Proceedings of the 2009 IEEE International Conference on Systems, Man, and Cybernetics
San Antonio, TX, USA - October 2009

# Image Fusion Quality Metrics by Directional Projection

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***Abstract*—Image fusion has been over-studied recently. Nevertheless, few works aim to how to evaluate the performance of image fusion algorithms. In this paper, we extend the work in image quality evaluation [1] to a novel metric for objective evaluation of image fusion. Firstly the input images and the result image are converted into local sensitive intensity (LSI) by Radon transform. Then we use the sensitive intensity to measure how many information have been transferred from each source into the fused result by the difference of LSI. Finally all the LSI pairs are incorporated into the expression according to Weber-Fechner law. Experimental results demonstrate that our proposed metric is compliant with subjective evaluations and outperforms other recently developed objective metrics of image fusion.**

***Index Terms*—Image Fusion, Local Sensitive Intensity, Radon Transform.**

## I. Introduction

Image fusion, which is taken as the branch of the information fusion, has attracted a considerable amount of research attentions recently. It could apparently enhance the information in respective source images and increase the reliability of interpretation by integrating multiple-source imagery using advanced image processing techniques. In general, Image fusion can take place on pixel, feature, and decision levels. Pix-level fusion can be classified as combination fusion while the other two can be seen as classification fusion. As more and more fusion algorithms has been designed, it is necessary to effectively evaluate the performance and characteristics of these different schemes.

It is clear image fusion performance can be assessed using informal subjective preference tests, which is the most reliable and trusted method of fusion assessment. In [2], audience of potential users is employed to evaluate a fusion system. But there are many disadvantages such as expensive, difficult to reproduce and verify. Hence, objective image fusion performance metrics that are consistent with human visual perception appear as a valuable alternative. A common idea is to propose an objective evaluation which has ground truth images and take them as references for comparison with the experimental result [3]. The widely used metrics for these comparisons include mean squared error (MSE), the root mean square error (RMSE), normalized least square error (NLSE), the peak signal-to-noise ratio (PSNR), correlation (CORR) and so on.

However, ground truth images are not available in many applications. Qu *et al.*have proposed evaluating the image fusion performance by using mutual information (MI) [4]. MI defines the amount of information that fused image contains about the input one, and describes the similarity of the image intensity distributions of the corresponding image pair. But it does not correlate well with the subjective quality of fused images. Then Xydeas *et al*. proposed to evaluate the performance by compare the edge information between the fused image and the source images, then used it to calculate the effect of noise on image fusion later [5][6]. Based on the image quality index introduced by Wang and Bovik in [7], a new fusion quality index given by Piella *et al.* produces a quality index which gives an indication of how much of the salient information contained in each of the input images has been transferred into the fused image without introducing distortions [8]. Yang *et al*. proposed a metric that performs different operations when evaluating different local regions according to the similarity level between the source images [9]. To some extent, these methods can evaluate image fusion performance automatically and effectively. However, there is no established direct relationship between these evaluation measures and the real perceptual results of humans. Thus in [10], Hong *et al*. proposed a projection based objective measure for the objective evaluation of image fusion. It is with high computation efficiency and its performance is comparable with other metrics.

In this paper, we propose a novel metric for objective evaluation of pixel-level image fusion. In the scenario of ground truth images are available, We model the image quality as the differences between the directional projection-based maps, which are built by Radon transform. If the ground truth image is unavailable, we can take the fused image as the ground truth image and incorporate the differences between the sources and the fused image respectively. Compared to other metrics, our proposed metric has three contributions. First of all, we introduce this type of methodology to evaluate the performance of image fusion by comparing the difference between the fused result and input images. Secondly, We perform the evaluation on a region-by-region basis. This is more suitable for the fusion application due to that one should examine image quality at a local level rather than a global level. Finally, compared to some other metrics such as mutual information based methods, our proposed methods requires much less computation.

