Multi-Sensor Fusion based on DWT, Fuzzy Histogram Equalization for Video Sequence

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Abstract: *Multi-sensor fusion is a process which combines two or more sensor datasets of same scene resulting a single output containing all relevant information. The fusion process can work in the spatial domain and the transform domain. The spatial domain fusion methods are easy to implement and have low computational complexity, but they may produce blocking artefacts and out of focus which means that the fused image got blur. In this paper, fusion algorithm has been proposed to solve this problem based on Discrete Wavelet Transform (DWT), Fuzzy Histogram Equalization, and De-blurring Kernel. In addition, two fusion techniques: Maximum selection and weighted average were developed based on Mean statistical technique. The performance of the proposed method has been tested on the real and synthetic datasets. Experimental results showed the proposed fusion method with traditional and developed fusion rules gives improvement in fused results.*

Keywords: *Multi-sensor fusion, discrete wavelet transform, fuzzy histogram equalization, de-blurring kernels, principle component analysis.*

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1. Introduction

Multi-sensor image fusion is process of combining complementary information from multiple sensor images to generate a single image that contains a more accurate description of the scene than any of the individual sensor images. The fusion process must satisfy the following requirements:

1. Preserve all relevant information in the fused image.
2. Suppress irrelevant parts of the image and noise.
3. Minimize any artefacts or inconsistencies in the fused image [6]. Fusion techniques can be applied in many applications including multi-focus imagery, concealed weapon detection, intelligent robots, surveillance systems, medical diagnosis, remote sensing, and image enhancement [19].

Fusion process is classified into three fusion levels: signal/pixel, feature, decision fusion levels. These methods can work in the spatial domain and the transform domain. The spatial domain fusion methods are easy to implement and have low computational complexity, but they may produce blocking artefacts and out of focus which means that the fused image got blur. The simplest fusion is the average fusion which takes two images and fuses them by taking the average of two images. This method produce a low contrast fused image. The weighted average approach has been proposed to solve the problem of the simple average fusion. In this method, the fused pixel is estimated as the weighted average of the corresponding input pixels. The weight estimation usually requires a specific value. Other methods have been developed, such as Intensity-Hue-Saturation (IHS), Principal Component Analysis (PCA) [4, 16]. The fused image obtained by these techniques is high spatial resolution-fused image, but it suffer from spectral degradation.

In contrast, transform domain fusion methods may achieve improved contrast and better signal-to-noise ratio than spatial domain fusion methods [24].

Popular transform domain method may be in a form of a pyramid or wavelet transform. It is first applied on each input image, and a composite image is then formed by selecting the coefficients from the multiscale representations of all source images.

Finally, a fused image is obtained from inverse transformation [20]. In [2], image fusion using Weighted Average DWT was proposed to solve the problem of classical average fusion. In [10], the authors proposed a new image fusion based on combination of the PCA and the DWT using weighted average of images in order to obtain enhanced fused image. Guo *et al.* [3] in proposed a new adaptive image fusion method based on local statistical feature of wavelet transform. In the low frequency coefficients, combining weighted average with selection was used as an adaptive fusion rule to obtain the approximate coefficients. To obtain the detail coefficients an adaptive weighted average method is used in the high frequency coefficients.

In this paper, our attention located on the pixel-level fusion based on maximum selection and weighed averaging techniques. The motivation lies on the enhancement of Maximum Selection (MAX) and

Weighed Averaging (WA) fusion results in order to get more focus in the spatial and spectral resolution fused frames for multi-sensor video sequences. Most fusion methods depending on WA technique operate directly on the pixels of sensor images. Input images can be enhanced by using multiresolution analysis such as Laplacian pyramid and wavelet transform [9] before performing weighed averaging fusion technique.

Wavelet filters provide better multi resolution approach which can be used to remove noise effect in video frames or images [15, 18]. The proposed fusion technique using Discrete Wavelet Transform (DWT), Fuzzy Histogram Equalization (FHE), and sharp kernels has been proposed in order to avoid the blurring or noise effect that causes the fusion process less effective. The experimental results have been compared with the results of the popular existing fusion techniques: DWT based image fusion [20] and PCA based image fusion [11, 23].

In section 2, background theories that are related to this work are presented. The proposed methodology is provided in section 3. The experimental results and analysis are provided in section 4. Finally, section 5 draws conclusions of this work.

