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Multi-Focus Image Fusion Based on Pixel Significance Using Counterlet Transform

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Abstract

The objective of image fusion is to merge multiple sources of images together in such a way that the final representation contains higher amount of useful information than any input one.. In this paper, a weighted average fusion method is proposed. It depends on using weights that are extracted from source images using counterlet transform. The extraction method is done by making the approximated transformed coefficients equal to zero, then taking the inverse counterlet transform to get the details of the images to be fused. The performance of the proposed algorithm has been verified on several grey scale and color test images, and compared with some present methods.

Keywords: *image fusion, counterlet transform (CT), pixel significance, weighted average.*

1. Introduction

Image fusion is known as the process by which we combine information from multiple images into a smaller group of images, generally an odd one. This image retains the most eligible information from the inputs with fewer artifacts. In addition to decreasing the amount of data, fusion algorithm creates more convenient images for machine or human perception and for extra image processing. In the CCD devices, the optical lenses have limited depth-of focus. So, it's difficult to obtain all relevant objects in focus in a one image. But by fusing all focused objects from the sequence of images obtained by gradually shifting the focal plane over the sight, we can produce the desired image. This leads to the issue of multifocus image fusion [1]. Many works have been executed in the field of multi-focus image fusion, as well as image fusion for other fields such as medical images, remote sensing, and fusion of thermal and visible images for surveillance application.Image fusion can be executed at any of the three processing levels: signal (pixel), feature (object) and decision (symbol). Pixel level fusion, defines the process of fusing visual information associated with each pixel from a number of registered images into a single fused image, representing a fusion at lowest level [2,3,4]. Since transform domain is very useful tool for representing, analysis and interpretation of information, various multiscale transforms have been used, like Laplacian, gradient, contrast ratio of low pass pyramids, discrete wavelet transform and multiscale geometric analysis transforms [5,6,7,8]. Various image fusion rules can be implemented such as 'maximum' or 'mean' where the fused coefficient is the maximum or the average of the source coefficients respectively. The maximum fusion rule is susceptible to noise while the mean fusion rule reduces contrast, so another fusion rule, 'mean-max', is used. In this rule 'mean' is used for frequency of low band and 'maximum' is for frequency of high band. Another method proposed by researches [9, 10] is the 'weighted average' of the source coefficients. In [11] adaptive weighted average in wavelet domain is proposed by computing pixel's significance through available information at bands of finer resolution. A fusion rule which can efficiently fuse multifocus images by calculating weighted average of pixels in wavelet domain. The weights are adaptively decided using the statistical properties of the neighborhood. The main idea is that the unbiased estimate's Eigen value of the covariance matrix of an image block depends on the strength of edges in the block and thus makes a suitable choice for weight to be given to the pixel. This gives more weightage to pixel with sharper neighborhood [12]. This method increases the fused image quality, especially sharpness with minimum fusion artifacts. In [13] a proposed weighted average method was represented. It computes the weights by measuring the strength of details in a detail image obtained by subtracting Cross Bilateral Filter (CBF) output from original image. The weights thus computed are multiplied directly with the original source images followed by weight normalization. This method has shown good performance. In this paper, a novel method of obtaining a detail image is proposed; it depends on using counterlet transform to the images to be fused, since counterlet transform is multi-direction and anisotropy in addition to multi-scale and localization properities, it can capture the contours of original images effectively with a few coefficients [14]. The proposed algorithm depends on applying CT to both multifocus images, make approximation bands equal to zero then apply inverse counterlet transform to obtain the detail images, then the weights can be computed to fuse images .

2. Counterlet Transform

The Contourlet transform, which is proposed by Do and Vetterli [14], is a multi-directional and a multi-resolution transform. It provides efficient approximation of images made of smooth contours, through implementing Laplacian Pyramid (LP) decomposition followed by Directional Filter Bank (DFB) applied on each subband's bandpass Fig.1(a). The images are decomposed into subbands by LP and each detail image is analyzed by DFB. The DFB has the property of capturing high frequency of input image while it leaks low frequency of signals, thus the DFB is merged with the LP. It means removing the low frequency from the input image before applying DFB. Fig. 1(b) shows the resulting frequency division, where the whole spectrum is divided both angularly and radially and the number of directions is increased with frequency. The discrete contourlet transform makes perfect reconstruction with less than 4/3 redundancy ratio [15].

