An Objective Quality Metric for Image Fusion based on Mutual Information and Muti-scale Structural Similarity

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***Abstract*—An objective image quality assessment method for image fusion based on mutual information and multi-scale structural similarity is presented. A simplified formula was deduced to compute the information amount transformed from the source images to the final fused image. With this formula we managed to resolve the overlapping information problem immediately and predigested the calculation extremely. Moreover we adopted the mutual information and the multi-scale structural similarity metric to image fusion schemes, and put forward a novel performance evaluation method without the interference of the reference image. Experimental results show that the proposed metric is well correlated with human subjective evaluations and thus can be used to distinguish the performance of different fusion methods.**

***Index Terms*—Image Quality Assessment (IQA), Image Fusion, Mutual Information (MI), Multi-scale Structural Similarity (MSSSIM)**

I. INTRODUCTION

Image fusion has become an important issue in image analysis and computer vision area during the last decade[1-3]. It provides an efficient way to merge the visual information from different images about a certain scene obtained by two or more imaging equipments. The fused image contains complete information for better human or machine perception and computer-processing tasks. The widespread use of image fusion methods in military applications, medical diagnostics, etc, has led to a rising demand of performance evaluation measures to compare the results obtained by different algorithms or to optimize the parameters for specific fusion methods.

The performance evaluation methods of image fusion are generally classified into two categories: subjective measures and objective measures. Subjective tests are often time consuming and expensive, while the exact same conditions for the test cannot be guaranteed [4]. For this reason, much attention had been put on objective measures in order to exactly distinguish the performance of different image fusion approaches. However, objective assessment is a difficult issue due to the variety of different application requirements and the lack of clearly defined ground-truth [5].

Although various quantitative models of image quality have been proposed, methods based on information theory and structural similarity [6] had been generally accepted. Entropy had been often used to measure the information content of an image. Mutual information (MI) is employed for evaluating fusion performance by QU et al [7] which use the sum of mutual information between each sources and the final fused image. Cvejic [8] used Tsallis entropy as the fusion performance metric. Zheng [9] managed to measure the fused image with Renyi entropy which could reduce the influence of overlapping information. In order to resolve the overlapping information problem, Vassillis Tsagaris [4] employed mutual and condition mutual information to represent the amount of information transferred from the source images to the final fused image. Based on the assumption that the HVS is highly adapted to exact structural information from the viewing field, Wang and Bovik had proposed an image quality metric named SSIM [6]and developed it into muti-scale SSIM (MSSSIM)[10,11] and information content weighting SSIM (IWSSIM)[12]. But in applications, for there are always no reference images, SSIM is not practical in image fusion. Setting aside the reference image, Piella [5] adopted SSIM to image fusion applications and gave some good quality metrics. Anish

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Mittal [13] proposed a completely blind image quality assessment, called Natural Image Quality Evaluator (NIQE), could also be used to predict the quality of fused images.

Mutual information defined in [7] had caused the overlapping information problem. Though Vassillis [4] considered the common information contained in the source and the result only once, the computation seemed very complicated, especially for multi inputs. The paper looked on all the inputs as a unity one and gives a simplified formula to represent the mutual information between the sources and the final fused image. Wang [12] had found information content weighting led to consistent improvement in the performance of IQA algorithm, and the overall performance is achieved by combining information content weighting with MS-SSIM. Based on the pooling methods proposed in[12] , we managed to get rid of the interference of the original image, integrated the mutual information with the multi-scale structural similarity metric, and put forward a novel performance evaluation metric for image fusion. Experimental results show that the proposed metric is compliant with human subjective evaluations and has a prior performance to the other metrics such as the Piella's metric and NIQE in different applications.