The organization of this paper is as follows. Section II



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TABLE I: The notation for Eqs. (1)-(7)

| | |
|---|---|
| R(m,n) | Reference image |
| F(m,n) | Fused Image |
| L | Maximum pixel value |
| $h_{RF}(i,j)$ | Normalized joint histogram of the reference image and the fused image |
| $h_R(i)$ | Normalized marginal histogram of the reference image |
| $h_F(j)$ | Normalized marginal histogram of the fused image |

is some metric expressions for image fusion algorithms. Our proposed novel image fusion metric will be elaborated in section III. Section IV will illustrate some experimental results and finally the paper is concluded in section V.

## II. Evaluation for Image Fusion

The expressions that correspond to the above metrics are listed below and the meaning of the symbols used in following equations is listed in Table 1. equations.
Root mean square error (RMSE):

$$\sqrt{\frac{\sum_{m=1}^{M}\sum_{n=1}^{N}[R(m,n)-F(m,n)]^2}{M\times N}} \quad (1)$$

Peak signal-to-noise ratio (PSNR):

$$10\log_{10}\left(\frac{L^2}{\frac{1}{M\times N}\sum_{m=1}^{M}\sum_{n=1}^{N}[R(m,n)-F(m,n)]^2}\right) \quad (2)$$

Normalized least square error (NLSE):

$$\sqrt{\frac{\sum_{m=1}^{M}\sum_{n=1}^{N}[R(m,n)-F(m,n)]^2}{\sum_{m=1}^{M}\sum_{n=1}^{N}[R(m,n)]^2}} \quad (3)$$

Correlation (CORR):

$$\frac{2\sum_{m=1}^{M}\sum_{n=1}^{N}R(m,n)\cdot F(m,n)}{\sum_{m=1}^{M}\sum_{n=1}^{N}R(m,n)^2+\sum_{m=1}^{M}\sum_{n=1}^{N}F(m,n)^2} \quad (4)$$

Mutual information (MI):

$$\sum_{i=1}^{L}\sum_{j=1}^{L}h_{RF}(i,j)\cdot\log_2\frac{h_{RF}(i,j)}{h_R(i)h_F(j)} \quad (5)$$

The difficulty of these comparison-based evaluation methods is that the reference is not always available. Moreover, in many cases, the image with similar RMSE or PSNR value may exhibit quite different quality. Thus some evaluation methods without human inspection have been developed recently. Xydeas and Petrovic have proposed a performance measure which compare the edge information of fused images with the counterpart of the input images. Their metric

$$Q_P^{A,B/F}=\frac{\sum_{m=1}^{M}\sum_{n=1}^{N}(w^A(m,n)Q^{AF}(m,n)+w^B(m,n)Q^{BF}(m,n))}{\sum_{m=1}^{M}\sum_{n=1}^{N}(w^A(m,n)+w^B(m,n))} \quad (6)$$

The effect of noise on image fusion is analyzed in their subsequent study. Qu *et al.* considered MI and directly used the summation of the MI between the fused image (F) and source images to represent the difference in quality. Here we take two source images (A and B) as example to express MI-based fusion performance measure:

$$M_F^{AB}=\sum_{i,j}h_{AF}(i,j)\log_2\frac{h_{AF}(i,j)}{h_A(i)\cdot h_F(j)} + \sum_{i,j}h_{BF}(i,j)\log_2\frac{h_{BF}(i,j)}{h_B(i)\cdot h_F(j)} \quad (7)$$

Where $h_{AF}(i,j)$ indicates the normalized joint grey-level histogram of image A and F, $h_K(i,j)$ (K=A,B,and F)is the normalized marginal histogram of image A, B, or F. However, the MI-based approach is insensitive to impulsive noise and is subject to great change in the presence of additive Gaussian noise.

