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Application of Statical Image Fusion in Medical Image Fusion

Mr. Sanket Choudhary[1], Prof. Vikas Gupta[2], Mr. Yash Kshirsagar[3]

[1]M. Tech Scholar, [2]Head of the Department, [3]Assistant Professor

Dept of Electronics and communication Engineering, Technocrats Institute and Technology, Bhopal

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Abstract: Image fusion provides a mechanism to combine two or more images into a single representation to aid human visual perception and image processing tasks. Such algorithms Endeavour to create a fused image containing the salient information from each source image, without introducing artifacts or inconsistencies. Image fusion is applicable for numerous fields including: defense systems, remote sensing and geosciences, robotics and industrial engineering, and medical imaging. In the medical imaging domain, image fusion may aid diagnosis and surgical planning tasks requiring the segmentation, feature extraction, and/or visualization of multi-modal datasets.

This paper discusses the implementation of an image fusion toolkit built upon the Insight Toolkit (ITK). Based on an existing architecture, the proposed framework (GIFT) offers a ‘plug-and-play’ environment for the construction of n-D multi-scale image fusion methods.

INTRODUCTION

Medical image fusion has been a popular research topic since last two decades. Generally, medical image fusion means the matching and fusion between two or more images of the same lesion area taken from different medical imaging equipment, and aims to obtain complementary information and increase the amount of information. Medical image fusion takes palace to combine the information of a variety of images with computer-based image processing method. Present research is going to be used for medical image fusion so as to get a better image which is clearer and contains more information. In the clinical diagnosis and treatment, the use of fused images can provide more useful information. It is important for lesion location, diagnosis, making treatment and pathological study [1].

In several application scenarios, image fusion is only an introductory stage to another task, e.g. human monitoring. Therefore, the performance of the fusion algorithm must be measured in terms of improvement in the following tasks. For example, in classification systems, the common evaluation measure is the number of the correct classifications. This system evaluation requires that the ”true” correct classifications are known. However, in experimental setups the ground-truth data might not be available. In many applications the human perception of the fused image is of fundamental importance and as a result the fusion results are mostly evaluated by subjective criteria. Objective image fusion performance evaluation is a tedious task due to different application requirements and the lack of a clearly defined ground-truth. Various fusion algorithms presented in this project. Several objective performance measures for image fusion have been proposed where the knowledge of ground-truth is not assumed.

In the medical imaging field, we can get different images of the same part of the same patient with different imaging devices, and the information provided by a variety of imaging modes is often complementary [2]. In the medical images, CT can clearly reflect the anatomical structure of bone tissues.

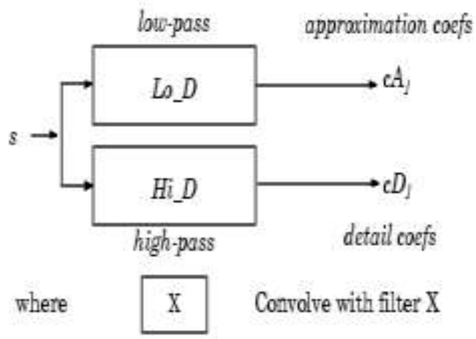
Oppositely, MRI can clearly reflect the anatomical structure of soft tissues, organs and blood vessels. CT, MRI and other modes of medical images reflect the human information from various angles. In the clinical diagnosis and treatment, the problems about the comparison and synthesis between image CT and MRI were frequently encountered. To solve the problem, we utilized the stationary wavelet transform to fuse and restructure them in this paper.