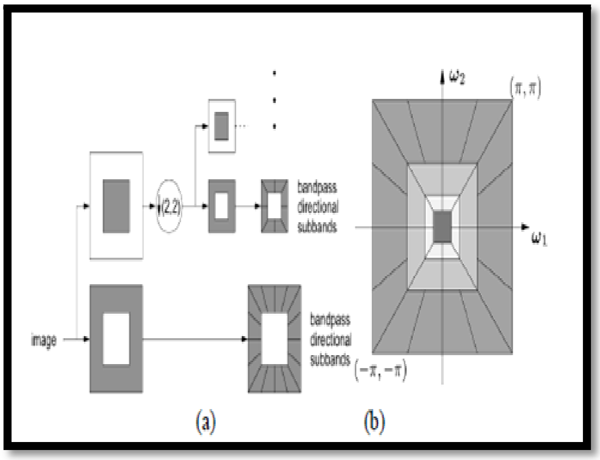

Fig. 1. The counterlet transfosrm: (a) Block diagram, (b) Resulting frequency division.

A. Laplacian Pyramid

Laplacian pyramid (LP), which was introduced by Burt and Adelson [16], achieves multiscale decomposition. The LP decomposition at each level results a band pass image by generating a down sampled low pass version of the original and the difference between the original and the prediction, as in Fig. 2(a). In this figure (a) and (b) are the analysis and synthesis filters, while 'S' is the sampling matrix. The process can be iterated on a coarse version. In Fig.2 (a) the outputs are a coarse approximation 'a1' and a difference 'a2' between the original signal and prediction. The process can be iterated by decomposing the coarse version repeatedly. The original image is convolved with a Gaussian kernel. The resulting image is a low pass filtered version of the original image. The Laplacian will be the difference between the original image and the low pass filtered image. A set of band pass filtered images is obtained by continuing the above process. After applying these steps several times, a sequence of images are obtained [15].

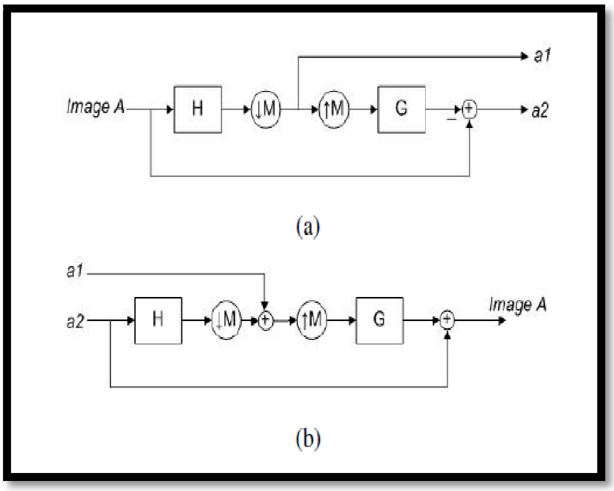

Fig. 2. Laplacian Pyramid. (a) One level of decomposition. (b) The reconstruction of Laplacian pyramid.

B. Directional Filter Bank (DFB)

The directional filter bank is a critically sampled filter bank. Images can be decomposed into directions of any power of two's number. The DFB leads to partitions of wedge-shaped frequency by implementing decomposition of n-level tree structure. A rule of tree expanding should be followed to get the required frequency partition. The high frequency content (smooth countours and directional edges) can be captured by DFB while low frequency components are exhausted poorly by the DFB [15].

3. The Proposed Algorithm

In [13] the proposed image fusion algorithm directly fuses two source images of a same scene using weighted average. The proposed method differs from other weighted average methods in terms of weight computation and the domain of weighted average. The weights are computed by measuring the strength of details in a detail image obtained by subtracting Cross Bilateral Filter (CBF) output from original image. The weights thus computed are multiplied directly with the original source images followed by weight normalization. The idea is to capture most of the focused area details in detail image such that these details can be used to find the weights for image fusion using weighted average proposed in [12]. In this paper, the weights are computed by measuring the strength of details in a detail image obtained by applying the counterlet transform to the images to be fused. The detail image, obtained by making the coefficient values of approximation band equal to zero then applying the inverse of counterlet transform, for image A and B to be fused. In multifocus images, unfocused area in image A will be focused in image B and the application of counterlet transform in such a manner on both images will capture the details which will be used to find the weights by measuring the strength of details. Fig. 3 shows the block diagram of the proposed system.

