



Performance measure for image fusion considering region information *

LIU Gang[†], LÜ Xue-qin

(School of Power and Automation Engineering, Shanghai University of Electric Power, Shanghai 200093, China)

[†]E-mail: lukelg@gmail.com

Received June 12, 2006; revision accepted Sept. 15, 2006

Abstract: An objective performance measure for image fusion considering region information is proposed. The measure not only reflects how much the pixel level information that fused image takes from the source image, but also considers the region information between source images and fused image. The measure is meaningful and explicit. Several simulations were conducted to show that it accords well with the subjective evaluations.

Key words: Image fusion, Information fusion, Image processing
doi:10.1631/jzus.2007.A0559

Document code: A

CLC number: TP317.4

INTRODUCTION

Image fusion can be defined as the process by which several images, or some of their features are combined to form different modalities or instruments. It is of great importance in many applications, such as object detection, automatic target recognition (ATR), remote sensing, computer vision, and robotics (Wang *et al.*, 2005; Blum, 2005). The widespread use of image fusion methods has led to a rising demand of pertinent quality assessment tools in order to compare the results obtained with different algorithms (Yang and Blum, 2005).

Fusion performance is often assessed using informal subjective preference test. Recently a restricted number of objective fusion performance measures was proposed with knowledge of ground-truth not being assumed. Xydeas and Petrovic (2000) proposed evaluating the relative amount of edge in-

formation transferred from the input images to the fused image. In (Qu *et al.*, 2002), mutual information is employed for evaluating fusion performance. A universal image quality index based metric for image fusion proposed by Gemma and Henk (2003) is also a kind of objective metric that utilizes local measures to estimate how well the salient information from the inputs is presented in the fused image. The salient information is based on an image quality index which can reflect the similarity of two images.

An objective performance should consider not only the edge information and pixel information relation between source images and fused image, but also the region information, because it is more important in some conditions (Zhang and Blum, 1997; Gemma, 2002). In this Letter, a new objective performance measure for image fusion considering region feature is proposed by using mutual information (MI).

* Project supported by the Shanghai Leading Academic Discipline Project (No. P1301), the Scientific Research Foundation of Shanghai University of Electric Power (No. K-2005-22), the Common Scientific Research Project of Shanghai Academic Committee (No. 06LZ015), and the Excellent Young Teacher Foundation of Shanghai (No. Z-2006-11), China

PERFORMANCE MEASURE FOR IMAGE FUSION

The purpose of image fusion is to combine and preserve in a single output image all the 'important'

visual information present in a number of input images. Recently some researchers recognized that it seems more meaningful to combine objects/regions rather than pixels. Zhang and Blum (1997) proposed a region-based fusion algorithm, which combines images guided by the identification of important features in each image, such as object and regions of interest. Gemma (2002) also proposed a region-based fusion scheme. Recently, Liu *et al.* (2006) proposed a fuzzy region feature-based fusion scheme to resolve the problem of region consistency. Due to its considering the region information, the region-based method is more suitable for the purpose of human visual perception and computer processing. However, there is no appropriate measure considering region information to evaluate the more efficient kind of image fusion method.

In this paper, we associate the MI measure in a fixed region. The fused image must be segmented. The process of the evaluation is as follows.

Given the total number of regions N . The fused image is first segmented to N regions by image segmentation algorithm. In this paper, we adopt K -mean algorithm for image segmentation. K -mean algorithm (MacQueen, 1967) is one of the simplest unsupervised learning algorithms that solve the clustering or image segmentation problem. The procedure follows a simple and easy way to classify a given dataset through a certain number of clusters (assume k clusters) fixed *a priori*. The main idea is to define N centroids, one for each segmentation region. These centroids should be placed in appropriate way because different locations cause different results. So, a good choice is to place them as much as possible far away from each other. The next step is to take each point belonging to a given dataset and associate it with the nearest centroid. When no point is pending, the first step is completed and an early groupage is done. At this point we need to re-calculate k new centroids from the previous step. After we have these N new centroids, a new binding has to be done between the same dataset points and the nearest new centroid. A loop has been generated. As a result of this loop we may notice that the N centroids change their location step by step until no more changes occur. In other words centroids do not move any more.

Therefore, the whole fused image is segmented as N regions in which every pixel position has the

same characteristic.

For every region, calculate the measure as in (Qu *et al.*, 2002)

$$MI_{FA}^i(f, a) = \sum_{f, a} p_{FA}^i(f, a) \log \frac{p_{FA}^i(f, a)}{p_F^i(f) p_A^i(a)}, \quad (1)$$

where MI_{FA}^i is the mutual information between image F and image A on the region i ; $p_{FA}^i(f, a)$ is the joint distribution on the region i and $p_F^i(f) \cdot p_A^i(a)$ is the distribution associated with the case of complete independence. When we compute the distributions $p_{FA}^i(f, a)$ and $p_F^i(f) \cdot p_A^i(a)$, the number of the sample point is assigned as the number of pixels within region i .

$$MI_{FB}^i(f, b) = \sum_{f, b} p_{FB}^i(f, b) \log \frac{p_{FB}^i(f, b)}{p_F^i(f) p_B^i(b)}, \quad (2)$$

where MI_{FB}^i , $p_{FB}^i(f, b)$ and $p_F^i(f) \cdot p_B^i(b)$ are the same as those in Eq.(1).

$$M_{F,AB}^i = MI_{FA}^i(f, a) + MI_{FB}^i(f, b), \quad (3)$$

where $M_{F,AB}^i$ is the pixel level information within region i that the fused image F contains about A and B .

