made in the present work to develop an image fusion methodology designing on multiresolution for the feature extraction and for better morphological details, the paper discussed about the Laplacian pyramid algorithm. Five sets of multifocus images obtained with different formats have been introduced to the sixteen different image fusion algorithms including the proposed method. Various statistical metrics were evaluated for each image fusion method. The careful comparison of the visual and objective metrics reveals that the proposed method shows best performance with not only having visual quality and also confirmed based on the variation of the statistical metrics.

Keywords:

Multifocus Image Fusion, Multiresolution, Laplacian Pyramid, Evolution Metrics, Image Quality

1. INTRODUCTION

Multi-sensor data fusion has now become a technique that needs more general, systematic solutions for a variety of applications. Several situations in the processing of images in a single image involve high spatial and high spectral details. This is key in remote sensing. The instruments, however, are not able to provide these knowledge either by design or as a result of observational constraints. One logical solution is data fusion for this.

The mechanism of image fusion is specified to collect all important information from multiple images and incorporate it in fewer, typically a single image. This image, consisting of all content, is more insightful and accurate than any single source image. The fused method can not only reduce the data, but it can also generate pictures, which are more suitable and more understandable to human and machine perceptuality [1]. In computer view, multi-sensor image fusion is the method of merging appropriate information of two or several images to a single image [2]. The final image would be more accurate than any image [3].

Methods for image fusion can be commonly divided into two categories-spatial domain fusion and domain fusion transformation. Methods of fusion such as averaging, Brovey method, principal component analysis (PCA) and IHS- methods come under approaches to space domains. Another essential form of spatial domain fusion is the technique that is based on high pass filtering. Here the specifics of the high frequency are inserted into upsampled version of MS images. Spatial domain approaches have the drawback that they create spatial distortion in the fused image. Spectral distortion is a detrimental factor when we go through more analysis, such as problem classification.

Analysis with multiresolution has become a very useful tool for analyzing remote sensing images. The discrete transformation of wavelets has become a very useful fusion tool. There are also several other forms of fusion, such as based on Laplacian pyramid, and curvelet transformation, etc. Such approaches show a higher performance of the fused image in spatial and spectral quality compared to other spatial fusion approaches.

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 [4]. Rapid innovative methodologies make it possible to produce fused images with high resolution containing spatial and spectral information [5]-[6]. The fusion of images has vast number of applications which includes medical imaging, police investigation, military, microscopical imaging, remote sensing, computer visual sense, and robotic visual sense and navigation.

Usually image fusion process is involved at one of the process 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 evolution of wavelet theory, the multi-scale decomposition algorithmic rule is used in the image fusion process [7]. 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 [8].

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 2D 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 [9]-[12]. These methods show the best performance than simplex methods like averaging, minimum and maximum [13]. There is a lot of development in proposing pixel level based fusion algorithms. Majority of the fusion algorithms are based on wavelet transform [14]-[15], pyramid transform [16], statistical signal processing [17], principal component analysis [14] [17], fuzzy logic [18], DCT [13] [19]-[20] and frequency portioning [21]. DCT method gives better results for image compression and also accepted as more suitable and time saving technique for many image preprocessing applications [14].

This paper focuses on the fusion of multi-focus images using discrete cosine transformation with multiresolution and laplacian pyramid is applied to sharp the contrast of an image. The feature extraction of the fused image is determined using various parametric analysis. The proposed method is also compared with already authorized fusion methods like LP, RP, DWT, DTCWT, CVT, NSCT, LP-SR, RP-SR, DWT-SR, DTCWT-SR, CVT-SR, NSCT-SR, MSVD, PC, SR, and MR. The result of MR-DCT with LP system shows that there is a much improvement in the statistical parameters than compared to other fusion methods.

2. NOISE ELIMINATION PROCESS

The size PxQ image f(x, y) does separate toward rows and concatenates those rows into a 1D f(x) array of data whose size will be PQ. This is explained in algorithm 1.