STATIONARY WAVELET TRANSFORM

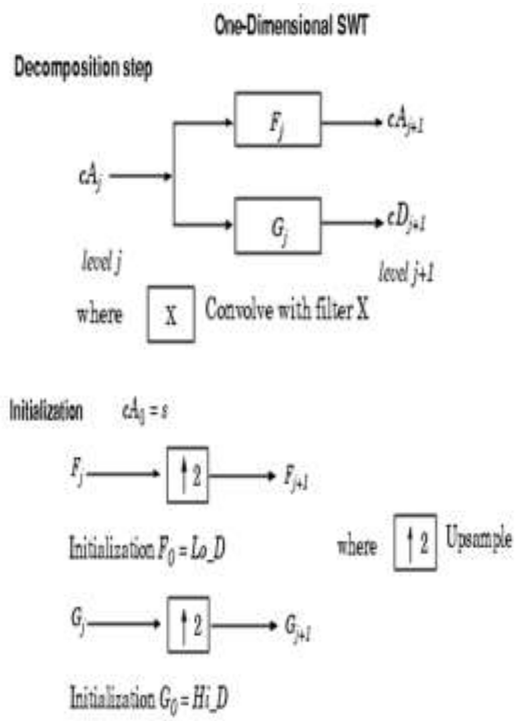
The Stationary wavelet transform (SWT) is a type of wavelet transform algorithm designed to overcome the lack of translation-invariance of the discrete wavelet transform (DWT). Translation-invariance is achieved by removing the down samplers and up samplers in the DWT and up sampling the filter coefficients by a factor of $2^{(j-1)}$in the j^{th} level of the algorithm. The SWT is an inherently redundant scheme as the output of each level of SWT contains the same number of samples as the input – so for a decomposition of N levels there is a redundancy of N in the wavelet coefficients. This algorithm is more famously known as "algorithme à trous" in French (word trous means holes in English) which refers to inserting zeros in the filters. It was introduced by Hold Schneider et al.

The stationary wavelet transform (SWT) can also be expressed as follows:

Given a signal s of length N, the first step of the SWT produces, starting from s, two sets of coefficients: approximation coefficients cA1 and detail coefficients cD1. These vectors are obtained by convolving s with the low-pass filter Lo_D for approximation, and with the high-pass filter Hi_D for detail.



The next step splits the approximation coefficients cA1 in two parts using the same scheme. But, with modified filters obtained by up sampling the filters used for the previous step and replacing s by cA_1. Then, the SWT produces cA_2 and cD_2. More generally



PROPOSED FUSION METHODOLOGY

In this proposed paper two medical images, one is CT and another MRI of 300 x 330 mm dimension and 24 bit depth are fused. For their fusion purpose, following mathematical relation were utilized:

The stationary wavelet decomposition is given by:

SWD = 0.5*(A1L1+A2L1)
Then decomposition factor 'D' is given by:

$$D = \lfloor H_1 L_1 \rfloor - \lfloor H_2 L_1 \rfloor$$

The value for horizontal, diagonal, and vertical component are given by

$$f_1(x) = \int D * H1L1$$

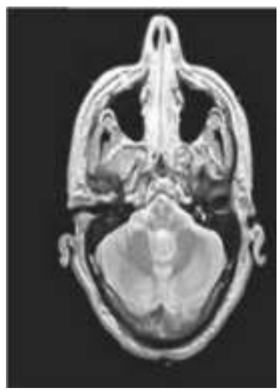
$$f_2(x) = \int D * V1L1$$

$$f_3(x) = \int D * D1L1$$

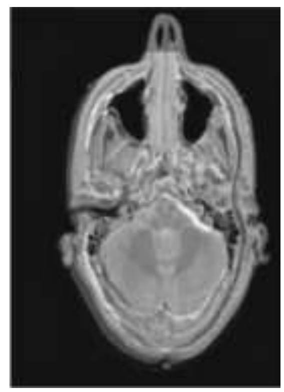
Fused image can be re-creating by using inverse SWT.

Where AfL1 is the value of stationary wavelet decomposition and H1L1 is the value of intensity in horizontal direction. V1L1 is the value of intensity in vertical direction.
The one-dimensional stationary wavelet transform can be computed quickly. The transform process is carried to 4 stages. At each scale, A_iL_i contains the low-frequency information from the previous stage, while A_iHi and A_iV_i contain the horizontal, and vertical respectively.

CT image



MRI Image



Fused Image

CONCLUSION

Image fusion is the process of image superposition using two different image types: anatomic (MRI) and functional (CT]). This process provides the functional (CT) information in an anatomic context provided by the MRI image. It can be easy to see from the result obtained from both data sets that methods proposed in this paper have a very good effect. According to computation results, the increased entropy indicates the enhancement of information content. Approach of Radon transform provides more information as compare to other methods.
The analysis of fused image can be done on the basis of some parameters. These parameters of an image or region are the best and simplest approaches for describing the texture. As we all know, information entropy, namely EN is a very important parameter for describing image information. It was presented by Shannon [3], and was defined as [4]:

$$EN = -\sum_{i=1}^{m} p_i \ln p_i$$

Where p_i is the probability of gray level (i), and the range of i is [0,…., m].

