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Medical Image Fusion Based on Redundancy DWT and Mamdani Type Min-sum Mean-of-max Techniques with Quantitative Analysis- A Review

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Abstract *– Medical image fusion has revolutionized medical analysis by improving the precision and performance of computer assisted diagnosis. This fused image is more productive as compared to its original input images. The fusion technique in medical images is useful for resourceful disease diagnosis purpose. This paper illustrates different multimodality medical image fusion techniques and their results assessed with various quantitative metrics. Firstly two registered images CT (anatomical information) and MRI-T2 (functional information) are taken as input. Then the fusion techniques are applied onto the input images such as Mamdani type minimum-sum-mean of maximum (MIN-SUM-MOM) and Redundancy Discrete Wavelet Transform (RDWT) and the resultant fused image is analyzed with quantitative metrics namely Over all Cross Entropy(OCE), Peak Signal –to- Noise Ratio (PSNR), Signal to Noise Ratio (SNR), Structural Similarity Index(SSIM), Mutual Information(MI). From the derived results it is inferred that Mamdani type MIN-SUM-MOM is more productive than RDWT and also the proposed fusion techniques provide more information compared to the input images as justified by all the metrics.*

Keywords*: Signal Processing Method, Precise Estimation of* L_{eq} *, Roughly Observed Data,*

I. Introduction

Nowadays, with the rapid development in high-technology and modern instrumentations, medical imaging has become a vital component of a large number of applications, including diagnosis, research, and treatment. In order to support more accurate clinical information for physicians to deal with medical diagnosis and evaluation, multimodality medical images are needed, such as X-ray, computed tomography (CT), magnetic resonance imaging (MRI), magnetic resonance angiography (MRA), and positron emission tomography (PET) images [1].

In the area of medical image fusion, there are several fusion techniques, but these techniques have certain limitations [1]. For example, Contrast Pyramid could not retain sufficient information from its source images, Ratio Pyramid method suffers by providing false information which never existed in the original images, and Morphological Pyramid creates many false edges. Therefore multimodality medical image fusion has emerged as a promising research area in the recent years. Image fusion basically aims at integrating information from the source images on pixel basis thus obtaining a more precise and complete information about an object.

The image fusion system processing flow is shown in Fig.1.The image fusion is the synthesis of multi-source image information which is retrieved from the different sensors. These images are then registered to assure the corresponding pixels are aligned properly. Afterwards they are fused using any of the transforms discussed below. It then generates fused image which is more accurate, all-around and reliable. It can result in less data size, more efficient Target detection, and target identification and situation estimation for observers. Also it can make the images more suitable for the task of the computer vision and the follow-up image processing [1].An important research issue in medical image processing, specifically in information computation, is fusion of multimodal information [5, 7, 8, 9, 10, and 11]. Medical images from different modalities often provide complementary information. Several diagnostic cases require integration of complementary information for better analysis. Fusion of multimodal medical images can provide a single composite image that is dependable for improved analysis and diagnosis.

Existing algorithms generally use Discrete Wavelet Transform (DWT) [3] for multimodal medical image fusion [5, 7, 8, and 11] because DWT preserves different frequency information in stable form and allows good localization both in time and spatial frequency domain. However, one of the major drawbacks of DWT is that the transformation does not provide shift invariance. This causes a major change in the wavelet coefficients of the image even for minor shifts in the input image. In medical imaging, it is important to know and preserve the exact location of these information; but shift variance may lead to inaccuracies. For example, in medical image fusion we need to preserve edge information, but DWT based fusion may produce secularities along the edges.