2. Theory

2.1. Discrete Wavelet Transform

In DWT, digital filtering techniques are used which gives time scale representation of the digital signal. The signal to be analysed is passed through filters at different cut off frequencies and at different scales. At every subsequent level, high pass filter gives detail information and low pass filter related to scaling function gives course approximations. At each decomposition level, the half band filter gives only half the frequency band. Thus, the frequency is reduced by half which in turn doubles frequency resolution. DWT of the original signal is obtained, reconstruction is exactly the reverse process of decomposition [7, 17, 21]. DWT is efficient because of its characteristics which are accurate reconstruction and multi-resolution analysis [13, 14, 22].

2.2. Fuzzy Histogram Equalization

Contrast enhancement produces an image that better in quality than the original image by changing the pixel intensities. Fuzzy Histogram Equalization (FHE) [25] can be used to enhance the visual of image. FHE was proposed to avoid the limitation of dynamic histogram equalization which cannot preserve the mean image-brightness. FHE technique involves four stages which are:

1. Fuzzy histogram computation.
2. Partitioning of the histogram.
3. Dynamic histogram equalization of the Partitions, and normalization of the image brightness.

2.3. De-Blurring Method (Sharp Kernels)

Sometime, the cause of the data focus problem is due to the different features of different types of sensors, such as Visual Sensors (VIS) and Infrared Sensors (IR) sensors. The nature of IR/Thermal video sensors produce noisy or blurred observations [8]. To obtain a sharpened frame/image, the basic concept is to convolve de-blurring kernel with the noisy or blurred image. For this work, one kernel which was selected can be defined as [1]:

- $k1 = \begin{bmatrix} 0 & 0 & 0 \\ -1 & 3 & -1 \\ 0 & 0 & 0 \end{bmatrix}$

2.4. Primitive Spatial Image Fusion Methods

- Maximum selection (MAX). It selects maximum of corresponding pixel intensities from both input images (*im1*, *im2*). The fused image can be obtained by [4]:

$$im\_fused = max[im1(x,y), im2(im2(x,y)] \quad (1)$$

- Weighted Average (WA). Because of different measurements of sensors, the simple average fusion technique cannot produce good result. WA has been proposed with predefined weight for each sensor measurements producing better result. Weights *w1* and *w2* are given for the first and second images respectively, the fused image can be obtained by [5]:

$$im\_fused = \frac{w1.im1(x,y) + w2.im2(x,y)}{w1 + w2} \quad (2)$$

2.5. Evaluation Metrics

Many focus measure operators that were used previously to measure the amount of focus in still images [12] were selected for performance assessment of the proposed fusion algorithm. These operates can be listed as follows:

1. Brenner's focus measure (BREN).
2. Image contrast (CONT).
3. DCT energy ratio (DCTE).
4. Gaussian derivative (GDER).
5. Gray-level local variance (GLLV).
6. Gradient energy (GRAE).
7. Helmli and Scherer's mean method (HELM).
8. Histogram entropy (HISTE).
9. Energy of Laplacian (LAPE).
10. Variance of Laplacian (LAPV).
11. Spatial frequency (SFRQ).
12. Variance of the image gradient (TENV).
13. Autocorrelation (VOLA).
14. Variance of wavelet coefficients (WAVV).
15. Ratio of wavelet coefficients (WAVR).

3. Proposed Methodology

The proposed method used the pixel level fusion to fuse multi-sensor video datasets using the traditional and the developed maximum selection and weighted average fusion techniques. The proposed method (see Figure 1) comprises the following steps:

1. Given vid1and vid2, read the first frame *fi* from original visible vid1and read the first frame *gi* from blurred/noisy video vid2. The DWT has been applied on the 2-D visible frame *fi*.
2. The output of DWT will become the input of Fuzzy Histogram Equalization (FHE) algorithm which gives better results than the traditional Histogram Equalization. FHE is used to enhance the output of DWT.
3. De-blurring kernel has been selected and is applied on the 2-D infrared or the blurred/noisy visible frame *gi*.

The kernel is used to handle the blur degradation of data before the multi-sensor fusion process. This will help to increase the quality of fused result.