Human visual system is highly adapted to structure information and a measurement of the loss of structural information can provide a good approximation of the perceived image distortion. Based on that, Wang *et al.* proposed a universal structure similarity based image quality index [7], which is defined by Eq. (8):

$$SSIM(A,B)=\frac{2\mu_A\mu_B+C_1}{\mu_A^2+\mu_B^2+C_1}\cdot\frac{2\sigma_{AB}+C_2}{\sigma_A^2+\sigma_B^2+C_2} \quad (8)$$

where $\sigma_{AB}$ is the covariance between source image $A$ and $B$ and $\mu_A$, $\sigma_A^2$, $\mu_B$, $\sigma_B^2$ are the mean and variance of $A$ and $B$ respectively. $C_1$ and $C_2$ are small constants given by $C_1=(K_1L)^2$, $C_2=(K_2L)^2$ respectively. $L$ is the dynamic range of the pixel value ($L=255$ for 8 bits/pixel gray scale images), and $K_1\ll 1$ and $K_2\ll 1$ are two scalar constants. The quality measurement is applied to local regions using a sliding window from top left to bottom right of the image. Then average the $SSIM$ over each image block to compute the final quality measure value:

$$SSIM=\sum_{k=1}^{N}(SSIM_k/N) \quad (9)$$

where $N$ is the total number of blocks. The equation above can measure the degree of linear correlation between image *i.e.*, how close the mean luminance is between source images $A$ and $B$, and how similar the contrasts of the images are. Note that the dynamic range is $[-1,1]$ and the best value "1" is achieved if, and only if the source images are identical to the fused image.

## III. Directional Projection-based Metric: DPM

For the simplicity of description, we take two input images (A and B) and one fused image (F) as an example. But it should be noted that our method can be implemented to an arbitrary number of input images. Meanwhile, each input image is registered and with size $M\times L$.

We first introduce Radon transform as follows:

$$\Re(s,\theta)[\mathbf{f}(\mathbf{x},\mathbf{y})]=\int_{-\infty}^{\infty}\int_{-\infty}^{\infty}\mathbf{f}(\mathbf{x},\mathbf{y})\delta(\mathbf{s}-\mathbf{x}\mathbf{cos}\theta-\mathbf{y}\mathbf{sin}\theta)\mathbf{dxdy} \quad (10)$$

where $\mathbf{f}(\mathbf{x},\mathbf{y})$ is a 2-D vector, s is the perpendicular distance from a line to the origin and q is the angle formed by the distance vector. Radon transform could be regarded as the projection procedure on different directions, so we name this kind of method the "directional projection". And $\Re(s,q)[\mathbf{f}(\mathbf{x},\mathbf{y})]$ is the vector of the directional projection-based map.

We divide the fused image into $K$ blocks with the block size $m \times l$, and denote the $n$th block as the vector $\bar{\mathbf{F}}_n \in \mathbf{R}^{m\times l}$. $\bar{\mathbf{DF}}_n \in \mathbf{R}^{p\times q}$ is defined as the vector of the directional projection-based map. In a similar way, we obtain the counterpart in input images of $a_n \in \mathbf{R}^{m\times l}$ and $b_n \in \mathbf{R}^{m\times l}$, which denoted as $\bar{\mathbf{da}}_n \in \mathbf{R}^{p\times q}$ and $\bar{\mathbf{db}}_n \in \mathbf{R}^{p\times q}$. They are computed as follows:

$$\bar{\mathbf{DF}}_n = \Re(s,\theta)[\bar{\mathbf{B}}_{\mathbf{n}}] \tag{11}$$

$$\bar{\mathbf{da}}_n = \Re(s,\theta)[\bar{\mathbf{a}}_{\mathbf{n}}] \tag{12}$$

$$\bar{\mathbf{db}}_n = \Re(s,\theta)[\bar{\mathbf{b}}_{\mathbf{n}}] \tag{13}$$

Define the local sensitive intensity as $FA_n$ and $FB_n$ as follows:

$$\bar{\mathbf{FA}}_n = \|\bar{\mathbf{DF}}_n - \bar{\mathbf{da}}_n\| \tag{14}$$

$$\bar{\mathbf{FB}}_n = \|\bar{\mathbf{DF}}_n - \bar{\mathbf{db}}_n\| \tag{15}$$

The global distortion intensity $FA$ or $FB$ is simply calculated as the mean of the local sensitive intensity

$$\mathbf{FA} = \mathbf{mean}(\mathbf{FA_n}), \mathbf{FB} = \mathbf{mean}(\mathbf{FB_n}) \tag{16}$$

