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A Study of Quality Assessment Techniques For Fused Images

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Abstract: ***Critical image processing tasks can be efficiently executed by fusion of images taken from range of distributed sensors. Advancements in digital image processing and communication technology with invent of new sensors experiencing the excessive need of effective image quality assessment of image fusion techniques. Various metrics have been discussed for quality measurement of fused image based on subjective or objective assessment. Objective quality assessment techniques are preferred over subjective since they do not involve the complexity in their practical implementation and validation. Based on availability of an ideally fused (reference) image, the metrics are classified into referential and non referential metrics. This paper presents an overview of different objective techniques for fused image quality assessment.***

Index Terms**:** ***Image Quality Assessment, Image Fusion, Performance Metric***

I. INTRODUCTION

Image fusion is the process of combining images acquired from different sensors into composite image so as to retain relevant information consistent with specific application. The images under the image fusion process are referred as source images whereas the resultant image as a fused image. Image fusion has wide range of application areas including medical image analysis, computer vision, satellite imagery and defense surveillance. [1]

Image quality is an attribute of an image that measures the apparent degradation of information. The need of image quality measurement arises in case of image fusion optimization problems [10]. In general, fusion results are being evaluated by human observer referred as subject. Validation in subjective quality assessment is complicated due to involvement of large number of human observers. This method is costly and time consuming. To overcome such difficulties many objective quality metrics are proposed [9]. Several metrics have performance in accordance with human visual system [2].

Quality metrics are classified into referential and non-referential metrics based on availability of reference image [2]. Reference image is an ideal or best result of image fusion. Assessment of a fused image can be carried out in two ways. In first method comparison between fusion result and known reference image (ground truth) is done. Availability of such an ideal image is limited. Practical implementation of such ideal metrics is not possible due to complexity in its design. Reference image is not needed in the second method and assessment carried out on the basis of input images.

The main objective of comparing different image fusion metrics is to find the correlation between them [4],[11]. The performance of metric varies with application and context of the fused image. Different metrics can be organized and ranked based on their performance in fusion process using suitable criteria. The performance calculation for metrics can be done for variety of applications under the influence of various noises. This paper gives an overview of different quality measurement metrics starting from very primitive techniques.

II. OBJECTIVE TECHNIQUES FOR FUSED IMAGE QUALITY MEASUREMENT

Various metrics are designed to accurately imitate human observation performance. In general metrics are proposed for distorted image with respect to reference image. In this context fused image is analogous to distorted image. Various image fusion metrics are discussed and classified on the basis of their statistical properties.

A. Primitive image quality measurement techniques

1) Entropy (H)

Information content in any information signal can be measured in terms of entropy. Entropy H of fused image F is given by

$$H = -\sum_{m=1}^{n} P(F_m)\, log_2(P(F_m)) \qquad (1)$$

where n is the number of grey levels and $P(F_m)$ is the probability of specific level occur in fused image [12]. When fused image has relatively uniform frequency content then it contains maximum entropy. Greater entropy for fused image indicates more information contents than original images

2)Standard deviation (σ)

The statistical moment M_F of the fused image histogram (f) is defined as

$$M_F = \sum_{i=0}^{n-1} (f_i - m)^n p(f_i) \qquad (2)$$

where m is the average intensity and n is the maximum possible intensity levels and $p(f_i)$ is the probability of specific level i occur in fused image. Average intensity is defined as

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$$m = \sum_{i=0}^{n-1} f_i p(f_i) \quad (3)$$

Standard deviation σ can be defined as the second moment about mean [12].

$$\sigma = \sqrt{M_2(f)} \quad (4)$$

The metric based on standard deviation (σ) can be effectively implemented in noise free environment. Average contrast in fused image is represented by standard deviation. There is direct variation between the standard deviation and amount of contrast in given image.