Finally, the output of FHE and the output of de-blurring kernel are fused by using fusion rules. The traditional MAX and WA fusion techniques were developed adaptively using statistical mean technique. The developed Adaptive Weighted Maximum selection (D-WMAX) and the Developed Adaptive Weighted Average (D-AWA) can be defined as follows: D-WMAX can be defined using the following procedure:

If mean_fi>mean_gi then
w1=mean_gi/mean_fi
w2=1-w1
Otherwise
w2=mean_fi/mean_gi
w1=1-w2
f_fused=max{w1.fi(x,y),w2.gi(x,y)}

D-AWA can be defined using the following procedure:

If mean_fi>mean_gi then
w1=mean_gi/mean_fi
w2=1-w1
Otherwise
w2=mean_fi/mean_gi
w1=1-w2
f_fused=(w1.*fi*(x,y)+w2*gi*(x,y))/w1+w2

These steps are repeated until the end of sequence is reached. The output of this algorithm is a single fused video sequence. The algorithm steps of developed fusion method can be illustrated in Algorithm 1.

Algorithm 1: Fuzzy DWT based fusion

Input: two registered video streams Vid1 and Vid2
n is the length of a sample video
K is a special (3×3) kernel
Output: fused video sequence

Steps:
1. *Given (3×3) Kernel (K)*
2. *Given the generated videos Vid1 and Vid2*
3. *For i=1 to n do*
4. *Read the current frame fi from Vid1*
5. *Read the current frame gi from Vid2*
6. *Apply Discrete Wavelet Transform (DWT) on fi: f_dwt =dwt(fi)*
7. *Compute Fuzzy histogram equalization on f_dwt*
8. *Compute Sharp filter (k) on gi by convolution process: g_sharp = gi* $\circledast$ *K*
9. *end for*
10. *Compute adaptive weights W1 and W2 for two frames*
11. *Apply one of fusion rules:*
12. *Maximum selection:*
$$f\_fused = max(w1.f\_dwt, w2.g\_sharp)$$
Weighted averaging:
13. $$f\_fused(x,y) = \frac{w1.f\_dwt(x,y) + w2.g\_sharp(x,y)}{w1 + w2}$$
14. *End algorithm.*

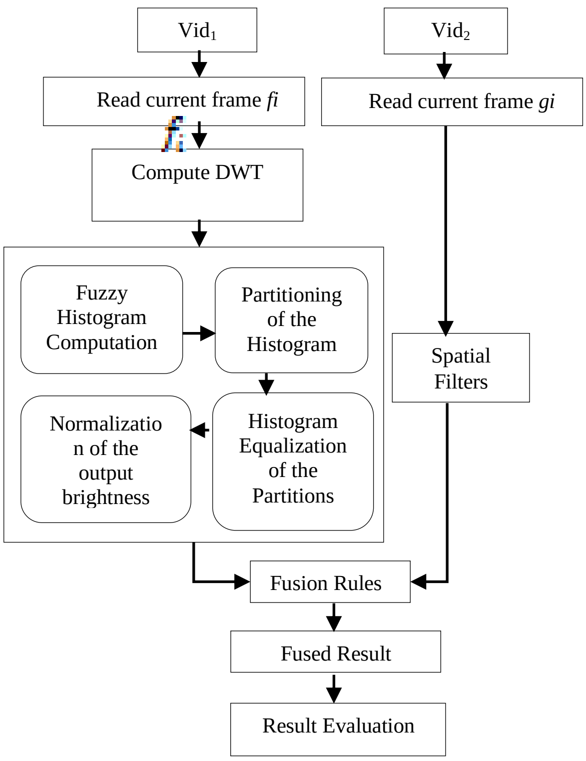

Figure 1. The proposed method scheme.

4. Experiment Results and Analysis

The incoming datasets of the proposed algorithm are different videos, each one contains *n* frames. It is assumed that the frames from each pair videos from one scene are already registered. For example, visible-visible videos for Metro scene and visible-infrared for City scene which can be obtained from (www.openvisor.org). In visible-visible video datasets, the first video is the original video while the second video is artificially generated by using noise or blur generator. The existing techniques: Maximum selection, WA, DWT, and PCA based fusion techniques and the proposed fusion method have been implemented and tested. Examples of visual results for each step of the proposed method are shown in Figures 2 and 3. The traditional MAX, traditional WA, the D-WMAX, the developed Adaptive WA (D-AWA) are used as fusion rules. All the results are compared with the results of PCA and DWT based fusion techniques.