Algorithm 1: Conversion from 2D array to 1D array

Input: *IR*: 2D image, *P*: number of rows and *Q*: number of columns

Output: *IR*: 1D array data

Step 1: Start

Step 2: *IR* (2:2:end, :) = IR (2:2:end, end:-1:1)

Step 3: *IR* = reshape (*IR'*, 1, *P***Q*)

Step 4: Stop

The 2D image can be built from the data in the 1D array by reversing the procedure set out in algorithm 2.

Algorithm 2: Conversion from 1D array to 2D array

Input: *IR*: 1D array data, *P*: number of rows and *Q*: number of columns

Output: *IR*: 2D image

Step 1: Start

Step 2: *IR* = reshape (*IR*, *P*, *Q*)'

Step 3: *IR*(2:2:end, :) = *IR*(2:2:end, end:-1:1)

Step 4: Stop

Likewise, the size $P \times Q$ image $f(x,y)$ is divided into columns and concatenates those columns to form a 1D data $f(x)$ array whose size will be PQ as shown below. The operation is: *IR* = C2DT1D (*IR*', *P*, *Q*). The fusion process is performed separately and combined on both row and column images to eliminate any noise or distortion created in the fusion process [22].

3. MULTIRESOLUTION - DCT

The study of multiresolution [22] is discussed below. Data from the 1D array is transferred via DCT. Find the first half of the coefficients of DCT as LF and the rest as coefficients of HF. As shown below, the LF coefficients are passed through IDCT to obtain the vector data for the next decompositional step. Let $f_l(x) = f(x)$ at $l = 1$ level and at each l^{th} level:

$$f_l(u) = \mathrm{DCT}(f_l(x)) \tag{1}$$

%low frequency components

$$X.L = \mathrm{IDCT}(f_l(u)(1{:}0.5n)) \tag{2}$$

% high frequency frequency

$$X.H = f_l(u)\ (0.5n{+}1{:}n) \tag{3}$$

where subscript l shows the degree of decomposition of multi-resolution.

Let the images to fuse be $f_1(x,y)$ and $f_2(x,y)$ and the process of image fusion is as follows:

$$X_f.L = 0.5{*}(X_1\{J\}.L{+}X_2\{J\}.L) \tag{4}$$

$$\mathrm{D} = (\mathrm{abs}(X_1\{i\}.H)\text{-}\mathrm{abs}(X_2\{i\}.H)) \geq 0 \tag{5}$$

$$X_f.H = D.{*}X_1\{i\}.H{+}(\sim D).{*}X_2\{i\}.H \tag{6}$$

The fused image can get using Eq.(4)-Eq.(6) by doing the procedure outlined in multiresolution.

4. LAPLACIAN PYRAMID (LP)

Laplacian pyramid [22]-[23] provides information on the sharp contrast changes to which human visual system is principally sensitive to. It gives both spatial and frequency domain localization. The procedure for Laplacian pyramid construction and reconstruction is illustrated in shown below.

Reduction Function of an Image (IR):

$$XY = \mathrm{size}(Image)/2 \tag{7}$$

$$IDCT = \mathrm{dct2}(Image) \tag{8}$$

$$IR = \mathrm{round}(\mathrm{idct2}(IDCT\ (1{:}\ XY\ (1),\ 1{:}\ XY\ (2)))) \tag{9}$$

Expand Function of an Image (*IE*):

$$XY = \mathrm{size}\ (\mathrm{Image}) * 2 \tag{10}$$

$$IDCT = \mathrm{dct2}(Image) \tag{11}$$

$$IE = \mathrm{idct2}(IDCT,\ [\ XY\ (1)\ XY\ (2)\ ]) \tag{12}$$

Pyramid Construction:

// Gaussian pyramid

$$Image = \mathrm{reduce}(Image_1) \tag{13}$$

// Laplacian pyramid

$$Idf\{i\} = Image_1 - \text{expand}(Image) \ // \ i = 1 \text{ to } k \tag{14}$$

$Image_1 = Image$

end

$$Fused\_Image = Image_1 \tag{15}$$

Image Reconstruction:

$//i = -1$ to 1

$$Fused\_Image = Idf\{i\} + \text{expand}(Fused\_Image) \tag{16}$$

5. PROPOSED METHOD

The proposed system structure is shown in Fig.1, which involves two processes: the MRDCT-based image fusion process and the LP process. The two steps process model is shown in algorithm 3.

