Fisher Classifier and Fuzzy Logic Based Multi-Focus Image Fusion

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***Abstract*—In this paper, we propose a new method of spatially registered multi-focus images fusion. Image fusion based on wavelet transform is the most commonly fusion method, which fuses the source images information in wavelet domain according to some fusion rules. We formulate image fusion process as a two class problem: in focus and out of focus classes. Two-class fisher classifier is used for this purpose and six dimensional feature vectors, which is obtained via dual-tree discrete wavelet transform sub-bands are used for training classifier. We use classifier output as a decision map for selecting wavelet coefficients between two images in the different directions and level of decomposition, equally. Also there is an uncertainty about selecting wavelet coefficients in the smooth regions of two images, which causes some misclassified regions. In order to solve this uncertainty and integrate as much information of each source image as possible into the fused image, we propose an algorithm based on fuzzy logic, which combines output of three fusion rules. This new method provides improved subjective and objectives results compared to the previous fusion methods.**

Keywords-Image fusion, multi-focus, dual-tree discrete wavelets transform, fisher classifier, fuzzy logic.

I. Introduction

Image fusion provides a means to integrate multiple images into a composite image, which is more appropriate for the purposes of human visual perception and computer-processing tasks such as segmentation, feature extraction and target recognition. Important applications of the fusion of images include medical imaging [1], microscopic imaging, remote sensing [2], computer vision, and robotics [3].

In this paper we concentrate on multi-focus image fusion. Due to the limited depth-of-focus of optical lenses in CCD devices, it is often not possible to get an image that contains all relevant objects “in focus”. To achieve all objects “in focus”, a fusion process is required so that all focused objects are selected.

Fusion techniques include the simplest method of pixel averaging to more complicated methods such as principal component analysis [4], and multi-resolution fusion [5]. Multi-resolution images fusion is a biologically-inspired method, fuses images at different spatial resolutions. Similar to the human visual system, this fusion approach operates by decomposing the input images into a resolution pyramid of numerous levels. Multi-resolution image fusion includes three steps as:

1. Decomposing the input images into a resolution pyramid of numerous levels. Each level contains one or more bands representing orientation or detail/approximation information.
2. Following this decomposition, the fusion now takes place between the corresponding coefficients or samples in each band.
3. The fused pyramid is then reconstructed to form the final fused output image.

Figure 1 depicts multi-resolution image fusion process using pyramid transform. The key step in multi-resolution image fusion is the coefficient combination step or fusion rules, specifically, the process of merge the coefficients in an appropriate way in order to obtain the best quality in the fused image. The three previously important developed fusion methods, which were implemented in wavelet transform domain, are as follows: Maximum selection (MS), which just picks the coefficients in each sub-band with the largest magnitude; Weighted average (WA), which is developed by Burt and Kolczynski [6] and used a normalized correlation between the two images sub-bands over a small local area.
The resultant coefficients for reconstruction are calculated from this measure via a weighted average of the two images coefficients; Window based verification (WBV), which is developed by Li et al. [7] and creates a binary decision map to choose between each pair of coefficients using a majority filter.

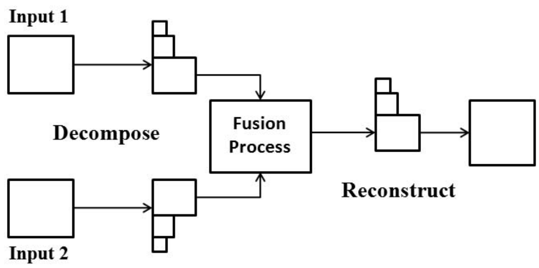

Figure 1: Multi-scale fusion block diagram using pyramid transform.

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These fusion rules ignore some useful information and are sensitive to noise. Selective operation made the fused coefficients completely dependent on the coefficients with larger average of local area energy and ignores the other corresponding coefficient. In the weighted average scheme, the weights were computed by a linear function, which cannot describe the uncertainty of each source image contributions. Also in coarser level of decomposition, images become smoother and there is not enough difference between wavelet coefficients for selecting one of them as in focus coefficient.