3) Peak Signal to Noise Ratio (*PSNR*)

PSNR for reference image *R* and fused image *F* is calculated on the basis of mean square error *(MSE)*. It is given by

$$PSNR(R,F) = 10\, log_{10} \frac{N^2}{MSE(R,F)} \quad (5)$$

where *N* represent maximum number of pixels in an image which takes value 255 for 8 bit grayscale images [14]. *PSNR* is accepted universally due to its easy mathematical implementation.

4) Relative mean (R_M)

The mean value of pixels in a band is the central value of the distribution of the pixels in that band [12]. Mean of reference and fused image is represented as μ_r and μ_f respectively. Relative shift in mean R_M is normally represented as percentage and given by

$$R_M = \left(\frac{\mu_f}{\mu_r} - 1\right) \times 100\% \quad (6)$$

The relative shift in the mean value signifies the changes in the histogram of the image due to processing.

B. Difference based techniques

Reference and fused image of size $M \times N$ are denoted by $r(x,y)_{ij}$ and $f(x,y)_{ij}$ respectively where *i* and *j* are row and column indices. Difference in the corresponding pixel between fused and reference image is the basis of constructing difference based techniques.

1) Average difference

The average difference D_A between fused and reference image is

$$D_A = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left(\left|r(x,y)_{ij} - f(x,y)_{ij}\right|\right) \quad (7)$$

2) Maximum difference

The maximum difference D_M between fused and reference image is

$$D_M = max\left(\left|r(x,y)_{ij} - f(x,y)_{ij}\right|\right) \quad (8)$$

C. Error based techniques

1) Mean Square Error (*MSE*)

Input reference image $r(x,y)_{ij}$ and fused image $f(x,y)_{ij}$ are of size $M \times N$ with row and column indices *i* and *j* respectively. Mean square error represents the square of the difference between respective pixel values of fused and reference image.

$$MSE = \frac{1}{MN} \sum_{i=1}^{M} \sum_{j=1}^{N} \left|r(x,y)_{ij} - f(x,y)_{ij}\right|^2 \quad (9)$$

Mean square error takes positive values irrespective of the amount of contents in reference or fused image [13]. It is accepted widely for its easy optimization. However its performance is degraded for cross artifact measurements [10].

2) Root Mean Square Error (*RMSE*)

The root mean square represents the root of the mean square error between them.

$$RMSE = \sqrt{MSE} \quad (10)$$

The limitation of RMSE is its dependence on multiplicative scale of fused image and availability of an ideal image [9].

3) Laplacian Mean square Error (MSE_L)

Laplacian denotes the second order rate of change of image pixel intensities [14]. Laplacian mean square error is defined as

$$MSE_L = \frac{\sum_{i=1}^{m}\sum_{j=1}^{n}[\nabla^2 r(x,y)_{ij} - \nabla^2 f(x,y)_{ij}]^2}{\sum_{i=1}^{m}\sum_{j=1}^{n}[r(x,y)_{ij}]^2} \quad (11)$$

It signifies the difference between original and neighboring image pixel intensities.

D. Spatial frequency based techniques

1) Spatial Frequency (f_{SP}) based

Spatial frequency technique is based on the frequency analysis in spatial domain [9]. It is defined for fused image *F* as

$$f_{SP} = \sqrt{(f_R)^2 + (f_C)^2} \quad (12)$$

Here row frequency (f_R) and column frequency (f_C) of fused image *F* of size $M \times N$ are given by

$$f_R = \sqrt{\frac{1}{MN} \sum_{i=1}^{M} \sum_{j=2}^{N} [F(i,j) - F(i,j-1)]^2} \quad (13)$$

$$f_C = \sqrt{\frac{1}{MN} \sum_{j=1}^{N} \sum_{i=2}^{M} [F(i,j) - F(i-1,j)]^2} \quad (14)$$

respectively.