Algorithm 3: Image Fusion based on Multiresolution and LP

Input: Images with multi-focus.

Output: All-in-Focus Image.

Steps:

Step 1: Start

Step 2: Two multi-focus images (I_1 and I_2) are taken as source images to apply image fusion algorithm. Input images are divided into row (I_1 and I_2) and column (I_1 and I_2) pixels.

Step 3: Row and column pixels of multi focus images are converted from 2D image into 1D array data.

Step 4: The resultant 1D array data (I_1) is decomposed into low (row and column frequency) and high (row and column frequency) frequency components using multiresolution. Similarly the I_2 image is also decomposed into low (row and column frequencies) and high (row and column frequencies) frequency components.

Step 5: Primary fusion process is applied on row components (both low and high frequency components) of I_1 and I_2 to obtain low and high frequency row components. Similarly the column components are also processed using this fusion process to obtain low and high frequency column components.

Step 6: Fused row and column frequency components are processed using Inverse Multi-resolute algorithm to obtain row and column components.

Step 7: Row and column components are converted from 1D array data into 2D image.

Step 8: From the processed row and column frequency components, final fused image is obtained using average fusion rule.

Step 9: Features extracted image is obtained after doing the laplacian pyramid process on final fused image.

Step 10: Stop

6. RESULT AND DISCUSSION

The standard image test pairs (clock, lena, pepsi, hockey, and stadium) with multi focus were chosen by online resources such as imagefusion.org, mathworks.com and github.com. These images were given as inputs for different standard fusion algorithms such as LP, RP, DWT, DTCWT, CVT, NSCT, LP-SR, RP-SR, DWT-SR, DTCWT-SR, CVT-SR, NSCT-SR, MSVD, PC, SR, and MR and Multiresolution + LP (proposed method).