In this paper we propose a new method for merging wavelet coefficients as a fusion rule based on Fisher classifier and fuzzy logic. Six dimensional feature vectors, which are obtained via dual-tree discrete wavelet transform (DT-DWT) sub-bands, are used for training classifier. We use classifier output as a decision map for selecting wavelet coefficients between two source images in the different directions and level of decomposition, equally. Also there is an uncertainty about selecting wavelet coefficients in the smooth regions of two images, which causes some misclassified regions. In order to solve this uncertainty and integrate as much information of each source image as possible into the fused image, we propose an algorithm based on fuzzy logic, which combines output of three different fusion rules.

For testing our new fusion algorithm with other wavelet based fusion algorithm we use DT-DWT, which introduces limited redundancy and allows the transform providing approximate shift invariance and directionally selective filters while preserving the usual properties of perfect reconstruction and computational efficiency.

The paper is structured as follows: In section II generation of decision map using Fisher classifier is explained. In Section III our proposed fuzzy fusion rule is presented. Section IV gives various results and comparisons. Finally, we conclude with a brief summary in section V.

II. Generation of decision map

In this section we explain about generation of decision map (dm) for selecting wavelet coefficients between source images. *First* the source images are decomposed using the DT-DWT in one level. *Second* the six directional sub-bands of DT-DWT are used for training Fisher classifier. *Finally* the classifier output is used as decision map. In the following subsection the DT-DWT is explained briefly.

A. Dual-Tree Discrete Wavelet Transform

The DT-DWT is a modified version of the DWT [8]-[11] and was proposed to overcome shift variance and directionality limitations of the DWT while maintaining the perfect reconstruction property with limited redundancy. The DT-DWT is basically two parallel DWT filter bank trees. The wavelet and scaling functions used in one tree can be defined as approximate Hilbert transforms of the functions in the other tree. The filters used in both trees are real, but the combined filters are referred as analytic. This combination led to complex extension of real signals. As complex wavelets can distinguish between positive and negative frequencies, the diagonal sub-bands can be discriminated from horizontal and vertical sub-bands. Later on, horizontal and vertical sub-bands are divided giving six distinct sub-bands at each scale (at orientation $\pm 15^{\circ}, \pm 30^{\circ}$, and $\pm 75^{\circ}$).

These orientated and scale dependant sub-bands are shown spatially in Figure 2, demonstrates the improved directional selectivity of the DT-CWT and Figure 3 shows an example of 2D DT-DWT for a given image.

B. Feature extraction

The high frequency coefficients reflect the image edges and detail information. According to imaging mechanism of optical system, the bandwidth of system function for images in focus is wider than that for images out of focus. Therefore the pixel values of clear images are larger than that of blurred images. As it can be observed in Figure 4 pixels in focus are larger than out of focus pixels.

Based on this fact, many publications used local features to generate the decision map, for selecting wavelet coefficients between high frequency sub-bands of source images, such as: mean and standard deviation [12], energy, gradient, fractal dimension, contrast, and standard deviation [2], spatial frequency, visibility, and information entropy [13], for image fusion.

In order to enhance the wavelet coefficient information in the fusion step, we used mean square of difference between central pixel and neighborhood pixels in the local window:

$$F(x, y)=\sqrt{\frac{1}{W} \sum_{l=-L}^{L} \sum_{k=-K}^{K}[sb(x, y)-sb(x+l, y+k)]^{2}} \tag{1}$$

where sb is the sub-band of the DT-DWT, $(2L+1, 2K+1)$ is the size of the local window and W is the number of pixels in the local window.

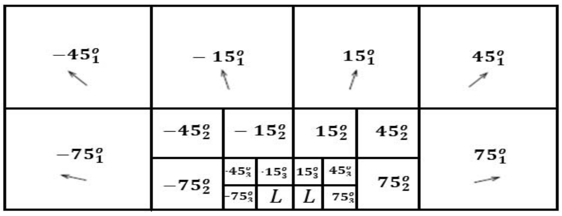


Figure 2: 2DDT- DWT, Scale and orientation labeled sub-bands.

