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SHORT COMMUNICATION

A new image quality metric for image fusion: The sum of the correlations of differences

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ABSTRACT

Measuring the quality of fused images is a very important stage for image fusion applications. The fused image must comprise maximum information from each of source images of the same scene taken by different sensors. Therefore, the amount of the information gathered in the fused images reflects the quality of them. This paper proposes a new quality metric by making use of this knowledge. The metric employed to compare the performance of different image fusion algorithms. In the experiments, subjective correspondence of the proposed metric and several well-known metrics are compared. Experimental results show the feasibility of the developed metric.

1. Introduction

The aim of the image fusion is to produce a more informative single image by transferring the complementary information from the images of the same environment acquired by different sensors. Image fusion can be used in different areas such medicine, optics, security, microscopy, etc. [1–5]. The success of fusion techniques depends on the fused image quality. Therefore, the quality assessment of the fused images is an important issue in this field.

The quality assessment of the fused images can be implemented by subjective or quantitative tests. The majority of evaluation methods developed so far have depended on human intervention consequently have the drawbacks of being time consuming, not performed in real time, expensive and irreproducible. Hence, an objective and automatic evaluation metric is required. These metrics rely on different approaches, all of which aim at performing evaluation as close human evaluation as possible.

In the literature, several quality metrics have been proposed. Quality metrics as "standard deviation" and "spatial frequency" estimate the quality by evaluating the fused image. Typically, these metrics provide a measure of dispersion of the fused image intensity [6]. However, the quality of the fused image also depends on the source images. Therefore, these approaches are ordinarily deficient to provide adequate information about the quality.

Another type of approach for quantitatively qualifying the fused images is based on generating a reference image that illustrates the ideal fused image. This type of metrics such as "mean square error" (MSE), "peak-signal-to-noise ratio" (PSNR) and "structural similarity" (SSIM) use the reference image and the fused image to determine the quality [2,7]. However, generally, the ideal reference is not available since construction of it is very difficult or impossible in most cases. Also, if the ideal fused image is available, there is no need to perform a fusion process on the input images.

In the literature, also, there are frequently used quality metrics that take into account the source images and the fused image without requiring a prior processing and the reference image. One of them is "quality of edges" (QE) metric that provides a framework to compute the edge information transferred from source images via Sobel operators [8]. In this metric, artificial edges occurred in the fused image affect the evaluation. Another popular metric is the "mutual information" (MI) that determine how much information is obtained from the source images [9]. Some improved versions of *MI* have also been proposed in the literature [10,11]. One of them is "nonlinear correlation information entropy" (NCIE) that measure nonlinear correlation between the source images and the fused image [10]. In [11], authors have proposed "shared chain mutual information" (SCMI) based quality metric. Beside of them, "feature mutual information" (FMI) is proposed to detect quality of the fused image by using MI [12].

In many cases, quantitative results of the metrics are not compatible with each other. Since, the problem is handled with different aspects. In addition to that, the metrics may produce inconsistent results with the visual evaluations [13]. Therefore, developing an image quality metric of which results should be consistent with those of the subjective evaluation is very essential.

In this paper, a new image quality metric is proposed based on the correlation between the difference images computed by employing the source images and the fused image. Instead of

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evaluating the fused image quality by directly employing the correlations between the source images and the fused image, the proposed metric computes the quality by considering the source images and their impact on the fused image. The metric does not comprise complex formulation and can be implemented easily.

The rest of the paper is organized as follows: Section 2 describes the proposed metric. In Section 3 experimental results are discussed and finally, the conclusion is presented.

2. The fusion methods

This section briefly presents the image fusion methods used for the comparisons in the experiments carried out in this paper. The methods are the well-known multiresolution transform based methods in the literature.

The Laplacian pyramid (LP) consists of a series of filtered and subsampled versions of the original image. The first level is produced by using the original image. To construct a level of LP, procedures of blurring, reducing image size, interpolating and differencing are employed successively on the previous pyramid level [2]. These procedures are repeated until the intended level of the pyramid is reached.

A gradient pyramid is constructed by employing a gradient operator to the filtered versions of the original image [14]. For the nth level of pyramid, the original image is filtered by a low-pass filter and down sampled n times. After that, gradient operator is implemented in the horizontal, vertical and diagonal directions. Thus, at each level, four sub-bands are produced.

In the morphological pyramid (MP), the features of the images are extracted by use of morphological filters such as opening, closing and dilation [15]. MP uses the same steps of LP. The only difference between them is the filters used for blurring.