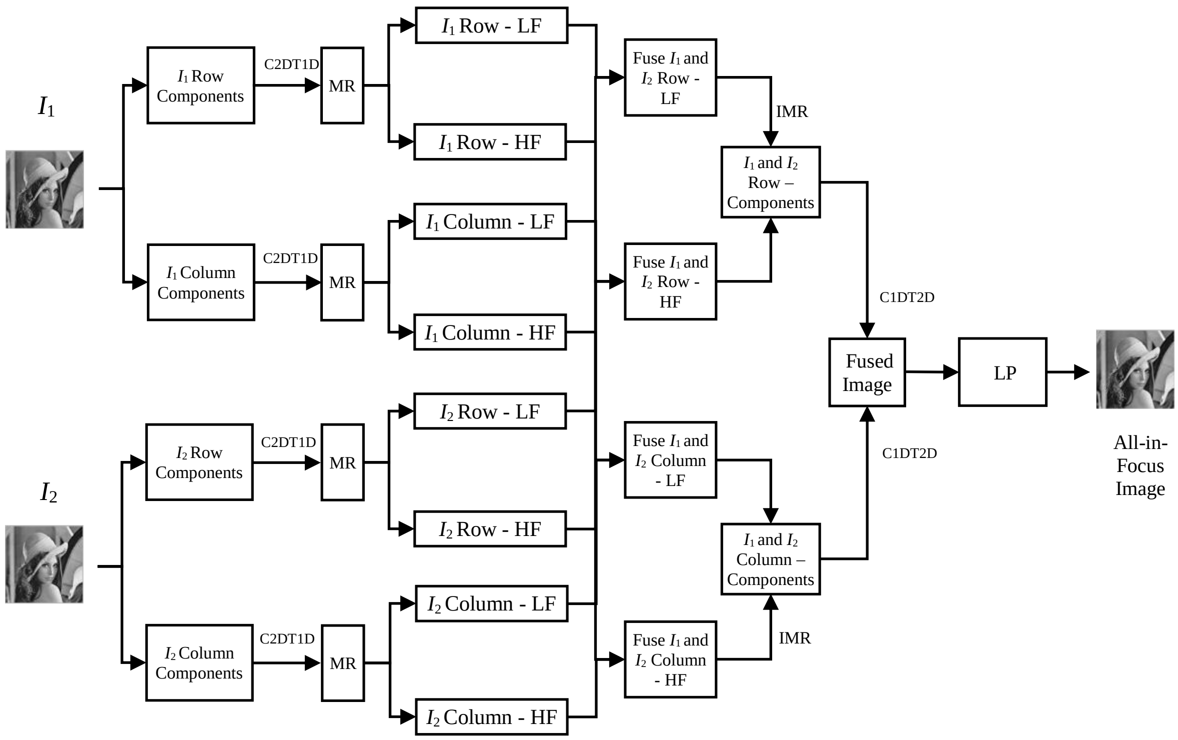


Fig.1. Flow diagram of proposed method

The performance of these algorithms was analyzed using different visual and quantitative measures. The proposed algorithm fuse source images with multiresolution process and also Normalization is used to increase the dynamic range of the gray levels in the image.

Different statistical measures [24]-[29] such as RMSE, MAE, PSNR, SSIM, MSSIM, QM, and $L^{AB/F}$ 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-Table.5. Based on the nature of these statistical measures, the values of PSNR, SSIM, MSSIM and QM 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.

The Fig.2 describes the standard clock images obtained by different image fusion algorithms. The image (Fig.2(t)) obtained from the proposed fusion algorithm shows better visual quality and less information loss. The statistical metrics evaluated for standard clock 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 except $L^{AB/F}$.

The standard lena images and images after various image fusion methods can be visualized in Fig.3. After the visual analysis of these images, the image obtained using the proposed method shows better quality and less information loss. The 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.

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

The visual information of hockey images both input and output of various image fusion algorithms are shown in Fig.5. The Table.4 gives the statistical measures of the fusion algorithms of the multifocus hockey image. After comparing the performance of the fusion methods, the proposed method shows good image quality and better statistical measures.

The Fig.6 shows the multifocus stadium images of various fusion algorithms. The fusion image obtained using proposed method shows better visual quality and appreciably no loss of information. The Table.5 gives the information about statistical measures of the stadium 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.

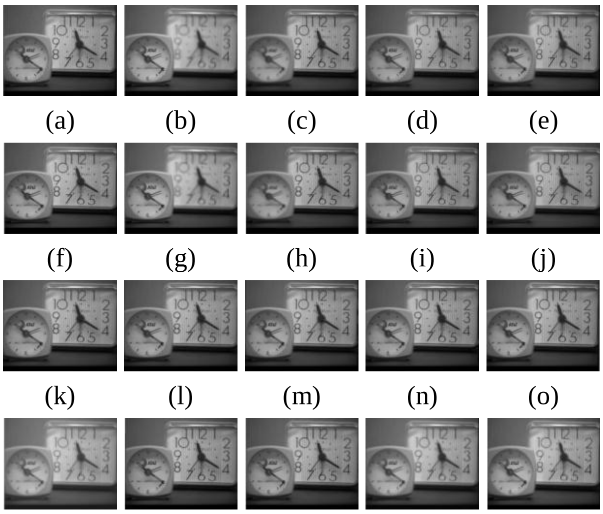


Fig.2. Multifocus Images (Clock): (a) Original Image (b) Input Image (X), (c) Input Image (Y), (d) LP, (e) RP, (f) DWT, (g) DTCWT, (h) CVT (i) NSCT (j) LP-SR (k) RP-SR (l) DWT-SR (m) DTCWT-SR (n) CVT-SR (o) NSCT-SR (p) MSVD (q) PC (r) SR (s) MR (t) Proposed Method