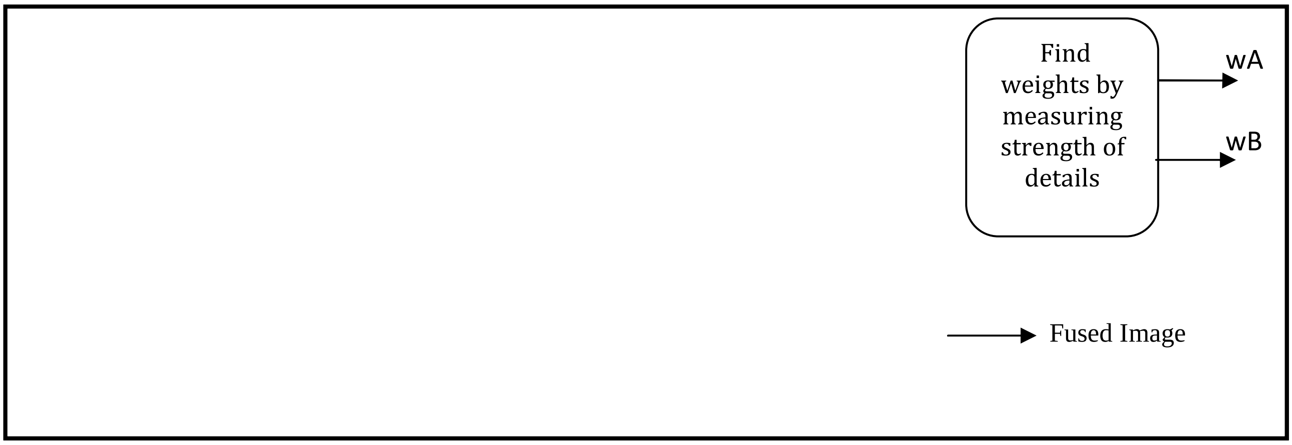

Fig. 3. The block diagram of the proposed fusion system.

Fig. 4 shows the details image obtained in the proposed algorithm with six numbers of levels for directional filter bank at each pyramid level. In order to show the power of counterlet transform in representing edges and other singularities along curves of images. Wavelet transform (Db2) is used to capture the details of the multifocuse images to be fused. Fig. 5 shows the details image obtained by extracting the high frequency bands of the image through making the low frequency bands equal to zero in wavelet domain. One can notice that counterlet transform is more efficient in representing details than wavelet transform.

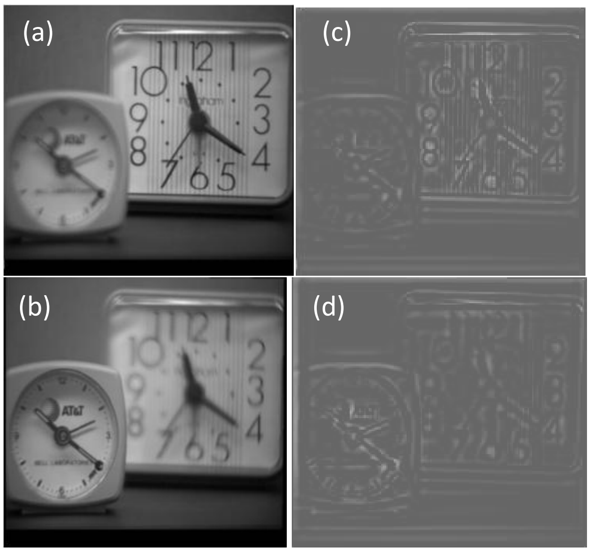

Fig. 4. multifocus clock source images in (a) and (b), details images in (c) and (d).using counterlet transform.

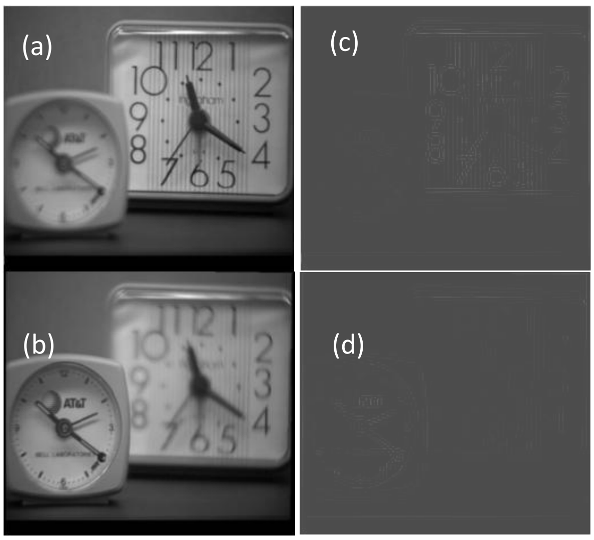

Fig. 5. multifocus clock source images in (a) and (b), details images in (c) and using wavelet transform.