Figure 3: An example of 2D DT-DWT.

(a) (b)

Figure 4: (a) Right focus "Flower" image, (b) a sub-band of DT-DWT.

It is followed by averaging in the local window for taking in account neighbor dependency:

$$NF(x,y)=\frac{1}{W}\sum_{l=-L}^{L}\sum_{k=-K}^{K}\left[F(x+l,y+k)\right] \tag{2}$$

We use differences between extracted features in the six sub-bands of the DT-DWT of two source images as feature vector:

$$FV_i(x,y)=NF_i^1(x,y)-NF_i^2(x,y) \tag{3}$$

where $i=1,2\ldots 6$ for the six sub-bands of the DT-DWT.

Thus, at the end of it we have a stack of six transformed images. We define our feature vector at each pixel as:

$$FV(x,y)=\left[FV_1(x,y),FV_2(x,y),\ldots,FV_6(x,y)\right] \tag{4}$$

C. *Fisher Classifier*

Having feature vector, for classification of wavelet coefficients as either in focus or out of focus we use Fisher classifier. Compared with the Neural Network (NN) and the Support Vector Machine (SVM), the Fisher classifier is easier to train, faster for classification, needs fewer training samples, and does not suffer from overtraining problems [14], [15]. Fisher classifier finds the optimal projection direction by maximizing the ratio of between class scatter to within class scatter, which benefits the classification. For a feature vector X, the Fisher classifier projects X onto one dimension Y in direction W using:

$$Y=W^TX \tag{5}$$

The Fisher criterion finds the optimal projection direction W_0 by maximizing the ratio of the between-class scatter to the within-class scatter, which benefits the classification. Let S_w and S_b be the within and between-class scatter matrices respectively,

$$S_w=\sum_{k=1}^{K}\sum_{x\in classK}(x-u_k)(x-u_k)^T \tag{6}$$

$$S_b=\sum_{k=1}^{K}(u_k-u_0)(u_k-u_0)^T \tag{7}$$

$$u_o=\sum_{k=1}^{K}u_k \tag{8}$$

where u_k is the mean vector of the kth class, u_0 is the global mean vector, and K is the number of classes. The optimal projection direction is the eigenvector of $S_w{}^{-1}S_b$ corresponding to its largest eigenvalue [16]. For a two-class classification problem, we do not need to calculate the eigenvectors of $S_w{}^{-1}S_b$. It is shown that the optimal projection direction is:

$$W_o=S_w{}^{-1}(u_1-u_2) \tag{9}$$

Let Y_1 and Y_2 be the projections of two classes on to the optimal projection direction W_0 and let $\mathrm{E}[\mathrm{Y}_1]$ and $\mathrm{E}[\mathrm{Y}_2]$ be the means of Y_1 and Y_2, respectively. Suppose $\mathrm{E}[\mathrm{Y}_1]>\mathrm{E}[\mathrm{Y}_2]$, then the decision can be made as:

$$C(X)=\begin{cases} class\ 1 & if \quad Y>\dfrac{E[Y_1]+E[Y_2]}{2} \\ class\ 2 & otherwise \end{cases} \tag{10}$$

We use classifier output as a decision map (DM) for selecting wavelet coefficients between two images in the different directions and level of decomposition, equally. In fact the fusion rule is defined as:

$$sb_{new\,i}^{\;j}=\left(sb_{1i}^{\;j}\times DM\right)+\left(sb_{2i}^{\;j}\times\sim DM\right) \tag{11}$$

where $j=1,2\ldots N-1$ which N is the level of the decomposition, $i=1,2\ldots 6$ which denote the six sub-bands of high frequency coefficients at each level, and "~" is "Not" which is a logical operation. Also in coarser level of decomposition we use an estimation of *DM* via down-sampling, because of in each level image is down sampled by factor 2.

