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Directional projection based image fusion quality metric

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ABSTRACT

In the past few decades, image fusion and its performance evaluation have attracted considerable research attention. However, it is still hard to objectively evaluate the fusion performance due to the diversity of image sources and the motivations for fusion. In this paper, we extend the work in image quality evaluation [8] to a novel metric for objective evaluation of image fusion. The input images and the fused image are firstly converted into local sensitive intensity (LSI) by Radon transform. We then employ the sensitive intensity for measuring how much information have been transferred from each source into the fused result by the difference of LSI. All the LSI pairs are finally incorporated into the expression according to the Weber–Fechner law. Experimental results demonstrate that our proposed metric outperforms other metrics while it is consistent with the subjective evaluation.

1. Introduction

Image fusion, which is taken as a branch of the information fusion, has attracted considerable research attention in the past few decades [3,7,15,23,27]. It is able to enhance the information in the respective source images, as well as increase the reliability of interpretation. Therefore it is employed in many fields such as remote sensing, medical diagnostics and machine vision. In general, image fusion can take place on pixel, feature, and decision levels. Pixel-level fusion can be seen as combination based fusion while the other two can be seen as classification based fusion. It is urgent to design effective metric for the evaluation of the fusion performance as more and more fusion algorithms are designed.

Intuitively image fusion performance can be assessed by informal subjective preference tests, which is the most reliable and trusted method. In [8], the audience of potential users is employed to evaluate a fusion system. But there are many disadvantages such as that it is expensive and difficult to reproduce and verify. Hence, objective image fusion performance metrics that are consistent with human visual perception appear as the valuable alternatives. A common idea is to propose an objective evaluation which has the ground-truths and take them as the references for comparison with the experimental results [28]. The widely used metrics for these comparisons include the correlation (CORR), the mean squared error (MSE), the root mean square error (RMSE), the normalized least square error (NLSE) and the peak signal-to-noise ratio (PSNR) etc.

However, the ground-truths are not available in many applications. Qu et al. propose to evaluate the image fusion performance by using mutual information (MI) [6]. Mutual information defines the amount of information that the fused image contains from the input one, and describes the similarity of the image intensity distributions between the corresponding

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image pairs. But it does not correlate well with the subjective quality of the fused image. Xydeas et al. propose to evaluate the performance by comparing the edge information between the fused image and the source images, then use it to calculate the effect of noise [4,29]. Based on the image quality index in [30], a new fusion quality index is given by Piella et al. which evaluates how much of the salient information contained in each of the input images has been transferred into the fused one without introducing distortions [33]. Yang et al. propose a metric that performs different operations while evaluating different local regions according to the similarity level between the source images [5]. To some extent, these methods are able to automatically and effectively evaluate the performance of image fusion. However, there is few established direct relationship between these evaluation measures and the real perceptual results of humans. Thus in [24], Hong propose a projection based objective measure for the quantitative 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 quantitative evaluation of the pixel-level image fusion. In the scenario of that the 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. Our method differentiates itself from other metrics with respect to the following 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 the 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 method requires much less computation.

The organization of this paper is as follows. We present some metric expressions for image fusion algorithms in Section 2. Our proposed novel image fusion metric is elaborated in Section 3. Section 4 illustrates some experimental results and the paper is finally concluded in Section 5.

2. Evaluation for image fusion

As described above, many image quality based metrics are employed for evaluating the performance of image fusion. Here we list some widely used metrics such as the correlation (CORR), the mutual information (MI), the root mean square error (RMSE), the normalized least square error (NLSE) and the peak signal-to-noise ratio (PSNR) as follows. Table 1 contains the meaning of the symbols used in following equations. The first common image quality metric is PSNR.

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

The unit of PSNR is dB. It ranges from 0 to infinity. If the value is high, the image quality is high. RMSE is the root mean square error. We can see that when white Gaussian noise is added to the image, its RMSE value retain unchanged. It means that the metric fails to evaluate the image quality in many cases. It is same to the metric of NLSE.

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

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

CORR indicates the correlated content between the source and the reference image while MI measures the quantity of mutual dependence of the two random variables.

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

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

Table 1
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 $R(m,n)$ and $F(m,n)$
$h_R(i)$	Normalized marginal histogram of the $R(m,n)$
$h_F(j)$	Normalized marginal histogram of the $F(m,n)$