2) Ratio of Spatial Frequency (E_{SP}) based

The modified metric based on spatial frequency is proposed by Zheng *et al.* [9]. Two new diagonal frequencies are defined in this improved technique based on spatial frequency *viz.* main diagonal frequency (f_{MD}) and secondary diagonal (f_{SD}) as

$$f_{MD} = \sqrt{\frac{1}{2^{1/2}} \cdot \frac{1}{MN} \sum_{i=2}^{M} \sum_{j=2}^{N} [F(i,j) - F(i-1,j-1)]^2} \quad (15)$$

$$f_{SD} = \sqrt{\frac{1}{2^{\frac{1}{2}}} \cdot \frac{1}{MN} \sum_{j=1}^{N-1} \sum_{i=2}^{M} [F(i,j) - F(i,j-1)]^2} \quad (16)$$

An improved calculation of equivalent spatial frequency is done using four types of gradient frequencies as

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$$f = \sqrt{(f_R)^2 + (f_C)^2 + (f_{MD})^2 + (f_{SD})^2} \qquad (17)$$

The reference spatial frequency is calculated by taking maximum absolute gradient values in four directions. For *A* and *B* as input image, reference gradient $Grad^{[D]}(I_R(x,y))$ is given as

$$Grad^{[D]}(I_R(x,y)) = max\{|Grad^{[D]}(I_A(x,y))|, |Grad^{[D]}(I_B(x,y))|\} \qquad (18)$$

where *[D]* represents any directional gradient *viz.* horizontal, vertical, mean diagonal and secondary diagonal. Thus new row frequency f_{RN} used as reference is defined as

$$f_{RN} = \sqrt{\frac{1}{MN}\sum_{i=1}^{M}\sum_{j=0}^{N}\left[Grad^{[D]}(I_R(x,y))\right]^2} \qquad (19)$$

Ratio of SF error (E_{SP}) between fused and reference images having spatial frequencies as f_{SPF} and f_{SPR} respectively is defined as follows:

$$E_{SP} = \frac{f_{SPF}}{f_{SPR}} - 1 \qquad (20)$$

Quality of fused images is better when ratio of spatial frequency approaches zero value. Certainly positive value of ratio denotes an over fused image whereas negative value an under fused image.

E. Image Information based techniques

1) Mutual information (I_M) based

In cases where ground truth (reference) image is not available, non referential technique based on mutual information is used. Mutual information is based on Kullback Leibler distance defined by

$$I_M(A,B) = \sum_{a,b} p(a,b)\, log_2 \frac{p(a,b)}{p(a)p(b)} \qquad (21)$$

Two images A and B from same or different sources are considered for image fusion purpose [7]. Here $p(a,b)$denotes the joint probability distribution function and $p(a), p(b)$ marginal probability distribution functions. The same procedure is applied for implementing the Tsallis divergence measure. Here the performance is measured by finding mutual information I_M^{FAB} between fused image *F* and input images *A* and *B*

$$I_M^{FAB} = I_M(F,A) + I_M(F,B) \qquad (22)$$

where

$$I_M(F,A) = \frac{1}{1-Q}\left(1 - \sum_{f,a}\frac{p(f,a)^Q}{p(f)p(a)^{Q-1}}\right) \qquad (23)$$

and

$$I_M(F,B) = \frac{1}{1-Q}\left(1 - \sum_{f,b}\frac{p(f,b)^Q}{p(f)p(b)^{Q-1}}\right) \qquad (24)$$

2) Normalised mutual information (I_{MN}) based

Both input images are not fused at same level in above technique. This poses the problem regarding metric boundness [8]. Y. Horibe improved the measure through the process of normalization. Normalized mutual information I_{MN}^{FAB} is given by

$$I_{MN}^{FAB}(A,B) = \frac{I_M^{FAB}(A,B)}{\max\{H(A),H(B)\}} \qquad (25)$$

It is observed that error between I_M^{FAB} and I_{MN}^{FAB} increases with source image entropy. Amount of information transferred to fused image from source image can be estimated after normalization [8].