II. Mutual Information

A. Rlated Work

Each source image or the final image is considered as being a discrete random variable. The entropy $H(X)$ for a discrete random variable X , is defined as

$$H(X) = -\sum p(x)\log p(x) \tag{1}$$

Where $p(x)$ is the probability density function of the variable X . The joint entropy $H(XY)$ for a pair of random variables X, Y with joint distribution $p(xy)$ is defined as

$$H(XY) = -\sum\sum p(xy)\log p(xy) \tag{2}$$

The conditional entropy of variable X given Y is

$$H(X/Y) = -\sum\sum p(xy)\log p(x/y) \tag{3}$$

The common information shared between variable X and Y i.e. the mutual information t is defined as

$$I(X;Y) = \sum\sum p(xy)\log\frac{p(xy)}{p(x)p(y)} \tag{4}$$

For image fusion, there are always multi resource images denoted by $X_1, X_2, ..., X_l$ being fused into a final image Y .Then the common information shared between inputs and outputs was defined by [QU 2002] as

$$CI_1 = \sum I(X_i, Y) \tag{5}$$

By (5) the common information contained in the source and the result may be computed not only once. This had lead to the overlapping information problem. Vassillis Tsagaris [4] employed mutual and condition mutual information to represent it as follow

$$\begin{aligned} CI_2 &= I(X_1;Y) + I(X_2;Y/X_1) \\ &+ ... + I(X_l;Y/X_{l-1},....X_1) \end{aligned} \tag{6}$$

B. The Simplified Formula

Here, we put all the inputs as an unity, denoted by $U = \{X_1, X_2, ..., X_l\}$, Then $H(U) = H(X_1X_2...X_l)$ is the joint entropy of all the inputs, and the common information between the inputs and the fused image can be obtained by

$$\begin{aligned} CI_3 &= I(U;Y) \\ &= H(U) + H(Y) - H(UY) \\ &= H(X_1X_2...X_l) + H(Y) - H(X_1X_2...X_lY) \end{aligned} \tag{7}$$

Actually, (6) and (7)is equivalent. Taking the case of two inputs as an example, we can get by (6)

$$CI_2 = I(X_1;Y) + I(X_2;Y/X_1) \tag{8}$$

Here, Where the condition MI is

$$I(X_2;Y/X_1) = \sum\sum\sum p(x_1x_2y)\log\frac{p(x_2y/x_1)}{p(x_2/x_1)p(y/x_1)} \tag{9}$$

Because $p(xy) = p(x)p(y/x)$, then the part of the logarithm in (9) can be calculated as

$$\frac{p(x_2y/x_1)}{p(x_2/x_1)p(y/x_1)} = \frac{p(x_1x_2y)p(x_1)}{p(x_1x_2)p(x_1y)} \tag{10}$$

Substituting (10) to (9), we can obtain

$$\begin{aligned} I(X_2;Y/X_1) &= H(X_1X_2) + H(X_1Y) \\ &- H(X_1X_2Y) - H(X_1) \end{aligned} \tag{11}$$

From (6),(7),(8),(11), we can get

$$CI_2 = H(Y) + H(X_1X_2) - H(X_1X_2Y) = CI_3 \tag{12}$$

Similarly, for more inputs, the same results can be deduced. Comparing with (6), the formula of mutual information in (7) is more intuitive and easier to calculate. Furthermore, the formula can be widely used in other applications where mutual information between multi variables needed.

III. Image Quality Metric Proposed

A MS-SSIM

Multi-scale structural similarity was introduced by Wang and Bovik [12] to measure the structural distortions of two images. The basic spatial domain SSIM is based on separated comparisons of local luminance, contrast and structure between the reference image and the distorted image to be evaluated. Given two local image patches x, y , extracted from the reference image and the distorted one, respectively, the luminance, contrast and structural similarities between them are evaluated as

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$$l(x,y)=\frac{2\mu_x\mu_y+C_1}{\mu_x^2+\mu_y^2+C_1}$$
$$c(x,y)=\frac{2\sigma_x\sigma_y+C_2}{\sigma_x^2+\sigma_y^2+C_2} \quad (13)$$
$$s(x,y)=\frac{\sigma_{xy}+C_3}{\sigma_x+\sigma_y+C_3}$$

And the local SSIM index is defined as

$$SSIM_{local}=\frac{(2\mu_x\mu_y+C_1)(2\sigma_{xy}+C_2)}{(\mu_x^2+\mu_y^2+C_1)(\sigma_x^2+\sigma_y^2+C_2)} \quad (14)$$

Here μ_x , σ_x and σ_{xy} represent the mean, stand deviation and cross-correlation evaluations, respectively. C_1 , C_2 , $C_3=C_2/2$ are small constants that have been found useful when the denominators are close to zero.