Fusion rule proposed in [12] is adopted in [13] to compute the weights using statistical prosperities of a neighborhood of detail coefficient instead of wavelet coefficient. The fusion algorithm is also adopted in this paper. In the fusion algorithm a window of size $w \times w$ around a detail coefficient $A_D(i,j)$ or $B_D(i,j)$ is considered as a neighborhood to compute its weight. This neighborhood is denoted as matrix X. Every row of X is treated as an observation and column as a variable to compute unbiased estimate $C_h^{i,j}$ of its covariance matrix, where i,j are the spatial coordinates of the detail coefficient $A_D(i,j)$ or $B_D(i,j)$.

$$covariance(x) = E[(x - E[x])(x - E[x])^T \quad ... (1)$$

$$C_h^{i,j} = \frac{\sum_{k=1}^{w}(x_k-\bar{x})(xk-\bar{x})^T}{(w-1)} \quad ....(2)$$

Where, x_k is the k^{th} observation of the $w-$ dimensional variable and $\bar{x}$ is the observations mean. It is observed that, diagonal of matrix $C_h^{i,j}$ gives a variances vector for each column of matrix X. Now, the eigenvalues of matrix $C_h^{i,j}$ is computed and the number of eigenvalues depends on size of $C_h^{i,j}$. Sum of these eigenvalues is directly proportional to horizontal detail strength of the neighborhood and is denoted as $HdetailStrength$ [12]. Similarly, unbiased covariance estimate $C_v^{i,j}$ is computed by treating each X column as an observation and row as a variable (opposite to that of $C_h^{i,j}$), and the sum of eigenvalues of $C_v^{i,j}$ gives vertical detail strength $VdetailStrength$. That is,

$$HdetailStrength(i,j) = \sum_{k=1}^{w} eigen_k \; of \; \mathrm{C}_\mathrm{h}^{\mathrm{i,j}} \quad ..(3)$$

$$VdetailStrength(i,j) = \sum_{k=1}^{w} eigen_k \; of \; \mathrm{C}_\mathrm{v}^{\mathrm{i,j}} \quad ..(4)$$

Where $eigen_k$ is the k^{th} eigenvalue of the unbiased estimate of covariance matrix. Now the weight given to a particular detail coefficient is computed by adding these two respective detail strengths. Therefore, the weight counts only on the details strength and not on actual intensity values.

$$wt(i,j) = HdetailStrength(i,j) + VdetailStrength(i,j) \quad ... (5)$$

After computing the weights for all detail coefficients corresponding to both the registered source images, the weighted average of the source images will result in a fused image. If wt_a and wt_b are the weights for the detail coefficients A_D and B_D belonging to the respective source images A and B, then the weighted average of both is computed as the fused image using Eq. 6

$$F(i,j) = \frac{A(i,j)wt_a(i,j)+B(i,j)wt_b(i,j)}{wt_a(i,j)+wt_b(i,j)} \quad \text{... (6)}$$

4. Performance Measures

In most of the applications, the evaluation of fusion performance is a challenging task as the ground truth is not available. In the literature many metrics are presented to evaluate the performance of image fusion [17, 18]. These classical evaluation metrics are considered here for extensive study, which are as follows [12]:

1) Average Pixel Intensity (API) or mean (F): an indicator of contrast.
2) Average Gradient (G): measure a degree of sharpness and clarity .
3) Standard Deviation (SD): this is the square root of the variance. It indicates data spread.
4) Entropy (H): estimates the amount of information available in the image.
5) Mutual Information (MI) or Fusion Factor: quantifies the overall mutual information between source image and fused images.
6) Fusion Symmetry (FS) or Information Symmetry: an indication of how much symmetric the fused image is with respect to source images.
7) Normalized Correlation (CORR): measures a relevance of fused image to source images.
8) Petrovic Metric Parameter $\mathrm{Q_{ABF}}$: measures the overall transferred information from source images to fused one.
9) Petrovic Metric Parameter $\mathrm{L_{ABF}}$: measures edge information loss.
10) Petrovic Metric Parameter N_{ABF} : measures artifacts or noise added in fused image due to fusion process.

Equations 7 to 20 are used to compute (1-7) parameters, assuming image size of (mxn).

$$API = \bar{F} = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(f_{i,j})}{mxn} \quad \text{...(7)}$$

$f_{i,j}$ is pixel intensity for position (i ,j) of image F.

$$SD = \sqrt{\frac{\sum_{i=1}^{m}\sum_{j=1}^{n}(f(i,j)-\bar{F})^2}{mn}} \quad \text{...(8)}$$

$$\bar{G} = \frac{\sum_i \sum_j ((f_{i,j}-f_{i+1,j})^2+(f_{i,j}-f_{i,j+1})^2)^{1/2}}{mxn} \quad \text{... (9)}$$

$$Entropy = -\sum_{f=0}^{255} pf(f) log_2\, pf(f) \quad \text{...(10)}$$

Where $pf(f)$ is the probability of intensity value f in image F.