3) Structural Information (I_S) based

In this metric structural information of fused image is basis of assessment. The structural information like mean, variance between fused and reference image is taken into consideration [5]. Amount of structural distortion is directly varies with image degradation. The metric assesses the image quality by measuring the structural difference between the reference and fused images. Structural information used in metric $I_S(R,F)$ consists of three components such as luminance, contrast and structural comparison [5]. Metric depending on structural information $I_S(R,F)$ is defined as

$$I_S(R,F) = \frac{(2\mu_R\mu_F + C_1)(2\sigma_{RF} + C_2)}{({\mu_R}^2 + {\mu_F}^2 + C_1)({\sigma_R}^2 + {\sigma_F}^2 + C_2)} \qquad (26)$$

where *R* and *F* represent the reference and fused images, respectively. μ_R and μ_F denotes the mean of reference and fused image respectively whereas standard deviation represented for reference and fused image as σ_R and σ_F respectively. Here C_1=6.5025 and C_2=58.52 for 8 bit gray scale image. Fused image can take values between zero and one but matches well with ground truth with increasing closeness of metric to unity [5].

F. Quality index based techniques

1) Universal Image quality index (I_{QU})based

More versatile and less computationally complex metric based on image quality index is proposed by Wang *et al.* named as universal image quality index. The model is based on three perspectives *viz.* loss of correction, luminance distortion and contrast distortion [6]. The proposed metric is capable of performing equally under varied situation and various applications with significant distortions. I_{QU} metric measures the similarity between the fused image (I_F) and the input images I_A and I_B by assuming that an ideally fused image should resemble both original input images. Let *r={ri|i= 1,2,......,N}* is reference or ground truth image while *f={fi|i= 1,2,......,N}* represents the fused resultant image. Universal Image quality index I_{QU} is then defined as

$$I_{QU} = \frac{4\sigma_{rf}\bar{r}\bar{f}}{({\sigma_r}^2 + {\sigma_f}^2)[\bar{r}^2 + \bar{f}^2]} \qquad (27)$$

where

$$\bar{r} = \frac{1}{N}\sum_{i=1}^{n} r_i \text{ and } \bar{f} = \frac{1}{N}\sum_{i=1}^{n} f_i$$

$${\sigma_r}^2 = \frac{1}{N-1}\sum_{i=1}^{n}(r_i - \bar{r})^2 \text{ and } {\sigma_f}^2 = \frac{1}{N-1}\sum_{i=1}^{n}(f_i - \bar{f})^2$$

$$\sigma_{rf} = \frac{1}{N-1}\sum_{i=1}^{n}(r_i - \bar{r})(f_i - \bar{f})$$

The equation for I_{QU} can be rewritten in terms of multiplication of three components *viz.* loss of correlation, luminance distortion and contrast distortion. Degree of linear correlation can take any value between -1 to 1 whereas contrast similarity and mean luminance proximity can take values between 0 to 1 [6].

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$$I_{QU} = \frac{\sigma_{rf}}{\sigma_r \sigma_f} \cdot \frac{2\sigma_r \sigma_f}{(\sigma_r{}^2 + \sigma_f{}^2)} \cdot \frac{2\bar{r}\bar{f}}{[\bar{r}^2 + \bar{f}^2]} \quad (28)$$

For images the equivalent quality index I_{QUe} is defined as summing average for sliding window w with j steps shown below

$$I_{QUe} = \frac{1}{M}\sum_{j=1}^{M} Q_j \quad (29)$$

2) Piella metric based

A new qualitative metric is proposed by Piella based on Wang and Bovik quality index technique with visual saliency as prime consideration [15]. Visual saliency reflects local relevance of an image. Certain parts of an image are pre-attentively distinctive. It provides immediate significant visual stimulation to human visual system. Piella suggested the technique using local variance as the salience of an image which is represented as $s(A|w)$ and defined by local weight $L_a(w)$ as

$$L_a(w) = \frac{s(A|w)}{s(A|w) + s(B|w)} \quad (30)$$

This metric suggest the information transfer from source to fused image. More importance is given to window weights and variants are defined where saliency is higher. Equivalent image quality index I_{QUe} over window cardinality $|W|$ for family of window W is computed by averaging as

$$I_{QUe}(A,B) = \frac{1}{|W|}\sum_{w \in W} I_{QUe}(A,B|w) \quad (31)$$

Based on this value three metrics are defined by Piella [15].