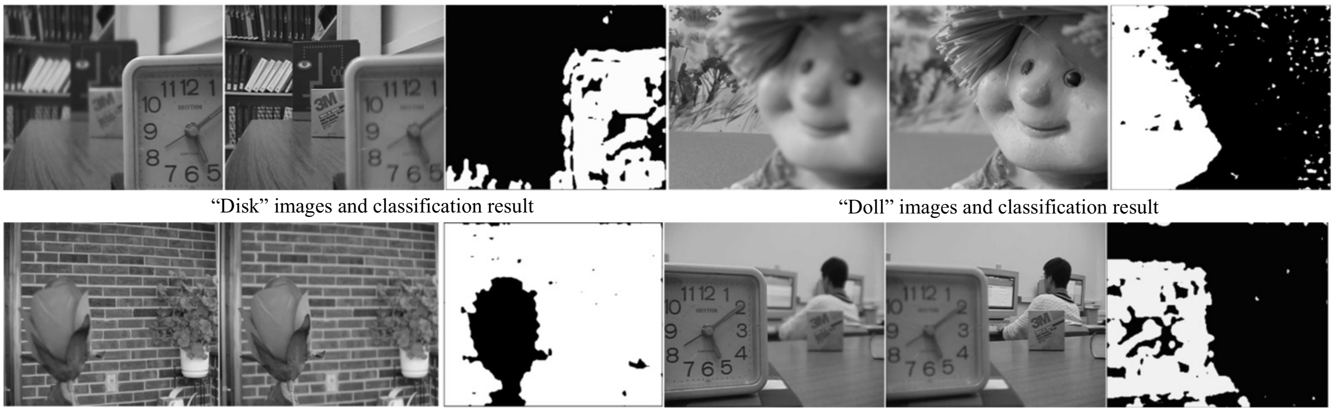
Figure 5 shows the train dataset and its corresponding class labels (black regions indicate out of focus area and white regions indicate in focus area for the first source image and vice versa), which is used from different multi-focus images. Also Figure 6 shows classification results for several test images.

III. Fuzzy fusion rule

The decision maps, which are obtained via Fisher classifier in the previous section, have some misclassified regions; therefore the fusion rule which uses these decision maps causes artifacts in the fusion results (see Figure 11).

(a) (b)

Figure 5: (a) Train images used in the experiment, (b) class labels.



“Disk” images and classification result

“Doll” images and classification result

“Flower” images and classification result

“Lab” images and classification result

Figure 6: Test images used in the experiment and their classification results.

Figure 7 shows histogram of difference between extracted features from two source images (equation 3) in the different level of decomposition. As it can be seen in Figure 7 most of wavelet coefficients in the feature space are related to smooth regions of the source images, which have not enough differences to classify them as in focus or out of focus coefficients. In order to solve this uncertain problem we use three different strategies for fusion rule. The *first fusion rule* uses the decision map, which is obtained via Fisher classifier:

$$Y_1 = (sb_1 \times DM) + (sb_2 \times \sim DM) \tag{12}$$

The *second fusion rule* uses the decision map, which is obtained via following formula:

$$dm(x,y) = \begin{cases} 1 & if \quad NF_1(x,y) \geq NF_2(x,y) \\ 0 & \quad otherwise \end{cases} \tag{13}$$

where $NF_{1,2}$ are obtained via equation 2 for the two source images. And then:

$$Y_2 = (sb_1 \times dm) + (sb_2 \times \sim dm) \tag{14}$$

Also a simple averaging is chosen as the *third fusion rule*:

$$Y_3 = \frac{(sb_1 + sb_2)}{2} \tag{15}$$

We want to design a good fusion rule to combine these three fusion rules to integrate as much information as possible into the fused image. We used a fuzzy classifier for this purpose. The simplest fuzzy rule-based classifier is a fuzzy if-then system, similar to that used in fuzzy control [17]. We labeled output of each fusion rules as a class. This classifier can be constructed by specifying classification rules as linguistic rules:

1. IF NF is large AND En is large THEN Y_2 is output.
2. IF NF is large AND En is small THEN Y_1 is output.
3. IF NF is medium AND En is large THEN Y_2 is output.
4. IF NF is medium AND En is small THEN Y_1 is output.
5. IF NF is small THEN Y_3 is output.