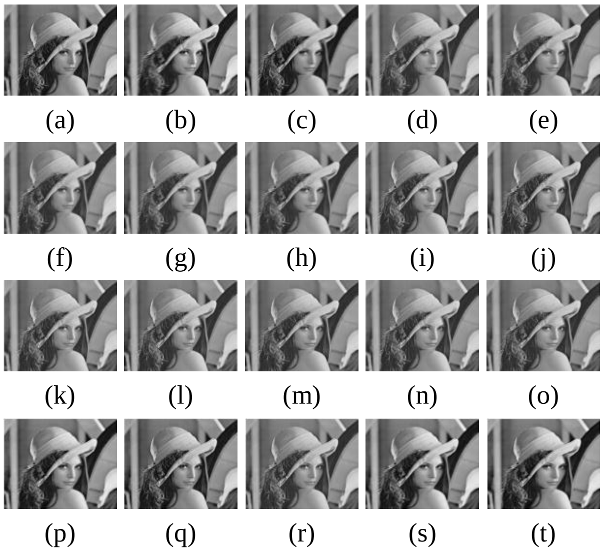


Fig.3. Multifocus Images (Lena): (a) Original Image (b) Input Image (X), (c) Input Image (Y), (d) LP, (e) RP, (f) DWT, (g) DTCWT, (h) CVT (i) NSCT (j) LP-SR (k) RP-SR (l) DWT-SR (m) DTCWT-SR (n) CVT-SR (o) NSCT-SR (p) MSVD (q) PC (r) SR (s) MR (t) Proposed Method

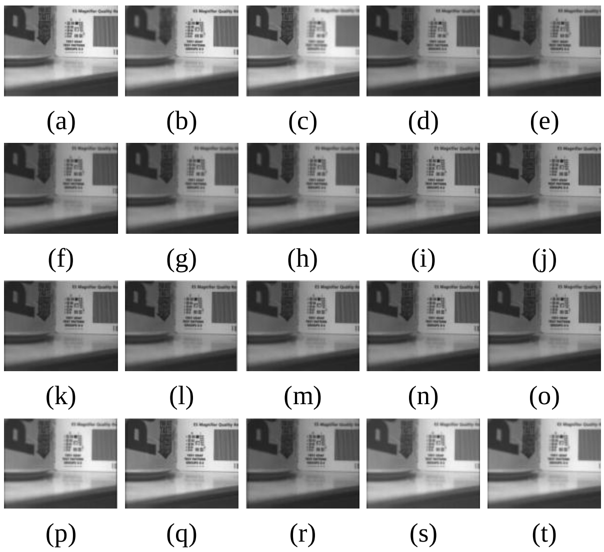
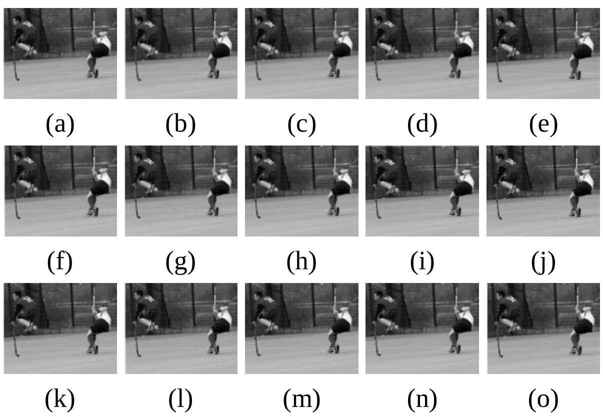


Fig.4. Multifocus Images (Pepsi): (a) Original Image (b) Input Image (X), (c) Input Image (Y), (d) LP, (e) RP, (f) DWT, (g) DTCWT, (h) CVT (i) NSCT (j) LP-SR (k) RP-SR (l) DWT-SR (m) DTCWT-SR (n) CVT-SR (o) NSCT-SR (p) MSVD (q) PC (r) SR (s) MR (t) Proposed Method



(p) (q) (r) (s) (t)