$$MI_{AF} = \sum_a \sum_f pA,F(a,f) log_2 \frac{PA,F(a,f)}{PA(a)PF(a)} \quad \text{...(11)}$$

$$MI_{BF} = \sum_b \sum_f PB,F(b,f) log_2 \frac{PB,F(b,f)}{PB(b)PF(f)} \quad \text{...(12)}$$

$$MI_{AB}^{F} = MI_{AF} + MI_{BF} \quad \text{...(13)}$$

$$MI_{FA} = \sum_a \sum_f p_{A,F}(a,f) log_2 \frac{p_{A,F}(a,f)}{p_A(a)p_F(f)} \quad \text{...(14)}$$

$$MI_{BF} = \sum_b \sum_f p_{B,F}(b,f) log_2 \frac{p_{B,F}(b,f)}{p_B(b)p_F(f)}. \quad \text{...(15)}$$

$$MI_{A,B}^{F} = MI_{AF} + MI_{BF} \quad \text{...(16)}$$

MI_{AF} is the mutual information between source image A and fused image B, while MI_{BF} is the mutual information between source image B and fused image F.MI_{AB}^{F}quantifies the overall mutual information measurement between source images and fused one.

$$FS = 2 - |MI_{AF}/(MI_{AF} + MI_{BF}) - 0.5| \quad \text{...(17)}$$

$$r_{AF} = \frac{\sum_i \sum_j (a_{(i,j)}-\bar{A})(f_{(i,j)}-\bar{F})}{\sqrt{((\sum_i \sum_j (a_{(i,j)}-\bar{A})^2)\sum_i \sum_j (f_{(i,j)}-\bar{F})^2)}} \quad \text{...(18)}$$

$$r_{BF} = \frac{\sum_i \sum_j (b_{(i,j)}-\bar{B})(f_{(i,j)}-\bar{F})}{\sqrt{((\sum_i \sum_j (b_{(i,j)}-\bar{B})^2)\sum_i \sum_j (f_{(i,j)}-\bar{F})^2)}} \quad \text{...(19)}$$

Here r_{AF} and r_{BF} represents normalized correlation between source image and fused image, the overall average normalized correlation can be calculated as:

$$CORR = (r_{AF} + r_{BF})/2 \quad \text{...(20)}$$

All the Petrovic Metrics, proposed by Petrovic and Xydeas [19], based on gradient information. This provides an in-depth analysis of fusion performance by quantifying: total fusion performance, fusion loss and fusion artifacts (artificial information created). A sobel edge detector is used to compute orientation and strength information at each pixel in source and the fused images respectively.

5. The Experimental Results

The experimental evaluation is performed on multi focus grey-scale and color images of size 256×256 pixels. In the counterlet transform, the LP filter is 'pkva' and DFB is '9-7' type, and the number of directional filter bank decomposition levels at each pyramidal level (from coarse to fine scale), by experimental test, is six for optimum results, neighborhood window is 5x5 to find detail strength. Fig. 6 displays the test multifocus grey scale images used and the resultant fused images, while Fig. 7 displays the test multifocus color images used and the resultant fused images.