A multi-scale SSIM (MS-SSIM) approach was proposed that incorporates SSIM evaluations at different scales. Let $x_{i,j}$ and $y_{i,j}$ be the *j*th local image patches (extracted from the *j*th evaluation window) at the *i*th scale, and let N_i be the number of evaluation windows in the scale, then the *i*th scale SSIM evaluation is computed as

$$SSIM_i=\begin{cases}\frac{1}{N_i}\sum_j c(x_{i,j},y_{i,j})s(x_{i,j},y_{i,j}) & i=1,\dots M-1\\ \frac{1}{N_i}\sum_j l(x_{i,j},y_{i,j})c(x_{i,j},y_{i,j})s(x_{i,j},y_{i,j}) & i=M\end{cases} \quad (15)$$

The MS-SSIM measure is defined as

$$MS-SSIM=\prod_{i=1}^{M}(SSIM_i)^{\beta_i} \quad (16)$$

Where the values β_i were obtained through psychophysical measurement.

B Pooling of the Local Quality Measures

Many state-of-the-art perceptual image quality assessment algorithms can be thought as a two–stage structure: local quality measurement followed by pooling [12]. While significant progress has been made in the first stage, much less is under stood about the pooling stage. The pooling stage is often done in ad-hoc ways, lacking theoretical principles and reliable computational models. The Minkowski pooling, local quality based polling, saliency-based polling and object-based pooling are the existing poling approaches. In the paper, in order to employ the mutual information content, the saliency-based method is used. The pooling rule can be denoted as follow.

$$Q=\frac{\sum_i^N w_i q_i}{\sum_i^N w_i} \quad (17)$$

Where w_i is the local information content weighting which denotes the local image perceptual significance, and q_i be the local quality value, N is the total number of local windows divided.

C The Proposed Metric for Image Fusion

Considering of image fusion, there is always no reference image. Based on Peallia and Wang's work, as MI is concerned, the paper gives a novel image quality metric.

Let A,B and F denote the two source image and the fused image respectively. The procedure of the proposed method can be illustrated as follow:

Firstly, all of them are divided into N patches. For the *i*th patch, the local MS-SSIM $MSAF_i, MSBF_i$ between A,B and F can be calculated by (16). Then the local weight indicating the relative importance of image A compared to image B can be calculated as follow

$$\lambda_i=\frac{MSAF_i}{MSAF_i+MSBF_i} \quad (18)$$

Then the local quality is

$$q_i=\begin{cases}MSAF_i & \lambda_i>0.5 \text{ and } MSAF_i>T\\ MSBF_i & \lambda_i<0.5 \text{ and } MSBF_i>T\\ (MSAF_i+MSBF_i)/2 & \text{otherwise}\end{cases} \quad (19)$$

Here, T is the threshold. In case $\lambda_i>0.5$ *and* $MSAF_i>T$, it indicates the *i*th patch of A and F is approximate closely and $MSAF_i>MSBF_i$. So the *i*th patch of A can be looked on as the reference resource for the *i*th patch of the fused image.

And the local information content weighting denoted by the corresponding proportion of MI to the entropy of the resource is obtained by

$$w_i=\begin{cases}I(A;F)/H(A) & \lambda_i>0.5 \text{ and } SAF_i>T\\ I(B;F)/H(B) & \lambda_i<0.5 \text{ and } SBF_i>T\\ I(U;F)/H(AB) & \text{otherwise}\end{cases} \quad (20)$$

Here, $U=\{A,B\}$ and $I(U;F)$ can be calculated by (7).

Finally, substituting (19), (20) into (17), the quality metric of the whole image can be obtained.

IV. EXPERMENTAL RESULTS

To test the effectiveness of the proposed fusion quality metric, we applied it to different fusion methods and compared it with the other existed objective metrics.