Fig.5. Multifocus Images (Hockey): (a) Original Image (b) Input Image (X), (c) Input Image (Y), (d) LP, (e) RP, (f) DWT, (g) DTCWT, (h) CVT (i) NSCT (j) LP-SR (k) RP-SR (l) DWT-SR (m) DTCWT-SR (n) CVT-SR (o) NSCT-SR (p) MSVD (q) PC (r) SR (s) MR (t) Proposed Method

(a) (b) (c) (d) (e)

(f) (g) (h) (i) (j)

(k) (l) (m) (n) (o)

(p) (q) (r) (s) (t)

Fig.6. Multifocus Images (Stadium): (a) Original Image (b) Input Image (X), (c) Input Image (Y), (d) LP, (e) RP, (f) DWT, (g) DTCWT, (h) CVT (i) NSCT (j) LP-SR (k) RP-SR (l) DWT-SR (m) DTCWT-SR (n) CVT-SR (o) NSCT-SR (p) MSVD (q) PC (r) SR (s) MR (t) Proposed Method

Table.1. Statistical measures of multifocus images (Clock) using different fusion algorithms

Algorithm	RMSE	MAE	PSNR	SSIM	MSSIM	QM	$L^{AB/F}$
LP	4.040135512	2.482776204	42.10083998	0.993677079	0.993677079	1.157888442	0.008939745
RP	5.009549836	2.709151509	41.16681229	0.99234258	0.99234258	1.155105583	0.022176718
DWT	5.975676746	3.546512604	40.40092834	0.986999387	0.986999387	1.519805616	0.055931185
DTCWT	5.719931345	3.412534118	40.59089115	0.986245242	0.986245242	0.800535809	0.035253066
CVT	6.423948702	3.772151447	40.08677866	0.983338836	0.983338836	0.724413454	0.077636425
NSCT	2.748584176	1.670740254	43.77370889	0.99678155	0.99678155	1.958431017	**0.003952269**
LP_SR	3.514596958	1.920812446	42.70604402	0.99658984	0.99658984	1.738034338	0.009516195
RP_SR	3.329755136	1.876898038	42.94067633	0.996654704	0.996654704	2.14130445	0.010180994
DWT_SR	3.010944871	1.795351877	43.37777127	0.997568866	0.997568866	2.359313465	0.005727458
DTCWT_SR	2.786052629	1.674921041	43.71490615	0.997677747	0.997677747	2.101490018	0.004171263
CVT_SR	3.281743452	1.869497733	43.00375303	0.997591601	0.997591601	1.945454445	0.018152747
NSCT_SR	2.777325888	1.67482329	43.72853088	0.99706412	0.99706412	1.993130648	0.003758642
MSVD	8.6216652	4.988844501	38.80888776	0.974829953	0.974829953	0.471968327	0.16596297
PC	5.085914999	2.057052612	41.10110833	0.997295624	0.997295624	2.438973953	0.027505212
SR	3.244520101	1.86342271	43.05329462	0.996603864	0.996603864	2.07240923	0.010511168
Proposed Method	**0.020481893**	**0.014404656**	**65.05109841**	**0.999979532**	**0.999997392**	**2.929402918**	0.0062

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

Algorithm	RMSE	MAE	PSNR	SSIM	MSSIM	QM	$L^{AB/F}$
LP	3.376611227	1.828758488	42.8799887	0.99392641	0.99392641	0.870630052	0.007080395
RP	4.044798257	1.971692369	42.09583066	0.991923169	0.991923169	0.787372239	0.019573538
DWT	5.228118528	2.825413704	40.98134506	0.987096328	0.987096328	1.23380443	0.055019667
DTCWT	5.189588322	2.767607294	41.01347023	0.985702127	0.985702127	0.559779783	0.051083173
CVT	5.611565064	2.994773263	40.67395928	0.983303856	0.983303856	0.515121698	0.082968119
NSCT	1.280296466	0.750104815	47.09169384	0.998835107	0.998835107	1.764792678	0.001700494
LP_SR	1.446302215	0.453164388	46.56220879	0.999022136	0.999022136	1.677288136	0.002287922
RP_SR	1.582117706	0.269338521	46.1724114	0.999166838	0.999166838	2.098107907	0.003693826
DWT_SR	0.756077128	0.118642401	49.3791383	0.999730738	0.999730738	2.445426222	0.001193508
DTCWT_SR	0.557201034	0.067079054	50.70468017	0.999842842	0.999842842	2.351012701	0.00074
CVT_SR	0.602017096	0.090616331	50.36871106	0.999813062	0.999813062	2.358795827	0.0009
NSCT_SR	1.207634491	0.686667819	47.34544422	0.998916653	0.998916653	1.783700891	0.001691926
MSVD	5.904515378	3.370568812	40.45295673	0.982295963	0.982295963	0.515487282	0.101096975
PC	0.822907911	0.05116272	49.01128693	0.999593195	0.999593195	2.462695013	0.003282375
SR	0.461720269	0.031191182	51.52100991	0.99987477	0.99987477	2.445900051	0.0007
Proposed Method	**0.018868618**	**0.013977515**	**65.4073984**	**0.999979567**	**0.999997404**	**2.92654202**	**0.0003**