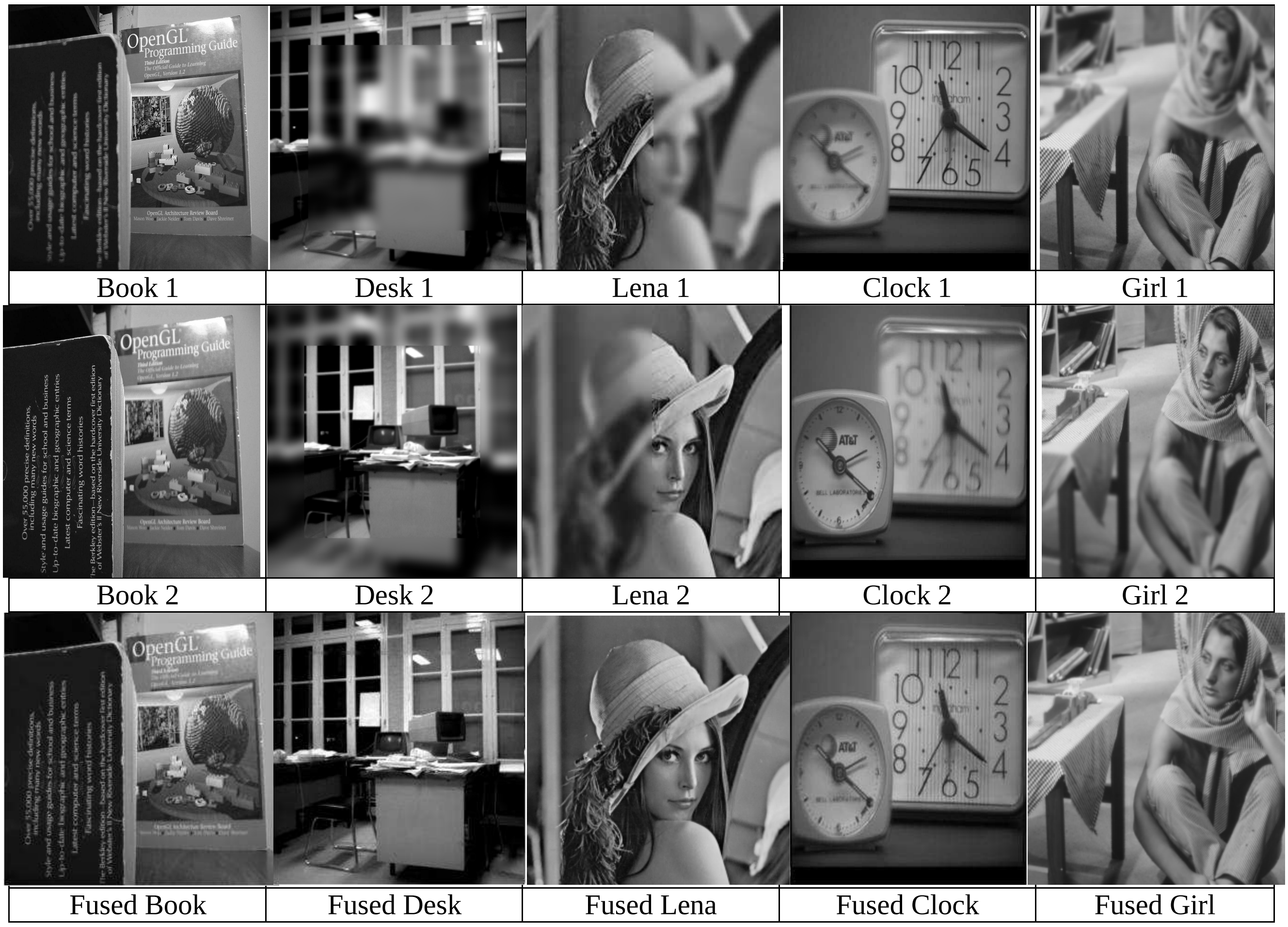

Fig. 6. The multi focus test grey scale images, and resultant fused images.