The cross entropy immediately reflects the pixel difference between two images, so the cross entropy can be used to evaluate the fuse image. Marked $M_1 = \{p_1, p_2, \ldots, p_i, \ldots, p_m\}$ and $M_2 \{q_1, q_2, q_3, \ldots, q_i, \ldots, q_n\}$the cross entropy between image M_1 and M_2 , namely CEN , was defined as:

$$CEN = \sum_{i=1}^{m} p_i \ln \frac{p_i}{q_i}$$

If CEN(M,M_1) and CEN(M,M_2) is the cross entropy between the original image and the fused image, the composite cross entropy can be calculated as:

$$CEN(M, M_1, M_2) = \sqrt{\frac{CEN(M, M_1) + CEN(M, M_2)}{2}}$$

Generally, if the entropy is larger and the cross entropy is less, the fusion algorithm is better; otherwise, it is worse [10]. Actually, in some case, the cross entropy is also larger while the entropy is larger, and using the above standard to evaluate the result is not always correct. Therefore, fetch in integrative entropy [5] to evaluate performance.

The absolute cross entropy between image M_1 and M_2 was defined as:

$$CEN\,(M_1, M_2) = \sum_{i=1}^{m} p_i \left| \ln \frac{p_i}{q_i} \right|$$

Then the integrative entropy, namely IEN, was defined as:

$IEN(M,M_1,M_2) = EN(M) - CEN'(M, M_1, M_2)$

For the fused images, if its entropy is larger and the average cross entropy is less, the fusion algorithm is superior; otherwise, it is poor. Similarly, the larger the integrative entropy is, the more effective [5] the fusion algorithm is.

For this present fusion method the values of above defined parameters are as follows:

The value of Entropy (EN) – 5.7831

Cross Entropy (CEN) – 0.5393

Integrative Entropy (IEN) – 5.2438

This could be considering as very good results.

REFERENCES

[1]. Hongbo Wu, YanqiuXing, "Pixel-based Image Fusion Using Wavelet Transform for SPOT and ETM+ Image", IEEE transactions, 978-1-4244-6789, 2010.
[2]. Yan Li-ping, Liu Bao-sheng and Zhou Dong-hua, "Novel image fusion algorithm with novel performance evaluation method," Systems Engineering and Electronics, Vol.29, No.4, pp.509-513, Apr 2007.
[3]. CE Shannon, "A Mathematical Theory of Communication," ACM SIGMOBILE Mobile Computing and Communications Review Vol.5, No.1, 2001
[4]. Zhang Jingzhou, Zhou Zhao, Teng Jionghua and Li Ting, "Fusion Algorithm of Functional Images and Anatomical Images Based on Wavelet Transform," 2009 2nd International Conference on Biomedical Engineering and Informatics, IEEE, pp.215-219, 136–140, Apr. 2005.
[5]. Niu˜nez, J., X. Otazu, O. Fors, A. Prades, V. Pala, and R. Arbiol, "Multiresolution-based image fusion with additive wavelet decomposition," IEEE Trans. Geosci. Remote Sensing, Vol. 37, No. 3, 1204–1211, May 1999.
[6]. Udomhunsakul, S. and P. Wongsita, "Feature extraction in medical MRI images," Proceeding of 2004 IEEE Conference on Cybernetics and Intelligent Systems, Vol. 1, 340–344, Dec. 2004.
[7]. Wang, A., H. J. Sun, and Y. Y. Guan, "The application of wavelet transform to multi-modality medical image fusion," Proceedings of the 2006 IEEE International Conference on Networking, Sensing and Control, (ICNSC), 270–274, 2006.
[8]. Garzelli, A., F. Nencini, L. Alparone, and S. Baronti, "Multiresolutionfusion of multispectral and panchromatic images through the curvelet transform," Proceedings of IEEE International Geoscience and Remote Sensing Symposium, (IGARSS), Vol. 4, 2838–2841, 2005.