II. Preprocessing Of Image Fusion

Two images taken in different angles of scene sometimes cause distortion. Most of objects are the same but the shapes change a little. At the beginning of fusing images, we have to make sure that each pixel at correlated images has the connection between images in order to fix the problem of distortion; image registration can do this. Two images having same scene can register together using software to connect several control points. After registration, resampling is done to adjust each image that about to fuse to the same dimension. After resampling, each image will be of the same size. Several interpolation approaches can be used, to resample the image; the reason is that most approaches we use are all pixel-by-pixel fused. Images with the same size will be easy for fusing process. After the re-sampling, fusion algorithm is applied. Sometimes we have to transfer the image into different domain, sometimes haven't depending on the algorithm. Inverse transfer is necessary if image has been transferred into another domain. Fig.1 summarizes these steps called, preprocessing of image fusion.

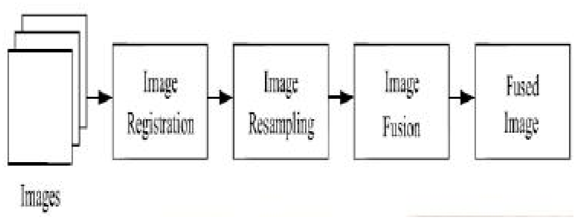

Fig.1. Preprocessing of image fusion.

II.1. Fusion of Multimodal Brain Images using RDWT

Medical images captured at different time instances can have variations due to geometric deformations. To optimally fuse two 2D/3D medical images, we first need to minimize linear and non-linear differences between them using registration technique. Medical image registration is about determining geometrical transformation that aligns points in one medical data set with corresponding points in another data set [6]. We first propose mutual information based non-linear registration algorithm for registering multimodal medical images. Mutual information is a concept from information theory in which statistical dependence is measured between two random variables.

III. Literature Survey

Chandra Prakash ET. Al [1] "Medical Image Fusion Based on Redundancy DWT and Mamdani Type Min-sum Mean-of-max Techniques with Quantitative Analysis "In this, author proposed two different fusion techniques algorithm which are analyzed with quantitative metrics for six sets of brain images acquired from CT and MRI-T2. The experimental result shows that Mamdani type MIN-SUMMOM outperforms RDWT from the visual perspective and is also more satisfactory as verified with the quantitative metrics. The fusion technique in medical images is useful for resourceful disease diagnosis purpose. This paper illustrates different multimodality medical image fusion techniques and their results assessed with various quantitative metrics. Firstly two registered images CT (anatomical information) and MRI-T2 (functional information) are taken as input. Then the fusion techniques are applied onto the input images such as Mamdani type minimum-sum-mean of maximum (MIN-SUM-MOM) and Redundancy Discrete Wavelet Transform (RDWT) and the resultant fused image is analyzed with quantitative metrics namely Over all Cross Entropy(OCE), Peak Signal –to- Noise Ratio (PSNR), Signal to Noise Ratio (SNR), Structural Similarity Index(SSIM), Mutual Information(MI). From the derived results it is inferred that Mamdani type MIN-SUM-MOM is more productive than RDWT and also the proposed fusion techniques provide more information compared to the input images as justified by all the metrics. In author work is find that lower value of OCE in case of MIN-SUM-MOM indicates better fused images, higher values of PSNR signifies better quality of images for MIN-SUM-MOM, higher values for SNR justifies that contrast information for fused images were higher in MIN-SUM-MOM, higher values of SSIM in case of MIN-SUM-MON justifies that the fused images were similar to the original input images and higher values of MI suggest that MIN-SUM-MOM gives better fusion results when compared to RDWT. Thus the fused image obtained from MIN-SUM-MOM is more informative and suitable from the clinical perspective, for efficient retrieval purpose and the fused images are also obtained quickly so it is advisable.