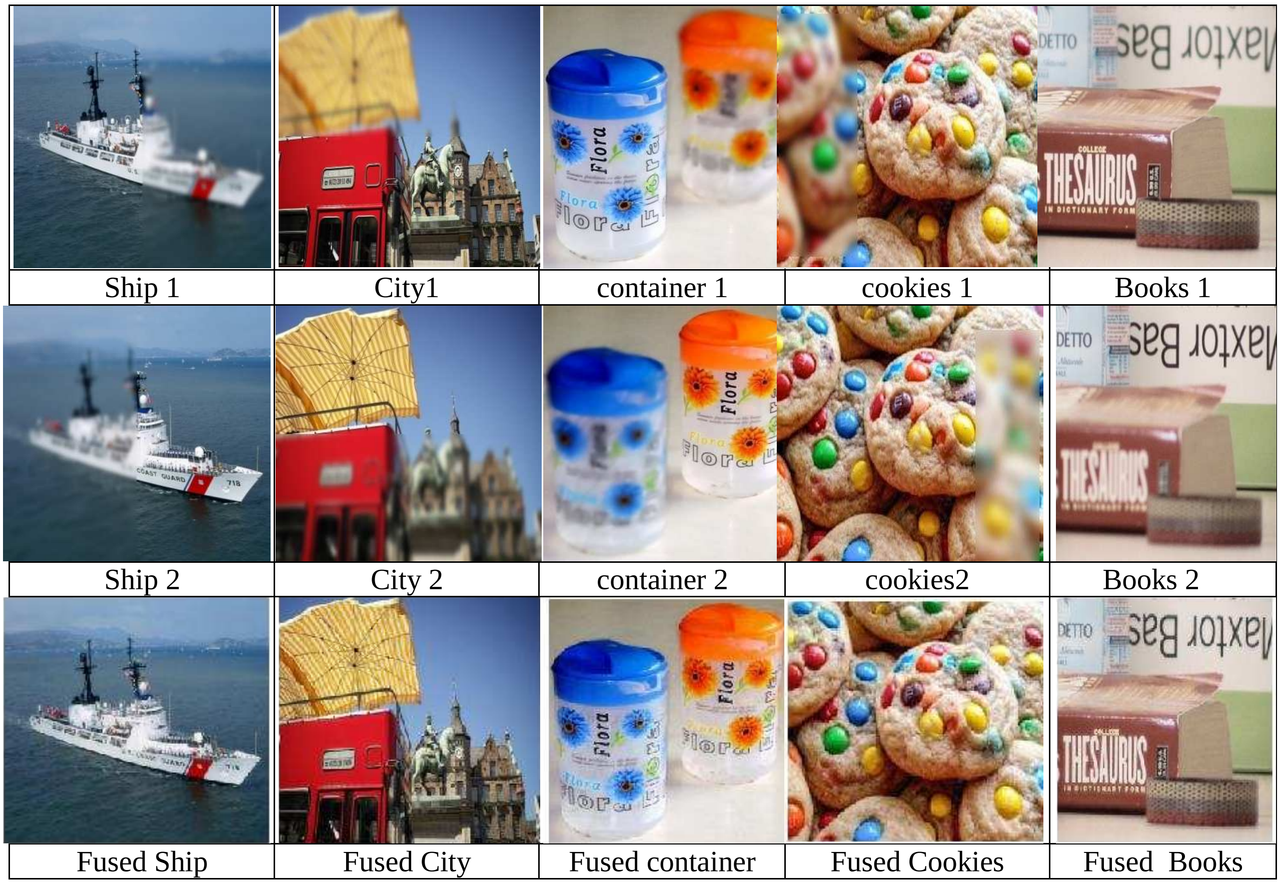

Fig. 7. The multi focus test color images, and resultant fused images.

Tables (1, 2) show the evaluation results of the outputted fused images for both grey scale and color images respectively. The evaluation of the proposed method is done by comparing with results obtained through using image fusion toolbox, kindly provided by Kumar [13]. The quality of the fused images are better when these parameters have higher values, excluding $L^{AB/F}, N^{AB/F}$ which should have lower values. In table (1), higher values are bolded except for $L^{AB/F}, N^{AB/F}$ where lower values are bolded.

Table 1,
Performance Comparison of Test Grey scale Multifocus Images.

Book	**API**	**SD**	$\bar{G}$	**H**	**MI**	**FS**	**CORR**	Q_{ABF}	L_{ABF}	N_{ABF}
Proposed	84.3228	58.4854	12.2766	7.2700	9.0737	1.999	0.9918	0.986	0.014	1.6769e-005
[13]	84.5140	59.4958	14.6905	7.2432	8.7287	1.998	0.9903	0.977	0.0232	2.7807e-005
Desk										
Proposed	80.5457	67.5398	13.2131	7.2389	6.3178	1.971	0.9636	0.876	0.030	0.0034
[13]	81.3517	66.8859	13.2674	7.4217	6.1486	1.996	0.9643	0.885	0.113	0.0116
Lena										
Proposed	98.7034	51.4480	12.9027	7.5352	7.2215	1.983	0.9786	0.905	0.092	0.0345
[13]	98.8909	50.4837	12.7901	7.4998	6.6233	1.966	0.9791	0.907	0.091	0.0098
Clock										
Proposed	96.3000	49.7317	8.0268	7.2733	7.8923	1.973	0.9889	0.913	0.087	0.0047
[13]	96.5571	50.2380	9.0733	7.2972	7.8681	1.958	0.9876	0.908	0.091	0.0014
Girl										
Proposed	116.9926	50.9372	11.7083	7.5477	7.5616	1.995	0.9916	0.935	0.064	0.0037
[13]	117.5374	51.3023	14.7759	7.5751	7.4948	1.998	0.9876	0.941	0.057	0.0060

Table 2,
Performance Comparison of Test colored Multifocus Images.

Ship	**API**	**SD**	$\bar{G}$	**H**	**MI**	**FS**	**CORR**	Q_{ABF}	L_{ABF}	N_{ABF}
Proposed	106.9133	48.443	8.7148	7.1714	8.1718	1.989	0.9886	0.889	0.109	0.0053
[13]	107.279	48.643	10.415	7.2026	8.2783	1.990	0.986	0.903	0.095	0.0085
City										
Proposed	114.7009	47.4911	13.074	7.5148	8.3899	1.981	0.9830	0.912	0.086	0.0127
[13]	115.3971	56.3815	17.839	7.7572	8.8351	1.980	0.9808	0.916	0.081	0.0112
Container										
Proposed	168.9581	53.1473	9.0436	7.4530	7.1750	1.986	0.9715	0.906	0.089	0.0256
[13]	169.6191	53.9541	10.924	7.4819	7.3406	1.990	0.9698	0.914	0.080	0.0257
Cookies										
Proposed	143.345	59.450	15.923	7.8245	9.9503	2.000	0.9826	0.969	0.038	0.0019
[13]	143.898	59.436	17.372	7.8375	9.875	1.981	0.981	0.961	0.036	0.0098
Books										
Proposed	162.848	51.9838	13.171	7.2913	6.7079	1.946	0.9821	0.924	0.079	0.0012
[13]	163.517	51.6543	15.071	7.327	6.4308	1.951	0.9798	0.916	0.082	0.0037