The multi-resolution (MR) based fusion approaches such as the Laplacian Pyramid, the gradient pyramid and

TABLE I.
COMPARISON FOR THE FISRT TEST

Metrics	Average	Laplacian	Gradient	SIDWT	Orignal
MI_1	0.7147	0.7464	0.5138	0.7010	0.8877
MI_2	0.6491	0.5443	0.4266	0.5365	0.6164
Pellia	0.8975	0.9046	0.8752	0.9036	0.9081
NIQE	19.11	26.69	27.11	27.17	24.94
Proposed	0.9556	0.9882	0.9587	0.9863	0.9920
IWSSIM	0.9565	0.9937	0.9496	0.9912	1
Rank	5	2	4	3	1

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the spatially-invariant wavelet transform (SIDWT) are used here. In all cases, a 4-level decomposition are performed, and the coefficients with maximum absolute value of the MR decompositions of each input at each position were selected for the fused image, except for the approximation coefficients from the lowest resolution where the average value were chosen. For comparison, the simple fusion method of averaging the input images was also used. The other objective metrics selected here for comparison are MI_1 , MI_2 defined by (5) and (7) respectively, Piella's metric [5], IWSSIM [12] and NIQE [13]. Note here the value of MI_1 , MI_2 being divided by the joint entropy of the inputs, so all of them takes values in the range $[0,1]$.

First, we perform our experiment in case the original image available. The two input images had been created by blurring the original 'cameraman' image of size 256×256 with a disk diameter of 8 pixels, and the blurring occurred at the left half and the right half respectively. The fused images are obtained by the four fusion methods described above. TABLE Ⅰ compares the quality of these fused images using different quality measures and gives the human subjective ranks. We also use these measures to evaluate the quality of the original image. We can see that most of them give the highest score to the original image except MI_2 and NIQE.

TABLE II.
COMPARISON FOR THE SECOND TEST

Metrics	Average	Laplacian	Gradient	SIDWT
MI_1	0.5842	0.5826	0.5235	0.5635
MI_2	0.6048	0.4205	0.3834	0.4189
Pellia	0.8518	0.8852	0.8553	0.8496
NIQE	7.3637	37.1759	8.3109	7.6396
Proposed	0.9523	0.9817	0.9691	0.9783
Rank	4	1	3	2

Piella's metric, IWSSIM and the proposed metric are all well correlated with the subjective rank.

The second test is performed without the original image for multi-focus image fusion. The two input images are the left and right focus test image 'Label'. The fused images are obtained by the same way as the first test. TABLE Ⅱ compares the quality of these fused images using MI_1 , MI_2 Piella's metric, NIQE and the proposed one. For there is no reference image, IWSSIM is not suited here. The subjective rank is also displayed in Table 2. Here we can see that although NIQE, Piella's metric, and the proposed method all give the highest score to the Laplacian method, the proposed method is prior to the others in the sense of keeping coherent with the subjective rank.

Finally, the same test is conducted on the computer tomography (CT) image and a magnetic resonance image (MRI) for medical application. We repeat the same computations as described in the second test. The results are shown in TABLE Ⅲ. Again, the subjective visual evaluation is consistent with the proposed quality metric as shown in Table 3. Note here MI_2 is obviously larger than MI_1, that means the interaction information can be negative. Therefore, the conditional MI is variable in theory, but the result may not be satisfied in practice [9].

TABLE III.
COMPARISON FOR THE THIRD TEST

Metrics	Average	Laplacian	Gradient	SIDWT
MI_1	0.5885	0.2933	0.3428	0.2960
MI_2	0.6826	0.3534	0.3992	0.3552
Pellia	0.2224	0.3598	0.2478	0.3051
NIQE	6.6588	5.8053	5.8617	5.6283
Proposed	0.6635	0.6786	0.7170	0.6845
Rank	4	3	1	2

V. CONCLUSION

In this paper we have simplified the formula of common information shared between the inputs and the final fused image. The formula are easy to calculate and applicable to other fields where mutual information between various variables needed. We also discussed a new objective quality metric for image fusion which does not require a reference image and shows better performance than the other existing measures. In the future, we will conducted more test in various applications and improve the performance of our method. Moreover we also plan to apply our metric in different image fusion schemes as a guide to optimize the parameters and improve the fusion performance.

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