Here we carefully propose that our predictive score of objective quality is a logarithmic function of the sensitive intensity which obeys the Weber-Fechner law [5] (a constant relative difference in the intensity corresponds to a constant absolute difference in the logarithm of the intensity). Therefore, the image quality measure by using directional projection $(DP)$ is defined as:

$$\mathbf{DPM} = \mathbf{log}(\mathbf{FA}\cdot\mathbf{FB}) = \mathbf{log}(\mathbf{FA}) + \mathbf{log}(\mathbf{FB}) \tag{17}$$

and it is clear that both $DPM$ are greater than zero.

In this work we build the directional projection-based maps based on Radon transform. The differences of the maps are desired to represent the variation of the images degradation, which model the sensitiveness of image content variation. The actual value is meaningless, but the comparison between two values for different fused images gives one measure of quality. The lower the predicted score of $DPM$ is, the better the image quality is.

## IV. Experimental Results and Discussion

In this section, we illustrate the utility of the proposed image fusion quality metric by applying to evaluate image quality obtained from different fusion scheme and make comparison with other quality metrics. Here, the logarithm in Eq. (17) adopt nature logarithm and each block size is equal to $8 \times 8$.

In the first experiment, two images with different localized artificial distortion are tested[1]. The introduced distortion can model several different types of degradation that may occur in visual sensor imaging, such as motion blur, out-of focus blur and finally shape distortion, due to low bit-rate transmission or channel errors. The ground truth image enable us to perform reference-based image fusion quality evaluation, which includes PSNR, RMSE, NLSE and CORR.

The artificially distorted images are fused by seven combinations of transforms and fusion schemes. Here we focus on independent component analysis (ICA) based fusion methods [12][13]. Images fused by derivative of ICA and different fusion rules, i.e., topographic ICA (TopoICA), topographic ICA with "mean" rule (TopoICA_m) and topographic ICA with "weight combination" rule (TopoICA_w) are illustrated in Fig. 2(f)-(i). Here, ICA and TopoICA bases are trained by 10000 $8 \times 8$ image patches selected randomly from 10 images of similar content to the ground truth and 40 out of the 64 possible bases are used to perform the transformation in either case [13]. Meanwhile, we select Wavelet Package (WP) decomposition (Sym 7 bases) with five-levels decomposition using Coifman-wickerhauser entropy [2] and Dual-Tree Wavelet Transform (DTWT) with four-levels of decomposition [3] for comparison. The fused result by WP and DTWT are illustrated in Fig. 2(d) and Fig. 2(e) respectively. The images fused by the methods above mentioned are firstly evaluated by the criteria: RMSE, NLSE, CORR and PSNR. Discarding the ground truth image, we also employ Qu's mutual information (MI), Piella's fusion quality index (SSIM), Xydeas' objective performance measure, projection based metric (PM) and our proposed directional projection based metric (DPM) to assess the fusion results.

The objective evaluation results are given in Table 1. It is composed of two parts. Ones is the result from the reference-based assessment; the other is from the metrics of blind assessment. The reference-based assessment is carried out by comparing with ground truth image and can indicate which fusion algorithm is the best. Meanwhile, we can further validate the blind metrics with such knowledge. In the case of the assessment with a reference image, we can see the TopoICA_m fusion algorithm is superior to others as it seems to balance the high detail with the low-detail information. We can see that the objective evaluation is consistent with the visual quality (see Fig. 2(i)). TopoICA_w scores second to TopoICA_m but better than others. The image fused by TopoICA_w (see Fig. 2(h)) seems sharper with correct constant background information. The TopoICA bases scores better than normal ICA base mainly due to better adaptation to local features [13]. WP (Sym7) and DTWT is inferior to other fusion algorithm. We can see "blur" and "ringing" artifacts clear in Fig. 2(d) and (e) respectively. In case of metric without reference, TopoICA_w is selected best by PM and our proposed DPM method. The performances above demonstrate the effectiveness of our proposed evaluation method.