The usage of local luminance is the main idea behind the contrast pyramid (CP) [16]. The CP is generated by the ratio of each successive level of Gaussian pyramid which constructed like LP by using low-pass or Gaussian filters.

The basic processes of the pyramid based image fusion are as follows: First of all, the source images are transformed to a pyramid. At each level of the pyramid, then, the fusion is implemented by selecting maximum coefficients from corresponding positions. Finally, the fused image is reconstructed by performing an inverse pyramid transform.

3. The quality metrics

This section explains image quality metrics used in the experiments. The reason for choosing them is that they employ the same strategy as the proposed metric. As is the case for the proposed metric, these metrics assesses the fused image quality by evaluating the source images and the fused image together without requiring a prior processing and the reference image.

3.1. Quality of edge (QE)

QE is one of the quality metrics that generates a quantitative quality value by employing source images and the fused image. As human perception is very sensitive to edge information, the metric makes use of this information transferred from the source images to the fused image via the edge information preservation values which can be calculated as:

$$Q^{\mathrm{AF}} = Q_g^{\mathrm{AF}}(i,j)Q_\alpha^{\mathrm{AF}}(i,j) \tag{1}$$

where $Q_g^{\mathrm{AF}}(i,j)$ and $Q_\alpha^{\mathrm{AF}}(i,j)$ are the edge strength and the orientation preservation values that derived from edge strength and orientation information yielded by a Sobel edge operator. The final QE is formulated as [8]:

$$\mathrm{QE} = \frac{\sum_{i=1}^{M}\sum_{j=1}^{N} Q^{\mathrm{AF}}(i,j)w^A(i,j) + Q^{\mathrm{BF}}(i,j)w^B(i,j)}{\sum_{i=1}^{M}\sum_{j=1}^{N} w^A(i,j) + w^B(i,j)} \tag{2}$$

where w^A and w^B are the weighting coefficients based on Sobel edge strength values of the source images.

3.2. Mutual information (MI)

Typically, MI based on dependence of the two random variables. This dependence can be calculated by using Kullback–Leibler measure for A and B random variables as [17]:

$$I_{A,B} = \sum_{a,b} p_{A,B}(a,b)\log\frac{p_{A,B}(a,b)}{p_A(a)p_B(b)} \tag{3}$$

where p_A and p_B are marginal probability distribution of the A and B variables, respectively and $p_{A,B}$ is the normalized joint distributions. If the A and B variables are the same, $I_{A,B}$ has the maximum value. In image fusion, the random variables are the image pixel values and probability distribution is the histogram values of the image.

The shared information that reveals how much information transferred to the fused image from the source images is used as a quality value by MI defined as [9]:

$$\mathrm{MI} = I_{A,F} + I_{B,F} \tag{4}$$

3.3. Feature mutual information (FMI)

FMI calculates the quality by means of MI [12]. The amount of information transferred is measured in terms of gradient map which contains edge strength, texture and contrast features on the neighbourhoods of the pixels. Therefore, in FMI, marginal distribution is defines as:

$$p_A(a,b)\frac{\left|\nabla I\right|}{\sum_{a,b}\left|\nabla I\right|} \tag{5}$$

where $\left|\nabla I\right|$ is the gradient of block centred with a pixel. The joint distribution between the fused image and the source images is expressed as:

$$p_{\mathrm{FA}}(a,b) = \begin{cases} \varphi h_U^{\mathrm{FA}}(a,b) + (1-\varphi)p_F(a,b)p_A(a,b) & \rho > 0 \\ \theta h_L^{\mathrm{FA}}(a,b) + (1-\theta)p_F(a,b)p_A(a,b) & \rho \le 0 \end{cases} \tag{6}$$

where $\varphi = \rho/h_U^{\mathrm{FA}}$, $\theta = \rho/h_L^{\mathrm{FA}}$ and ρ is correlation coefficient between A and F. h_U^{FA} and h_L^{FA} are correlation coefficients corresponding to Fréchet's upper and lower bound, respectively.

Let $I_{A,F}$ and $I_{B,F}$ be the amount of information shared between the fused image and the source images (A and B), respectively. $I_{A,F}$ and $I_{B,F}$ are defined by Kullback–Leibler measure (see Eq. (3)) with these definitions of joint and marginal distribution. FMI value is then formulated as:

$$\mathrm{FMI} = \frac{I_{A,F}}{H_A + H_F} + \frac{I_{B,F}}{H_B + H_F} \tag{7}$$

where $H_A = I_{A,A}$, $H_B = I_{B,B}$, and $H_F = I_{F,F}$.

4. The sum of the correlations of differences (SCD)

The aim of the image fusion is to merge the images that depict the same scene with different sensing technology. The most