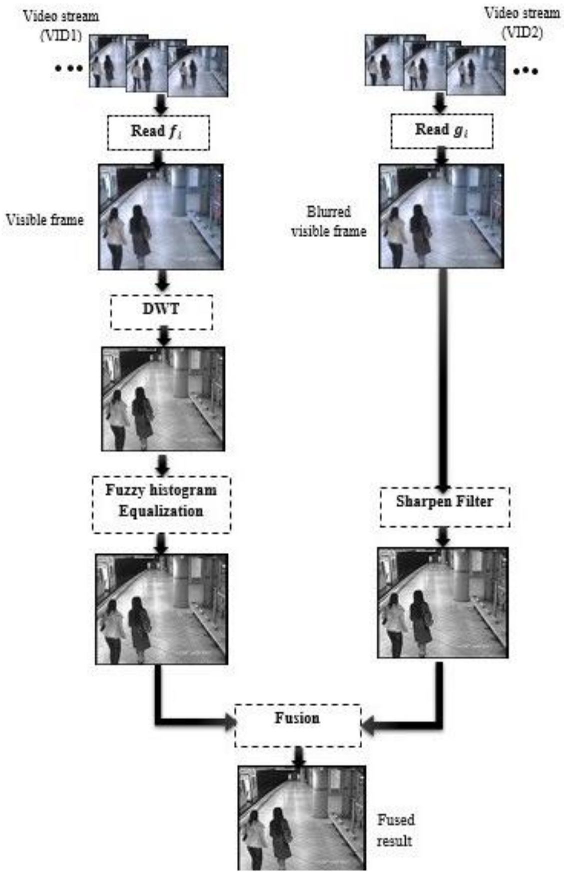

Figure 2. Example of visual results of the proposed fusion method forMetro visible-visible.

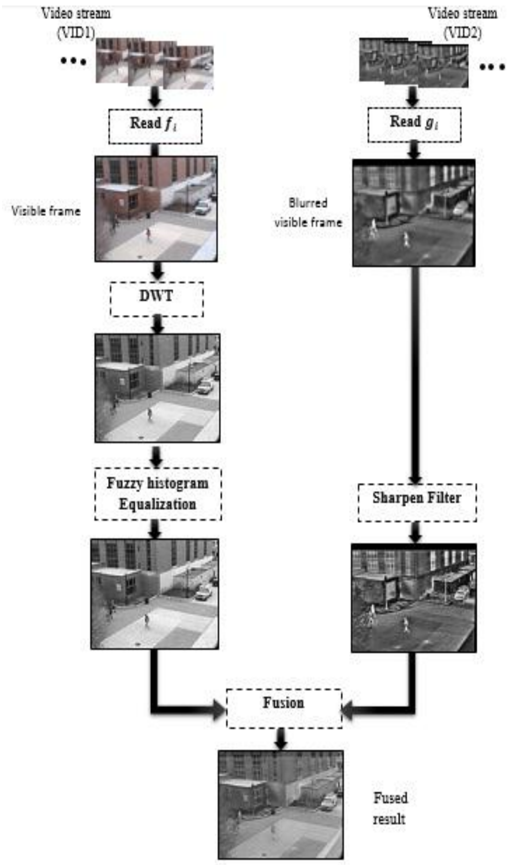

Figure 3. Example of visual results of the proposed fusion method forCity visible-infrared

Tables 1 and 2 summarize the objective assessment of the existing fusion methods and the proposed fusion method using some performance evaluation metrics (as mentioned in subsection 2.5). In the Tables, the left column is the performance metrics for computing the amount of focus in the fused results, where higher values indicate good results. The next columns represent the proposed method with fusion rules (MAX, D-WMAX, WA, and D-AWA) and the original fusion techniques (DWT and PCA).

Table 1. Results of performance evaluation metrics for the developed fusion technique compared with DWT and PCA based fusion techniques for visible Metro video and its corresponding visible blurred video.

Metric\Method	MAX	D-WMAX	WA	D-AWA	DWT	PCA
BREN	26.3912	32.8718	24.9954	32.8718	18.6325	17.2878
CONT	31.7988	43.0759	33.9198	43.0759	24.6824	23.6477
DCTE	0.1296	0.1906	0.1592	0.1906	0.1720	0.1719
GDER	6.6820e+36	6.7523e+36	6.3272e+36	6.7523e+36	5.6837e+36	5.7003e+36
GLLV	2.6323e+06	3.7344e+0	2.6341e+06	3.7344e+06	1.7410e+06	1.6445e+06
GRAE	41.8985	52.6894	42.7425	52.6894	31.1851	31.4565
HELM	3.3206	5.0164	3.8283	5.0164	3.0006	2.8387
HISE	7.8108	7.8417	7.8075	7.8417	7.7177	7.7087
LAPE	47.3702	54.9061	45.0147	54.9061	34.8661	33.8492
LAPV	187.3336	542.1921	282.7801	542.1921	174.2388	101.6647
SFRQ	3.9276	4.6271	3.9865	4.6271	3.1955	3.2140
TENV	2.8279e+09	8.7824e+09	3.9419e+09	8.7824e+09	1.4337e+09	9.9780e+08
VOLA	162.4541	296.5237	195.7340	296.5237	100.5077	96.0017
WAVV	17.1777	46.8658	24.5188	46.8658	17.8466	9.8967
WAVR	0.0845	0.2267	0.1099	0.2267	0.0741	0.0411

Table 2. Results of performance evaluation metrics for the developed fusion technique compared with DWT and PCA based fusion techniques for visible City video and its corresponding infrared video.