The second experiments will focus on four existing image fusion algorithms:discrete wavelet transform based fusion [3],

[1]Downloaded from http://www.commsp.ee.ic.ac.uk/ nikolao/research.htm

[2]WaveLab v8.02, available at http://www-stat.stanford.edu/wavelab/

[3]Code available online at http://taco.poly.edu/WaveletSoftware/

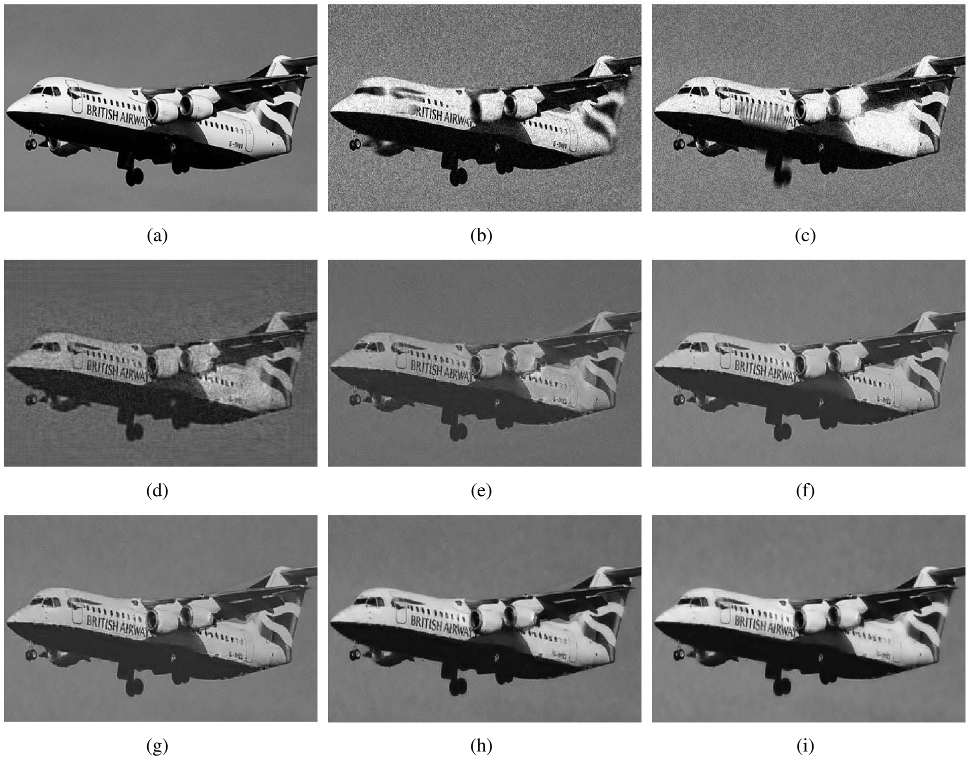


Fig. 1: Artificial distorted image fusion quality metrics : (a) original image, (b)-(c) distorted images, (d)-(i) are fused images using (d) wavelet package (Sym7), (e) dual-tree wavelet, (f) independent component analysis (ICA), (g) topographic ICA, (h) topographic ICA with weight combination fusion rule, (i) topographic ICA with mean fusion rule.

