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REVIEW ON MULTIMODALITY MEDICAL IMAGE FUSION

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ABSTRACT

Multimodal medical image fusion is a powerful tool in clinical application. Such as noninvasive diagnosis, image-guided radiotherapy and treatment planning. The complementary nature of medical imaging sensors of different modalities, such as detail of bony anatomy provided by CT and detail of soft tissue anatomy provided by MR image has brought a great need of image fusion. In this paper, a review on multimodality medical image fusion is submitted.

Keywords: Multimodal medical image fusion, non-subsample contourlet transform, phase congruency, directive contrast.

INTRODUCTION

The need for better diagnosis and clear interpretation of the obtained images give rise to image fusion. The term fusion means to combine the information acquired in several domains. Image fusion has become a popular technique used within medical diagnosis and treatment. Image fusion is the process of integrating information from two or more images of an object into a single image. The integrated image is more informative for explanation and analysis. It is possible that several images of same object provide different information based on different resolution and viewing angle, to merge the different information and obtain a new and improved image we have a fusion technique. Fused images can be created by combining information from multiple modalities [1] such as magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET) and single positron emission computed tomography (SPECT). Multimodality Medical Image Fusion is an important task for the retrieval of complementary information from source images of different modality, which plays an important role in medical diagnosis. The complementary nature of medical imaging sensors of different modalities, such as computed tomography (CT : provide dense structures like bones and implants with less distortion) and magnetic resonance imaging (MRI : provide better visualization of normal and pathological soft tissue) etc, has brought a great need of image fusion. The Multimodal medical image fusion not only helps in diagnosing diseases, but it also reduces the storage cost by reducing storage to a single fused image instead of multiple-source images.

METHODS INVOLVED IN IMAGE FUSION

Along with the developing of mathematical tools and fusion rules, the image fusion methods are continually renewing. Recently, various fusion methods based on multiscale transforms(MSTs) have been proposed and some satisfactory results have been obtained (i.e. Pyramid,Wavelet etc.). These multiscale methods can decompose the image into low-frequency subbands and high-frequency subbands, detailed and coarse features remain in the two types of subbands for different demands[2,3]**.** MST-based image fusion methods provide much better performance than the previous simple methods. At present the descrete wavelet transform becomes the most popular multiscale method in image fusion because of its good local characteristics at the spartial and frequency domain[4,5]. However, the wavelet transform has limitations such as limited directions (only three directions, horizontzl, vertical, diagonal) and non-optimal-sparse representatiom of images. In order to solve these limitations, the new multiscale transforms (i.e. Curvelet, Contourlet, etc.) are introduced in image fusion.[6,7].
The contourlet transform proposed by Do and Vetterli. This transformation is a multidirection and

multiresolution image expression method. Contourlet transformation has good direction sensitivity, and catch accurately the image edge information. However, because of the need for up sampler and down sampler, the Contourlet transform lacks the shift invariance, which usually cause the Gibbs effect. A. L. da cunha et al. proposed a new Contourlet transform with shift invariance, called non-subsample contourlet transform (NSCT).

Non-Subsampled Contourlet Transform (NSCT) [8] **:** NSCT is a fully shift-invariant, mult-iscale directional expansion to undergo frequency partioning[8]. In NSCT nonsubsample filter banks replace the up sampler and down sampler as filter banks to obtain the shift invariance. Because of advantages such as multiscale, multi-directions,good spatial and frequency localization and shift invariance, many image fusion methods based on NSCT have been proposed and provide with high performance.

The nonsubsampled contourlet transform is divided into two parts nonsubsampled pyramids and nonsubsampled directional filter banks. The former stage ensures the multiscale property by using two-channel non-subsampled filter bank, and one low-frequency image and one high-frequency image can be produced at each NSP decomposition level. The subsequent NSP decomposition stages are carried out to decompose the low-frequency component available iteratively to capture the singularities in the image. As a result, NSP can result in k+1 sub-images, which consists of one low- and high-frequency images having the same size as the source image where denotes the number of decomposition levels. Fig. 1 gives the NSP decomposition with k = 3 levels.

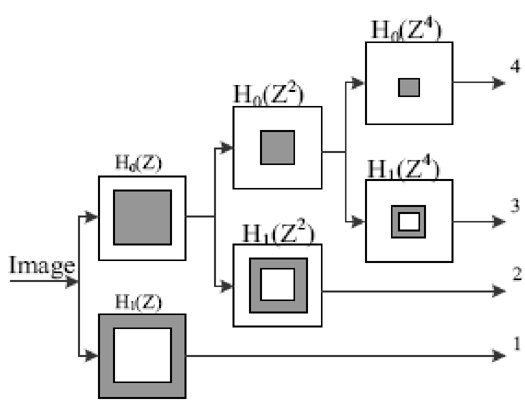

Figure 1 Three-stage non-subsampled pyramid decomposition[9]

The NSDFB is two-channel non-subsampled filter banks which are constructed by combining the directional fan filter banks. NSDFB allows the direction decomposition with stages in high-frequency images from NSP at each scale and produces directional sub-images with the same size as the source image. Therefore, the NSDFB offers the NSCT with the multi-direction property and provides us with more precise directional details information. A four channel NSDFB constructed with two-channel fan filter banks is illustrated in Fig. 2.