If the fusion process is performed by hand, the first part to be fused is some important image regions, and then the important pixels. The best fusion result occurs when the pixel comes from one of the source image regions within important region. Therefore, for the i th region, a measure can be calculated as follows:

$$Q_{F,AB}^i = \max\{MI_{FA}^i, MI_{FB}^i\} \times M_{F,AB}^i. \quad (4)$$

To reflect region information of the source images, the measure should consider the similarity between one source image and the fused image within one region. It is appropriate to use the maximization process of the MI in Eq.(4).

Calculate performance measure for the whole fused image as

$$Q_{F,AB} = \sum_{i=1}^N Q_{F,AB}^i / N. \quad (5)$$

EXPERIMENTS

In this section, we use the proposed fusion quality to evaluate different image fusion schemes in order to verify the performance measure. Schemes 1 and 2 are based on discrete wavelet transform and discrete wavelet frame transform respectively. The larger values of high subbands and average of low subbands of two input images were used for reconstructing the new image. Scheme 3 is based on discrete wavelet transform. The fusion scheme is similar to (Zhang and Blum, 1997)'s region-based algorithm, but we adopt a different segmentation algorithm (K-mean algorithm). Scheme 4 is based on Laplacian pyramid, with the fusion scheme similar to that of (Gemma, 2002). Scheme 5 is (Liu et al., 2006)'s image fusion method based on fuzzy region feature. In all cases, we perform a 3-level decomposition. Fig.1 shows the original images A and B corresponding to CT and MRI, respectively.

Figs.2a~2d show the fusion results corresponding to Schemes 1~4 respectively. The assessment of the scheme proposed in this letter can be done as follows.

First, the fused image is segmented into 3 regions, $N=3$. And then, for every region, calculate MI measure MI_{FA}^i , MI_{FB}^i and $M_{F,AB}^i$. Region information measure $Q_{F,AB}^i$ can be calculated by Eq.(4). Finally, the proposed measure $Q_{F,AB}$ is obtained by Eq.(5). The results are shown in Table 1 showing that the performance of region-based Schemes 3, 4 and 5 are better than those of Schemes 1 and 2. The conclusion is identical to the visual perception (Fig.2).

It must be pointed out that the fusion performance comparison must be carried out at the same image level since at different levels it has different

meanings. There is no universal performance assessment scheme because evaluating image fusion performance in a real application is a complicated issue. As an example, consider a simple case in which the fused image is the average of two input images. According to the proposed measure, we know that $Q_{F,AB}$ in Scheme 5 is larger than those in Schemes 1~4.

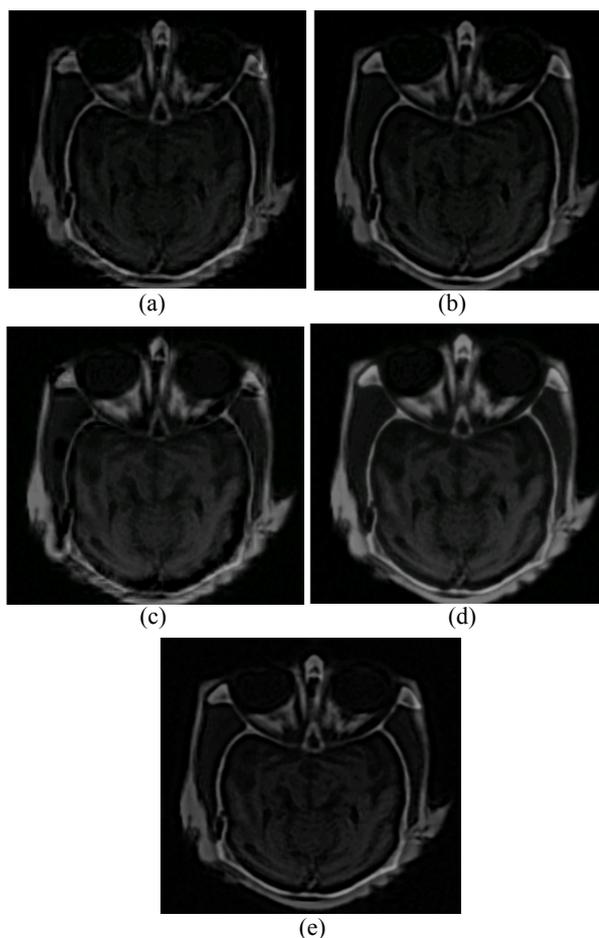


Fig.2 Results of the fused images. (a)~(e) are respectively the results of Schemes 1~5