TABLE II: Comparison of different quality measures for the fused images in Fig. 2

| Metric | WP (Sym7) | DTWT | ICA | TopoICA | TopoICA_w | TopoICA_m |
|---|---|---|---|---|---|---|
| RMSE | 35.7257 | 32.9745 | 24.6243 | 23.7982 | 21.9450 | **20.2910** |
| NLSE | 0.2711 | 0.2502 | 0.1868 | 0.1806 | 0.1665 | **0.1539** |
| CORR | 0.9551 | 0.9639 | 0.9819 | 0.9828 | 0.9851 | **0.9878** |
| PSNR | 17.0713 | 17.7675 | 20.3042 | 20.6216 | 21.3040 | **21.9857** |
| MI | **1.817** | 1.8035 | 1.7903 | 1.7909 | 1.8031 | 1.8028 |
| SSIM | 0.1682 | 0.1785 | 0.2123 | **0.1957** | 0.1785 | 0.1738 |
| Xydeas | 0.1462 | 0.1478 | **0.1846** | 0.1815 | 0.1327 | 0.1314 |
| PM | 2.3935 | 2.3463 | 2.1884 | 2.1765 | 2.0158 | **1.9018** |
| DPM | 1.4236 | 1.2245 | 0.9610 | 0.9413 | 0.8566 | **0.6824** |

biorthogonal multiwavelet based fusion [16], pyramid transform based fusion [17] and first order contrast based fusion [15]. Because that in this study, we aim to the image quality metric but not on a thorough evaluation of different image fusion algorithms. All the source images are downloaded from [18].

The first algorithm is "discrete wavelet transform (DWT)" [3], where the input source images are decomposed using a Daubechies wavelet filter with filter length 4 ("db2" in Matlab), the coefficients of the fused image are computed by choosing the corresponding coefficients of source images with largest amplitude in the wavelet domain and by averaging the coefficients of lowest resolution. The number of decomposition levels equals to 3. This fusion algorithm emphasizes the edge information in the fused image. One other fusion algorithm is based on "biorthogonal multiwavelet transform (BMWT)" [16], where the one level decomposition with GHM base is performed on source images. Then "average and selection" fusion rule generated the composite wavelet coefficients. The third fusion algorithm is "pyramid transform" based method where the input image are decomposed using a ratio pyramid decomposition and the fused image is reconstructed by averaging the low resolution components and selecting the coefficients with the largest amplitude for the rest of the coefficients , the number of decomposition levels is 2 [17]. The final fusion algorithm is a "first order contrast (FOC)"

Fig. 2: Source images acquired by multiple types of sensors.

based method [15]. This method measure the salience map of each source and then compute the importance weight based on the saliency. Then use the weighted gradient to construct the ”contrast form”, and thus gradients with high saliency are properly highlighted in the target gradient. Finally, the fused image is reconstructed from the target gradient field by variational method. In this way, salient features in the sources are well preserved.

Discrete wavelet, pyramid transform and biorthogonal multiwavelet transform are multi-resolution based methods, which are designed to keep the detail information from the source images. However, the artifacts of ”ringing” effects are inevitably introduced by the non-linear operation on the wavelet coefficients, such as ”maximum selection” rule. It can be depressed by adopting appropriate fusion rules and other postprocessing, which include consistency validation and so on. First order contrast based fusion can preserve the salient features in source images and displays superior performance than other fusion methods. But it should be noted that the latter's computation cost is comparatively higher the former methods. Figure 2 displays the fused images of one pair of remote sensing images by the method described above. It is clear that the Fig. 2(f) shows better texture information and more details than others. Meanwhile, the ”ringing” effect is more severe in Fig. 2(c), which is fused by DWT method.

Several other fusion quality metrics such as standard deviation (SD), mutual information (MI) [5], Xydeas proposed ($Q^{ABF}$) [4], together with our proposed method are tested in our experiment. Figure 3 shows the objective evaluation results on eight pairs of source images using the metrics list above. From Fig. 3(a), we see the SD metrics of FOC and BMWT are less than other two methods. It is consistent with the subjective evaluation owing to that lower SD value corresponds to the variance of spectral information between source images and the fused result. The Xydeas proposed metric scores FOC higher that others, which is similar to the SD metric and subjective evaluation (see Fig. 3(b)). The BMWT based fusion method is ranked highest while FOC is lowest in Fig. 3(c), which is contradictory to the above two metrics. Figure 3(d) is the objective evaluation by our proposed directional projection based metric. We can see that the FOC scores higher than other fusion methods, which is consistent with perceptually obtained results and comparable with SD and Xydeas proposed metric.