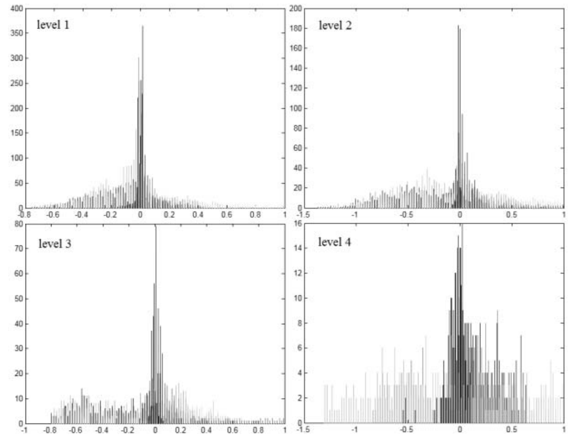


Figure 7: Histogram of difference between extracted features in the different level of decomposition.

where $En = |En_1 - En_2|$ and $NF = |NF_1 - NF_2|$. $En_{1,2}$ are the energy of wavelet coefficients in the local window and $NF_{1,2}$ are obtained via equation 2 for the two source images.

Each linguistic value is represented by a membership function. Figure 8 shows triangular membership functions for NF, which is normalized and T_1 is a constant value. For the pair of values $[NF, En]$, the degree of satisfaction of the antecedent part of the rule determines the firing strength of the rule. The firing strengths of these five rules are calculated as:

$$\tau_1 = \mu^1_{Large}(NF) \times \mu^2_{Large}(En) \quad \tau_2 = \mu^1_{Large}(NF) \times \mu^2_{Small}(En)$$

$$\tau_3 = \mu^1_{Medium}(NF) \times \mu^2_{Large}(En) \quad \tau_4 = \mu^1_{Medium}(NF) \times \mu^2_{Small}(En)$$

$$\tau_5 = \mu^1_{Small}(NF)$$

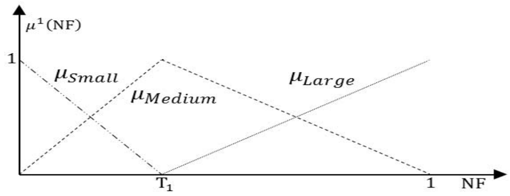


Figure 8: Fuzzy membership function for the linguistic terms of NF.

Table 1: Some well-known triangular norms

T-norms	
Minimum	$\min(x, y)$
Algebraic product	$x \cdot y$
Weak	$\begin{cases} \min\,(x, y) & \textit{if} \quad \max\,(x, y) = 1 \\ 0 & \textit{otherwise} \end{cases}$
Bounded sum	$\max(0, x + y - 1)$

The AND operation is typically implemented as *minimum* but any other t-norm may be used. Some well-known triangular norms are shown in Table 1.We have chosen *algebraic product* for the AND operation. The rules "vote" for the class of the consequent part. The weight of this vote is τ_i. To find the output of the classifier, the votes of all rules are aggregated. Among the variety of methods that can be applied for this aggregation, we considered the maximum aggregation method. Let k is the class labels, j denotes number of rules and $i \rightarrow k$ denotes that rule i votes for Y_k (the fusion rule). Then

$$If \quad \tau_i = \max_{j=1\dots5} \tau_j \quad AND \quad i \rightarrow k \quad THEN \quad Class \quad is \quad Y_k \tag{16}$$

For building fuzzy membership functions of NF and En, T_1 and T_2 must be defined. We obtained $0.04 \le T_1 \le 0.07$ and $0.08 \le T_2 \le 0.15$ using test images and try and error.