Table.3. Statistical measures of multifocus images (Pepsi) using different fusion algorithms

Algorithm	RMSE	MAE	PSNR	SSIM	MSSIM	QM	$L^{AB/F}$
LP	3.394757308	1.869426938	42.85671199	0.99096639	0.99096639	1.377042335	0.005912038
RP	3.784052373	1.965768303	42.38522792	0.988352009	0.988352009	1.260219002	0.024329608
DWT	5.208042559	2.684242249	40.99805406	0.98388609	0.98388609	1.548450446	0.11362151
DTCWT	5.111583838	2.570903428	41.07924442	0.982539251	0.982539251	1.12418495	0.073929262
CVT	5.685989894	2.789473574	40.61673847	0.979008839	0.979008839	1.040653043	0.197415919
NSCT	1.690562441	1.057270897	45.88448715	0.996385571	0.996385571	1.728545838	0.00070
LP_SR	1.483228073	0.935957428	46.45271994	0.996520143	0.996520143	1.632615148	0.00067
RP_SR	1.834257671	0.961724577	45.53019587	0.996183699	0.996183699	1.978649248	0.006174735
DWT_SR	1.474847108	0.935159509	46.4773293	0.996741773	0.996741773	2.254490318	0.001286681
DTCWT_SR	1.546095745	0.908732812	46.27243546	0.996524733	0.996524733	1.819531389	0.001357503
CVT_SR	1.420883862	0.88028884	46.63921349	0.996540223	0.996540223	1.675036596	0.001050388
NSCT_SR	1.689312147	1.077252626	45.88770026	0.996088636	0.996088636	1.746609973	0.0007
MSVD	8.450150922	3.957128299	38.89615465	0.970969741	0.970969741	0.704906694	0.394117364
PC	1.832290468	1.075313568	45.53485608	0.99426248	0.99426248	2.315735686	0.002318425
SR	3.688755474	1.71433445	42.49600064	0.988705676	0.988705676	1.130443629	0.042653967
Proposed Method	**0.014763233**	**0.010048915**	**66.47298447**	**0.999984129**	**0.999998341**	**2.950614838**	**0.00024**

Table.4. Statistical measures of multifocus images (Hockey) using different fusion algorithms

Algorithm	RMSE	MAE	PSNR	SSIM	MSSIM	QM	$L^{AB/F}$
LP	3.860400907	0.75291463	42.29847522	0.999699229	0.999699229	1.195912135	0.001856466
RP	3.856462567	0.727426011	42.3029081	0.999675396	0.999675396	1.136500222	0.001221731
DWT	4.256881869	1.692272368	41.87388332	0.997658002	0.997658002	1.241178441	0.006940856
DTCWT	3.305494461	1.282886851	42.97243497	0.998585683	0.998585683	0.613326167	0.002986592
CVT	3.302606179	1.505441626	42.97623142	0.9979018	0.9979018	0.5628002	0.004541942
NSCT	3.930251759	0.573815796	42.2205956	0.999822591	0.999822591	2.059551314	0.00090
LP_SR	4.095119455	0.86569065	42.04213356	0.998942871	0.998942871	1.22241373	0.002505257
RP_SR	3.730157759	0.39513246	42.44752731	0.999593361	0.999893361	2.143033439	0.00094