Metric\ Method	MAX	D-WMAX	WA	D-AWA	DWT	PCA
BREN	59.2909	54.0611	63.0695	60.1696	52.9428	53.5529
CONT	51.9374	45.0568	58.3033	54.0209	45.3970	51.6983
DCTE	0.0913	0.0795	0.0788	0.0734	0.0613	0.0828
GDER	2.9677e+36	2.2164e+36	3.6820e+36	3.3480e+36	2.8101e+36	6.0750e+36
GLLV	5.6176e+05	3.0709e+05	1.0346e+06	8.0739e+05	5.2376e+05	1.8700e+06
GRAE	75.1090	68.0737	81.3142	77.4845	64.3715	67.2024
HELM	2.4308	2.0392	1.7744	1.5678	1.4225	2.1547
HISE	7.3428	7.1257	7.5142	7.4114	7.1655	7.7060
LAPE	76.1031	71.6866	78.8230	76.6847	67.6328	68.2082
LAPV	793.6623	605.6294	987.6257	841.6886	783.4844	955.9214
SFRQ	6.0599	5.6675	6.4091	6.1999	5.3682	5.5368
TENV	2.0618e+09	1.0852e+09	3.6803e+09	2.6644e+09	1.4628e+09	5.7354e+09
VOLA	134.9297	94.2813	168.3148	137.7523	31.3227	157.6504
WAVV	72.8398	54.6836	91.1133	75.6982	81.1972	102.2727
WAVR	0.4530	0.3712	0.4580	0.3973	0.4013	0.3955

As shown in the Table 1, the results of performance metrics for the proposed fusion technique with the four fusion rules are high values compared with the values of performance metrics for existing methods (DWT and PCA). In addition, the proposed method with D-AWA fusion for all metrics gives better values compared with other values. The performance metrics results for D-AWA fusion produces higher values against the results for the traditional WA. Also the results of the developed adaptive weighted maximum selection (D-WMAX) gives higher values than the results of the traditional MAX fusion. In the Table 2, all performance metric values for the proposed fusion technique are higher values especially with WA fusion rule compared with the values of performance metrics for existing methods, except GDER, HISE, and WAVV values for PCA based fusion method.

From experiments, differing results in Table 2 and Table 1 is due to the different modalities of visible and infrared videos. As a result, the proposed fusion method has improved performance compared with the original PCA and DWT fusion techniques.

5. Conclusions

In this paper, multi-sensor fusion has been proposed based on Discrete Wavelet Transform, Fuzzy Histogram Equalization, and De-blurring Kernels. The goal is to obtain the enhancement of MAX and WA fusion results in order to get more focusing in the spatial and spectral resolution fused images for multi-sensor video sequences. The performance of the proposed method have been implemented and tested on the real and synthetic video datasets by using many in-focus operators. The experimental results showed that the proposed fusion method with the traditional and developed fusion rules gives good quality in fused result compared with the results of the existing fusion techniques.

References

[1] Al-Ameen Z., Sulong G., and Johar G., "Fast Deblurring Method for Computed Tomography Medical Images Using A Novel Kernels Set," *International Journal of Bio-Science and Bio-Technology*, vol. 4, no. 3, pp. 9-20, 2012.

[2] Dammavalam S., Maddala S., and Prasad K., "Quality Assessment of Pixel-Level Image Fusion Using Fuzzy Logic," *International Journal on Soft Computing*, vol. 3, no. 1, pp. 13-25, 2012.

[3] Guo Y., Xie M., and Yang L., "An Adaptive Image Fusion Method Based On Local Statistical Feature of Wavelet Coefficients," *in Proceedings of International Symposium on Computer Network and Multimedia Technology*, Wuhan, pp. 1-4, 2009.

[4] Maruthi R., "Spatial Domain Method for Fusing Multi-Focus Images using Measure of Fuzziness," *International Journal of Computer Applications*, vol. 20, no. 7, pp. 48-57, 2011.