## V. Conclusions

In this paper, a directional projection based metric for the objective evaluation of pixel-level Image fusion is proposed. We convert the input images and the result image pair into LSI by Radon transform. Then measure the difference between input images and fused image pairs by LSI. Different from other objective evaluation methods, our proposed metric firstly introduce this type of methodology to evaluate the performance of image fusion by comparing the difference between the fused result and input images. Moreover, less computational cost is needed in our method. The experiments demonstrated that this metric corresponds well to subjective judgement and outperforms some other objective evaluation metrics.

But it should be emphasized that this method together with the method proposed in [10] just aim to probing into the objective image fusion algorithms. Most existing metrics use image quality method to evaluate the image fusion. Actually there are some differences between them. In image fusion algorithm metric, it should be more emphasized that how much useful information have been transferred to the fused result and whether the quality of the fused image has been enhanced. Nevertheless, image quality with reference is focusing on the discrepancy between the fused result and the reference image. In this scenario, some objective metrics can be proposed to measure such kind of discrepancy. Thus in the future works, objective metric for image fusion algorithm should focus on the goal of the image fusion. We believe that after understanding the goal of fusion, more promising solutions will be proposed.

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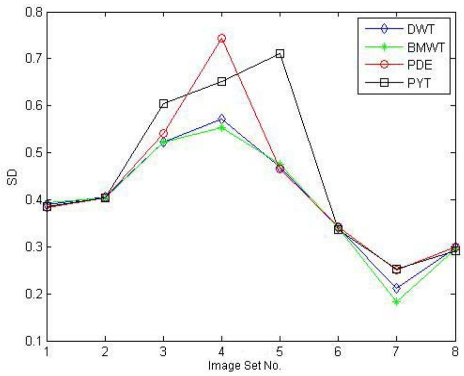
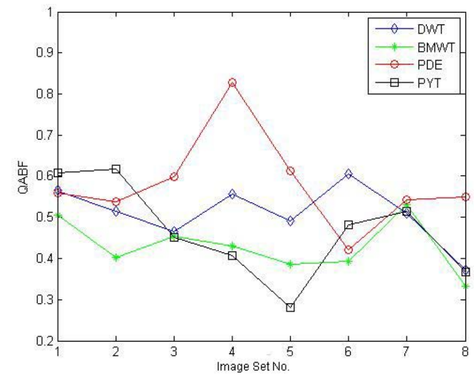
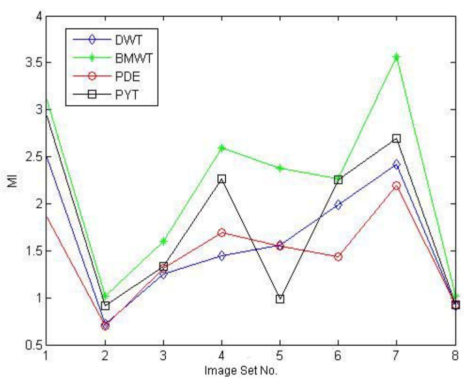


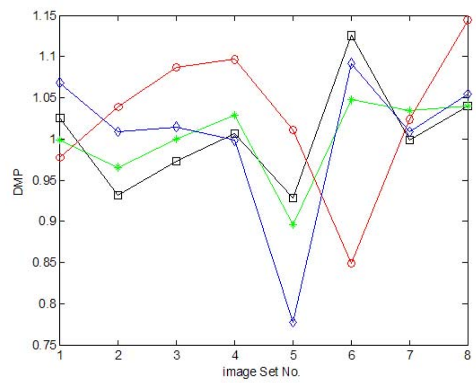

(a)




(b)




(c)




(d)

Fig. 3: Eight sets of image fusion performance metric by (a) standard deviation (SD), (b) Xydeas proposed ($Q^{ABF}$), (c) Mutual information (MI), (d) our proposed method (DMP).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