a. Based on similarity I_{QUS} is defined, which represents similarity between input image A and fused image F over window w

$$I_{QUS} = \frac{1}{|W|}\sum_{w \in W} [L_a(w) I_{QUe}(A,F|w) + (1 - L_B(w)) I_{QUe}(B,F|w)] \quad (32)$$

b. Based on window weight the metric I_{QUW} is defined by

$$I_{QUW} = \sum_{w \in W} [c(w)[L_a(w)\, I_{QUe}(A,F|w) + (1 - L_a(w)) I_{QUe}(B,F|w)] \quad (33)$$

where

$c(w) = \frac{max\{s(A|w),s(B|w)\}}{\sum_{w' \in W}\{s(A|w'),s(B|w')\}}$ denotes equivalent saliency of window.

c. Based on edge information edge dependant quality metric I_{QUE} is defined as

$$I_{QUE} = I_{QUW}(A,B,F)^{1-\propto}. I_{QUW}((\nabla A, \nabla B, \nabla F)^{\propto}) \quad (34)$$

where $\nabla A, \nabla B, \nabla F$ represents gradient of respective image. The parameter $\propto$ represents importance of edge information in an image which takes value between 0 and 1.

G. Gradient based techniques

1) Harris response based (M_{HR})

This metric uses the gradient information matrix based on eigen values which reflects the geometric structure of an image pixel. The Harris response was proposed by Harris and Stephens to find out corner points [5]. Three steps are formulated for calculating Harris response R.

Step 1-Calculating the directional derivatives of reference and fused image I_R and I_F.

Step 2-Calculating the determinant and trace for fused image to calculate improved quality metric based on Harris response.

Step 3- Unify the eigen values for quality assessment.

The geometrical structure of a point in an image can be described by the eigen values. Each eigen value is not independent, thus they cannot be separately used. The Harris response R is defined by the eigen values for fused image written as

$$R = det(F) - k.tr(F)^2 \quad (35)$$
$$= \lambda_{max}\lambda_{min} - k(\lambda_{max} + \lambda_{min})^2$$

Here k is constant normally taken equal to 0.06 whereas *det* is determinant and *tr* is trace of fused image matrix [9]. λ_{max} and λ_{min} represents maximum and minimum eigen values of fused image matrix F. R can take any positive or negative value. R gets changed when image distortions are introduced in the form of noise. Then proposed image quality metric M_{HR} for fused image is defined as

$$M_{HR} = \frac{1}{N}\sum_{i=1}^{N} \frac{2R_R(i)R_F(i)}{(R_R(i))^2 + (R_F(i))^2} \quad (36)$$

where R and F denote the reference and fused images of size N. Quality of image increases as value of above metric approaches to one. Similarity between fused image and reference image increases as M_{HR} approaches to one [9].

III. CONCLUSION

The metrics takes different values with varied condition and application. Addition of noise in an image changes the metric value since it denotes the relative changes in information content of fused images. Formulation of exact relationship between subjective and corresponding objective technique is still an open problem. Metric can take different values in specific range for variety of applications. The fusion metrics can be applied to different image fusion techniques. The choice of metric is dependent on the area of application. No metric in the study is found to have equal performance for all applications. The changes in metric value with respect to noise and blurring operation can be studied. The image quality should not affect metric value. Future scope includes the proposal of global metric which can perform equally well in all applications under all conditions including addition of noise in source images.

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