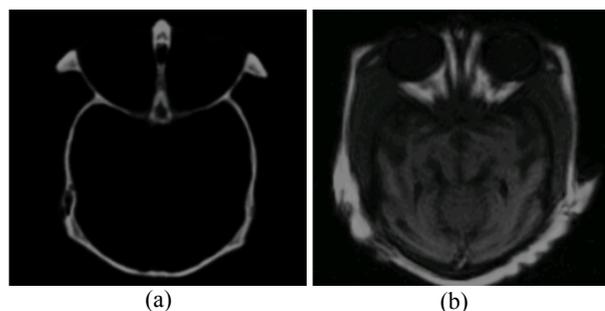


Fig.1 Original images. (a) CT image; (b) MRI image

Table 1 The proposed measure on Schemes 1~5

Scheme	MI_{FA}^1	MI_{FB}^1	MI_{FA}^2	MI_{FB}^2	MI_{FA}^3	MI_{FB}^3
1 ^a	0.7389	0.0464	0.6584	0.1342	0.7336	0.7117
2 ^b	1.0635	0.0676	0.8280	0.3396	1.1323	1.1073
3 ^c	1.0705	0.0833	1.2682	0.1774	1.0363	0.5890
4 ^d	1.4305	0.0940	1.4801	0.1843	1.2214	0.7990
5 ^e	1.2330	0.5513	1.0475	0.8904	1.2614	1.1547

^a: $Q_{F,AB}=0.7208$; ^b: $Q_{F,AB}=1.5685$; ^c: $Q_{F,AB}=1.5842$; ^d: $Q_{F,AB}=2.3706$; ^e: $Q_{F,AB}=2.4259$

CONCLUSION

We have proposed a measure for objectively evaluating image fusion performance considering region information, which does not require a reference image. By means of the proposed measure, features and visual information from input images and new fused images can be measured. The region consistency can also be reflected by the measure. The experiment showed that the proposed measure is meaningful and explicit.

References

- Blum, R.S., 2005. Minimax Robust Image Fusion Using an Estimation Theory Approach. Proc. 8th International Conference on Information Fusion, 1:461-468. [doi:10.1109/ICIF.2005.1591891]
- Gemma, P., 2002. A General Framework for Multiresolution Image Fusion: From Pixels to Regions. Technical Report PNA-R0211, ISSN 1386-3711. Center for Mathematics and Computer Science (CWI), Amsterdam, the Netherlands.
- Gemma, P., Henk, H., 2003. A New Quality Metric for Image Fusion. Proc. IEEE International Conference on Image Processing, 3:173-176.
- Liu, G., Jing, Z.L., Sun, S.Y., 2006. Multiresolution image fusion scheme based on fuzzy region feature. *J. Zhejiang Univ. Sci. A*, 7(2):117-122. [doi:10.1631/jzus.2006.A0117]
- MacQueen, J.B., 1967. Some Methods for Classification and Analysis of Multivariate Observations. Proc. 5th Berkeley Symposium on Mathematical Statistics and Probability. University of California Press, Berkeley, 1:281-297.
- Qu, G.H., Zhang, D.L., Yan, P.F., 2002. Information measure for performance of image fusion. *Electron. Lett.*, 38(7): 313-315. [doi:10.1049/el:20020212]
- Wang, Z.J., Djemel, Z., Armenakis, C., Li, D., Li, Q.Q., 2005. A comparative analysis of image fusion methods. *IEEE Trans. Geosci. Remote Sensing*, 43(6):1391-1402. [doi:10.1109/TGRS.2005.846874]
- Xydeas, C.S., Petrovic, V., 2000. Objective image fusion performance measure. *Electro. Lett.*, 36(4):308-309. [doi:10.1049/el:20000267]
- Yang, J., Blum, R.S., 2005. Multi-frame Image Fusion Using the Expectation-Maximization Algorithm. Proc. 8th International Conference on Information Fusion, 1:469-471. [doi:10.1109/ICIF.2005.1591892]
- Zhang, Z., Blum, R.S., 1997. A Region-based Image Fusion Scheme for Concealed Weapon Detection. Proc. 31st Annu. Conf. Information Sciences and Systems. Baltimore, MD, p.168-173.



Editor-in-Chief: Wei YANG
 ISSN 1673-565X (Print); ISSN 1862-1775 (Online), monthly

Journal of Zhejiang University

SCIENCE A

www.zju.edu.cn/jzus; www.springerlink.com
jzus@zju.edu.cn

JZUS-A focuses on "Applied Physics & Engineering"

➤ **Welcome Your Contributions to JZUS-A**

Journal of Zhejiang University SCIENCE A warmly and sincerely welcomes scientists all over the world to contribute Reviews, Articles and Science Letters focused on **Applied Physics & Engineering**. Especially, Science Letters (3~4 pages) would be published as soon as about 30 days (Note: detailed research articles can still be published in the professional journals in the future after Science Letters is published by *JZUS-A*).