We use this fuzzy fusion rule in each high frequency sub-band at each level of decomposition of DT-DWT, separately. Also for fusing of low frequency sub-bands we use an estimation of decision map, which is obtained via Fisher classifier, using down-sampling:

$$sb_{new\,i}^{\;N} = \left(sb_{1i}^{\;N} \times \hat{DM} \right) + \left(sb_{2i}^{\;N} \times \sim \hat{DM} \right) \tag{17}$$

where $i = 1, 2$ which is low frequency sub-bands in the last level of decomposition and $\widehat{DM}$ obtains via down-sampling with respect to level of decomposition. After merging the wavelet coefficients, the final fusion result is obtained by inverse wavelet transform.

IV. Experimental Results

The images used in the experiments are selected from multi-focus datasets; publicly available at the Image fusion web site [19] and additional multi-focus images, which is provided by us (Figure 9).

The image PSNR and Petrovic index [18], used to evaluate the fused image. It should be mentioned that for image fusion experiment, a ground-truth image was used by cutting and pasting method.

First we show the results of using fuzzy method compared to three fusion rules in the DT-DWT domain. Figure 10 demonstrate the average PSNR and Petrovic index between the 9 pair images used in the experiments.

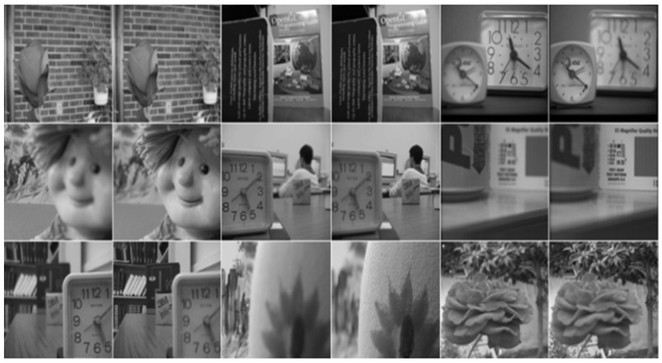


Figure 9: The test images used in the experiment.

As it can be seen in Figure 10, improvement which is obtained via fuzzy method is significant and very close to the best results (the best results is related to method, which is used handmade decision map as a ideal decision map for fusing wavelet coefficients). Also for visual comparisons Figure 11 show the results of fuzzy and Fisher classifier methods; artifacts, which are seen in the results of Fisher method are eliminated in the results of fuzzy method.

Then to compare our fuzzy image fusion method with other fusion algorithms, the image fusion methods based on the averaging, principle component analysis (PCA) and wavelet based fusion (MS, WA [6], WBV [7], and our proposed method) are used in the DT-CWT scheme. Figure 12 shows the average PSNR and Petrovic index between the 9 pair images used in the experiments for 7 fusion methods. As it can be observed in Figure 11 our proposed method has better results (more than +3.83 dB in PSNR and +0.022 in Petrovic index) compare to other fusion algorithms and very close to the best results.

V. Conclusions

In this paper, we have presented a new wavelet based multi-focus image fusion method using Fisher and Fuzzy classifier. Proposing a new fusion rule for merging wavelet coefficients, which is the second step in the wavelet based image fusion, is the main novelty of this paper. Also this new method used DT-DWT for finer frequency decomposition and shift invariant property compared to discrete wavelet transform. The experimental results demonstrated that the proposed method outperforms the standard fusion methods in the fusion of multi-focus images.

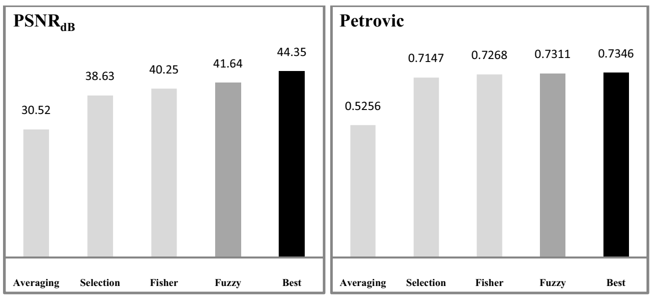


Figure 10: PSNR and Petrovic Index for different fusion methods.