[5] Jin D. and Lin S., Advances in Electronic Engineering, Communication and Management, Springer, 2012.

[6] Kannan K., Perumal A., and Arulmozhi K., "Performance Comparison of Various Levels of Fusion of Multi-Focused Images using Wavelet Transform," *International Journal of Computer Applications*, vol. 1, no. 6, pp. 77-84, 2010.

[7] Kumar S. and Jain Y., "Performance Evaluation and Analysis of Image Restoration Technique using DWT," *International Journal of Computer Applications*, vol. 72, no. 18, pp. 11-20, 2013.

[8] Lan X., Zhang L., Shen H., Yuan Q., and Li H., "Single Image Haze Removal Considering Sensor Blur and Noise," *EURASIP Journal on Advances in Signal Processing*, vol. 2013, no. 1, pp. 1-13, 2013.

[9] Li S. and Yang B., "Multifocus Image Fusion by

Combining Curvelet and Wavelet Transform," *Pattern Recognition Letters*, vol. 29, no. 9, pp. 1295-1301, 2008.

[10] Mazaheri S., Sulaiman P., Wirza R., Dimon M., Khalid F., and Tayebi R., "Hybrid Pixel-Based Method for Cardiac Ultrasound Fusion Based on Integration of PCA and DWT," *Computational and Mathematical Methods in Medicine*, vol. 2015, pp. 1-17, 2015.

[11] Naidu V. and Raol J., "Pixel-Level Image Fusion Using Wavelets and Principal Component Analysis," *Defence Science Journal*, vol. 58, no. 3, pp. 338-352, 2008.

[12] Pertuz S., Puig D., and Garcia M., "Analysis of Focus Measure Operators for Shape-From-Focus," *Pattern Recognition*, vol. 46, no. 5, 2013.

[13] Rajan K. and Murugesan V., "Hyperspectral Image Compression Based on DWT and TD with ALS Method," *The International Arab Journal of Information Technology*, vol. 13, no. 4, pp. 435-442, 2016.

[14] Sheet D., Garud H., Suveer A., Mahadevappa M., and Chatterjee J., "Brightness Preserving Dynamic-Fuzzy-Histogram Equalization," *IEEE Transactions on Consumer Electronics*, vol. 56, no. 4, pp. 2475-2480, 2010.

[15] Suraj A., Francis M., Kavya T., and Nirmal T., "Discrete Wavelet Transform Based Image Fusion and De-Noising in FPGA," *Journal of Electrical Systems and Information Technology*, vol. 1, no. 1, pp. 72-81, 2014.

[16] Tawade L., Aboobacker A., and Ghante F., "Image Fusion Based on Wavelet Transforms," *International Journal of Bio-Science and Bio-Technology*, vol. 6, no. 3, pp. 149-162, 2014.

[17] Van Fleet P., Discrete Wavelet Transformations: an Elementary Approach with Applications, John Wiley and Sons, 2011.

[18] Vidya V., Farheen N., Manikantan K., and Ramachandran S., "Face Recognition Using Threshold Based DWT Feature Extraction and Selective Illumination Enhancement Technique," *Procedia Technology*, vol. 6, pp. 334-343, 2012.

[19] Wang P., Pattern Recognition, Machine Intelligence and Biometrics, Springer Berlin Heidelberg, 2011.

[20] Yang Y., Huang S., Gao J., and Qian Z., "Multi-Focus Image Fusion Using an Effective Discrete Wavelet Transform Based Algorithm," *Measurement Science Review*, vol. 14, no. 2, pp. 102-108, 2014.

[21] Yassin A., Ghadban R., Salah S., and Neima H., "Using Discrete Wavelet Transformation to Enhance Underwater Image," *International Journal of Computer Science Issues*, vol. 10, no. 2, pp. 220-228, 2013.

[22] Young R., Wavelet Theory and its Applications, Springer Science and Business Media, 2012.

[23] Zebhi S., Sahaf M., and Sadeghi M., "Image Fusion using PCA in CS Domain," *Signal and Image Processing: an International Journal*, vol. 3, no. 4, pp. 153-161, 2012.

[24] Zhang Y., Chen L., Zhao Z., Jia J., and Liu J., "Multi-Focus Image Fusion Based on Robust Principal Component Analysis and Pulse-Coupled Neural Network," *Optik-International Journal for Light and Electron Optics*, vol. 125, no. 17, pp. 5002-5006, 2014.

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