Yong Yang et al [2] "Medical Image Fusion via an Effective Wavelet-Based Approach" In this author work the fusion of multimodal medical images plays an important role in many clinical applications for they can support more accurate information than any individual source image. Author presents a novel wavelet-based approach for medical image fusion, which consists of three steps. In the first step, the medical images to be fused are decomposed into sub images by wavelet transform. In the second step, after considering the characteristics of HVS and the physical meaning of the wavelet coefficients, the coefficients of the low-frequency band and high-frequency bands are performed with different fusion strategies: the former is selected using a maximum visibility scheme, and the latter is selected by a maximum local variance rule. In order to improve the quality of the resultant image, all the combined coefficients are then performed by a window based consistency verification. In the last step, the fused image is constructed by the inverse wavelet transform with the composite coefficients. The performance of the proposed method is qualitatively and quantitatively compared with some existing fusion approaches. Experimental results show that the proposed method can preserve more useful information in the fused image with higher spatial resolution and less difference to the source images.

Richa Singh et al [3] "Multimodal Medical Image Fusion using Redundant Discrete Wavelet Transform" In this author work a novel medical image fusion algorithm is proposed that incorporates properties of RDWT decomposition, normalized mutual information based non-linear registration, and entropy based information selection. The proposed algorithm utilizes different features of Redundant Discrete Wavelet Transform, mutual information based non-linear registration and entropy information to improve performance. Experiments on the Brain Web database show that the proposed fusion algorithm preserves both edge and component information, and provides improved performance compared to existing Discrete Wavelet Transform based fusion algorithms. The algorithm is evaluated on the Brain Web database and experimental results showed that the proposed algorithm conserves important edge and spectral information without much of spatial distortion.

R.J.Sapkal et al [4] "Image Fusion based on Wavelet Transform for Medical Application" In this author work puts forward an image fusion algorithm based on Wavelet Transform. It includes multi resolution analysis ability in Wavelet Transform. Image fusion seeks to combine information from different images. It integrates complementary information to give a better visual picture of a scenario, suitable for processing. Image Fusion produces a single image from a set of input images. It is widely recognized as an efficient tool for improving overall performance in image based application. Wavelet transforms provide a framework in which an image is decomposed, with each level corresponding to a coarser resolution band. The wavelet sharpened images have a very good spectral quality. The wavelet transform suffers from noise and artifacts and has low accuracy for curved edges. In imaging applications, images exhibit edges & discontinuities across curves. In image fusion the edge preservation is important in obtaining complementary details of input images.

Yufeng Zheng et al [5] "A new metric based on extended spatial frequency and its application to DWT based fusion algorithms" In this author presented a new metric for image fusion based on an extended definition of spatial frequency, which is the ratio of spatial frequency error (rSFe). Experiments showed that evaluation with rSFe is very consistent with the RMSE (root mean square error) and IQI (image quality index) metrics, but the rSFe metric is sensitive to small changes in image quality and can also provide more information of the fusion process—under-fused (rSFe < 0) or over-fused (rSFe > 0)—that makes it useful for iterative fusion processes such as the one proposed here. With the absolute value and the sign of rSFe back propagated (BP) to the fusion algorithm, an iterative BP-fusion procedure can be directed, thus an optimized fused image can be provided. The iterative BP-aDWT (advanced DWT), which incorporated PCA (principal component analysis) and morphological processing into a regular DWT fusion procedure, has been shown to significantly improve upon the regular DWT or Laplacian pyramid on the basis of the quantitative IQI metric and the qualitative perceptual evaluation with rank ordering on the fused imagery.

IV. Problem Formulation

In author work[1-3] not extend this fusion technique in order to fuse multiple sensor images (CT, MRI, PET and SPECT), motion images and color images for providing better fusion result for dealing with real time scenario.

V. Conclusion

A novel medical image fusion algorithm is proposed that incorporates properties of RDWT decomposition, normalized mutual information based non-linear registration, and entropy based information selection. The algorithm is evaluated on the CT and MRI and experimental results with help of proposed algorithm conserves important edge and spectral information without much of spatial distortion. The fusion of multimodal medical images plays an important role in many clinical applications for they can support more accurate information than any individual source image.

This paper presents a novel wavelet-based approach for medical image fusion, which consists of three steps. In the first step, the medical images to be fused are decomposed into sub images by wavelet transform.

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