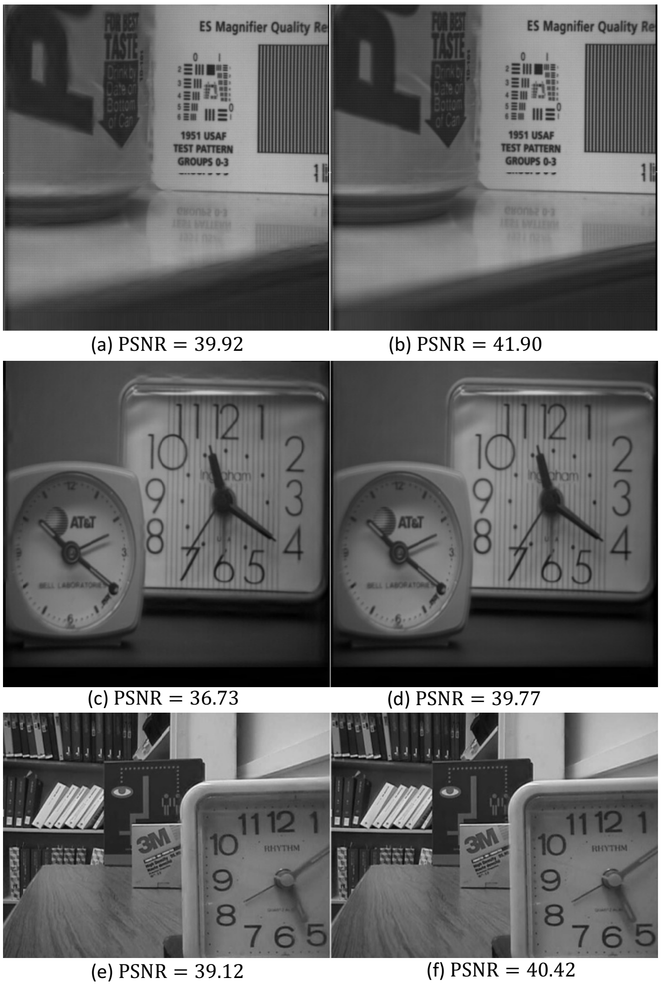


Figure 11: Fusion results (a), (c) and (e) using Fisher classifier, (b), (d) and (f) using fuzzy method.

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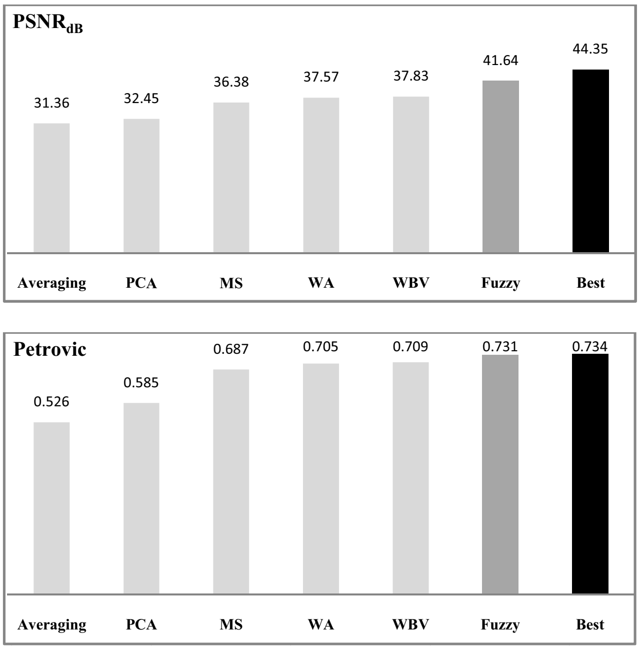

Figure 12: PSNR and Petrovic Index for different fusion methods.

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