DWT_SR	3.208574355	0.477567076	43.10167823	0.999547038	0.999847038	2.227417103	0.001107718
DTCWT_SR	3.817464939	0.363924273	42.34704874	0.9990295	0.99990295	2.158725457	0.00061
CVT_SR	2.375421332	0.394064929	44.40739278	0.999842442	0.999842442	2.119438012	0.00089
NSCT_SR	4.127784332	0.498999238	42.00762932	0.99987722	0.99987722	2.064092054	0.0009
MSVD	12.50686951	6.079739815	37.19331312	0.972172428	0.972172428	0.22049222	0.25584926
PC	1.120436034	0.152765765	47.67092863	0.999417035	0.999417035	2.181453407	0.004599574
SR	3.079476772	0.223903379	43.28002998	0.99928899	0.999928899	2.212044777	0.00032
Proposed Method	**0.01549735**	**0.010052416**	**66.26222498**	**0.999999524**	**0.999999524**	**2.90476451**	**0.0003**

Table.5. Statistical measures of multifocus images (Stadium) using different fusion algorithms

Algorithm	**RMSE**	**MAE**	**PSNR**	**SSIM**	**MSSIM**	**QM**	$L^{AB/F}$
LP	3.223940783	1.017870381	43.08092875	0.999604065	0.999604065	1.121705935	0.00086
RP	3.189647052	0.992540269	43.12737301	0.999527546	0.999527546	1.003414877	0.00075
DWT	6.293364712	3.533436055	40.1759703	0.995429844	0.995429844	1.099425075	0.009174106
DTCWT	4.364783134	2.454274518	41.7651726	0.997724794	0.997724794	0.464416318	0.002807108
CVT	4.838205595	2.957511992	41.31795611	0.996424134	0.996424134	0.425316817	0.005177586
NSCT	2.838353507	0.453144612	43.63413446	0.9993967	0.9998967	2.196968139	0.00049
LP_SR	5.213062894	1.589705391	40.99386966	0.997392165	0.997392165	1.046351428	0.002630029
RP_SR	2.808939855	0.303716554	43.6793749	0.999893205	0.999893205	2.291295648	0.00054
DWT_SR	3.214674327	0.50626775	43.09342949	0.999729194	0.999729194	2.373782048	0.00090
DTCWT_SR	2.042391212	0.208965724	45.06340998	0.99922875	0.999922875	2.32416969	0.00046
CVT_SR	2.147116074	0.362315461	44.84624408	0.999875754	0.999875754	2.218026811	0.00058
NSCT_SR	2.907240308	0.425461162	43.52998999	0.99908587	0.999908587	2.201249853	0.00048
MSVD	12.9425817	7.66408798	37.04459015	0.9873047	0.9873047	0.167868193	0.064370128
PC	4.003209909	0.4453125	42.14071568	0.998961179	0.998961179	2.3547238	0.010202747
SR	1.646613927	0.107817035	45.99888146	0.99916894	0.999916894	2.336919456	0.000406
Proposed Method	**0.032085658**	**0.024220157**	**63.10168978**	**0.999978846**	**0.999997594**	**2.86431418**	**0.00024**

The results illustrates that not only the proposed fusion algorithm applied to all five 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 [23], [30]-[31].

7. CONCLUSION

It was proposed and applied to image fusion Multiresolution (MR) using Normalization technique. A variety of other methods were developed using and compared LP, RP, DWT, DTCWT, CVT, NSCT, LP-SR, RP-SR, DWT-SR, DTCWT-SR, CVT-SR, NSCT-SR, MSVD, PC, SR, and MR. Various quality control methods are tested to check the reliability of images. The proposed MR with LP shows better measurement efficiency, which in effect improves image quality without losing information or without losing artifacts, among different techniques used on various pairs of multifocus images.

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