From the results, we can notice that, the performance of the proposed method is slightly better than [13] in terms of overall mutual information between source images and fused image (MI), while for other performance measures, the proposed method is slightly better or less than proposed method in [13] in few tenths. Also the proposed method was compared with methods in [5] where it is proposed to fuse multifocus images in the multiresolution DCT domain with pixel level fusion rule, and [11], [12] for ‘book, desk’ images. Table (3) shows the comparison results.

Table 3,
Performance comparison of proposed method and methods in [5, 11, 12].

Book	**API**	**SD**	$\bar{G}$	**H**	**MI**	**FS**	**CORR**	Q_{ABF}	L_{ABF}	N_{ABF}
Proposed	84.3228	58.4854	12.2766	7.2700	9.0737	1.999	0.9918	0.986	0.0143	1.6769e-005
[5]	85.1322	61.0523	11.7826	7.2996	7.3344	1.989	0.9821	0.885	0.1115	0.0033
[11]	84.7978	61.0248	11.7600	7.3045	7.0857	1.990	0.9819	0.884	0.1116	0.0045
[12]	85.4582	61.2135	11.8963	7.3141	7.2377	1.992	0.9821	0.880	0.1155	0.0045
Desk	**API**	**SD**	$\bar{G}$	**H**	**MI**	**FS**	**CORR**	Q_{ABF}	L_{ABF}	N_{ABF}
Proposed	80.5457	67.5398	13.2131	7.2389	6.3178	1.971	0.9636	0.899	0.030	0.0034
[5]	81.4877	64.6112	13.0945	7.5262	5.2655	1.991	0.9659	0.888	0.1064	0.0048
[11]	80.8079	64.3038	12.8823	7.4497	4.8638	1.947	0.9636	0.857	0.1328	0.0102
[12]	80.6225	64.0681	12.8277	7.4846	4.8645	1.980	0.9656	0.876	0.1157	0.0078

From the results, we can perceive that there is very small change in values of parameters. The proposed algorithm offer highest value for $\bar{G}$ and MI, which means highest sharpness and clarity degree, and highest overall mutual information between source images and fused one respectively. It also clearly offers superiority with respect to Petrovic Metrics, it gives highest value for quality factor Q_{ABF}, and lowest values for loss of edge information L_{ABF} and noise or artifacts added due to fusion N_{ABF}.

6. Conclusion

In this paper, multifocus image fusion was proposed, it depends on using detail images extracted from the source images by applying counterlet transform, making approximation subband equal to zero, then applying applying inverse counterlet transform, the resultant image is the detail image only. Weights are computed by measuring the strength of horizontal and vertical details, these weights are used to fuse the source images directly. The experimental results show that the proposed method offers superior or similar performance as compared to other methods in terms of visual quality and quantitative parameters. It offers good performance over other fusion methods.

Notation

API	Average Pixel Intensity
$A_{D(i,j)}, B_{D(i,j)}$	Detail coefficients
$C_h^{i,j}, C_v^{i,j}$	unbiased covariance estimate
CBF	Cross Bilateral Filter
Corr	Normalized Correlation
FS	Fusion Symmetry
G	Average Gradient
H	Entropy
MI	Mutual Information
SD	Standard Deviation
$Q_{ABF}, L_{ABF}, N_{ABF}$	Petrovic metric parameters
w_{ta}, w_{tb}	weights of detail coefficients of images A, B respectively.

7. References

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دمج الصور متعددة التركيز بالاعتماد على أهمية البكسل و تحويلة Counterlet

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الخلاصة

إن الهدف من دمج الصور هو ضم المعلومات ذات الصلة لصور متعددة في صورة واحدة تحتوي على كل المعلومات المهمة من الصور المتعددة . في هذا البحث ، تم إقتراح طريقة دمج تعتمد على اسلوب المعدل الموزون و ذلك بإستعمال أوزان يتم حسابها من صور التفاصيل المستخلصة من الصور المصدر المراد دمجها باستعمال تحويلة counterlet. تعتمد طريقة إستخلاص التفاصيل من الصور المصدر على جعل معاملات التقريب مساوية للصفر ومن ثم تطبيق معكوس تحويلة counterlet . تم التحقق من أداء الطريقة المقترحة بتنفيذها على العديد من الصور متعددة التركيز ومقارنتها بطرق دمج أخرى.