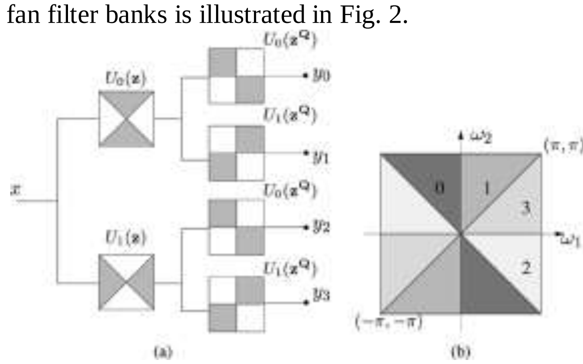

Figure 2 (a) four-channel nonsubsampled direction filter bank (b) corresponding frequency decomposition [10]

Block diagram of NSCT-simple framework:

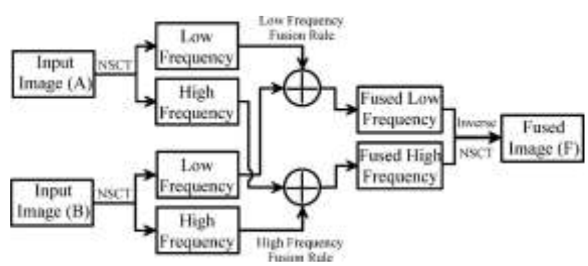

Figure 3 Block diagram of NSCT-simple framework[8]

It takes a pair of source image denoted by A and B to generate a composite image F by applying NSCT it devided into two parts,Low frequency component and High frequency component like wise for image B also, then after with the help of low frequency fusion rule it combine low frequency component of both images and with the help of high frequency fusion rule it combine high frequency component of both images. Then by applying inverse NSCT we get Fused image.

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Fusion rule :
Other important factor which influences the fusion quality is the fusion rule used for combining the coefficients of different sub-bands. Since low- and high-frequency sub-bands carries different information of source images, different fusion rules are used for combing LF sub-band and HF sub-bands. LF subband is smoothed version of original image and it represents the outline of the image. HF sub bands represents details like edges and contours of original image.
(a) The low-frequency coefficients of the fused image can be simply acquired by averaging the low-frequency coefficients of the input images. This rule decreased contrast in the fused images [15] and cannot give the fused subimage of high quality for medical images.
(b) The popularly used larger absolute rule is implemented in the value of a single pixel of the current high-frequency subband. The disadvantage of this method is that the coefficients only know the value of a single pixel but not any of the relationship between the corresponding coefficients in high-frequency subbands [16].
(c) Most fusion rules of the NSCT-based methods are implemented inmultifocus images [17] and remote sensing images [18]. The results are not of the same quality as those of the multimodal medical images. For example, Chai et al.[16] proposed a NSCTmethod based on features contrast of multiscale products to fuse multifocus images. However, it has been proven that this algorithmis not able to utilize prominent information present in the subbands efficiently and results in the poor quality when it is used to fuse multimodal medical images and when the coefficient of low frequency subband are fused by phase congruency and high frequency subband is directive contrast, gives the better result [8].
Phase congruency in NSCT domain : Other important factor which influences the fusion quality is the fusion rule used for combining the coefficients of different sub-bands. Since low- and high-frequency sub-bands carries different information of source images, different fusion rules are used for combing Low frequency sub-band and High frequency sub-bands. Low frequency subband is smoothed version of original image and it represents the outline of the image. High frequency sub-bands represents details like edges and contours of original image.Phase congruency that provide a contrast and brightness-invariant representation is applied to fuse low-frequency coefficient.This approach is based on the Local Energy Model, which suggest that significant features can be found at points in the image, where ever the Fourier components are maximally in phase. The phase congruency feature is invariant to illumination and contrast changes. The main properties, which acted as the motivation to use phasecongruency for multimodal fusion, are as follows.[8]

- A feature that is free from pixel mapping must be preferred.
- The phase congruency feature is invariant to illumination and contrast changes. The capturing environment of different modalities varies and resulted in the change of illumination and contrast.
- The edges and corners in the images are identified by collecting frequency components of the image that are in phase.

Directive contrast in NSCT domain : The contrast feature measures the difference of the intensity value at some pixel from the neighboring pixels.The human visual system is highly sensitive to the intensity contrast rather than the intensity value itself.

Therefore, local contrast is developed and is defined as[8]

$$C = \frac{L - L_B}{L_B} = \frac{L_H}{L_B}$$

Where, L is the local luminance and LB is the luminance of the local background. Generally, LB is regarded as local low-frequency and hence, L- LB = LH is treated as local high-frequency.

PERFORMANCE MEASURES OF IMAGE FUSION

Human visual perception can help to judge the effects of fusion results. However, it is easily influenced by visual psychological factors. The effect of image fusion should be based on subjective vision and objective quantitative evaluation criteria. Some objective evaluation merits, such as entropy, average gradient, standard deviation, Mutual information, Structural Similarity based Metric, and Edge Based Similarity Measure and so forth, are employed to describe the information contained in the fused images.

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CONCLUSION

In this paper, multimodality medical image fusion has been reviewed from the different published research works and it is concluded that although quite good results have been reported by NSCT based method, there is still much room to improve the fusion performance in the coefficient selection (fusion rule) with less information distortion than other fusion methods.

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