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A Survey on Various Medical Image Fusion Techniques

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Abstract: *Image fusion is a method of integrating all relevant and complementary information from images of same source or various sources into a single composite image without any degradation. Three major fusion methods have been dealt in the literature of image fusion – pixel level, feature level and decision level. In this paper, a novel pixel level fusion called Iterative block level principal component averaging fusion is proposed by dividing source images into smaller blocks, thus principal components are calculated for relevant block of source images. Analyzing quantitative and qualitative metrics such as average mutual information and mean structural similarity index clearly demonstrate that the proposed algorithm proves superior than other algorithms for the fusion of noise free and noise filtered MR images.*
Keywords: *Image fusion, PCA, AMI, SOM, SSIM,DTCWT.*

I. Introduction

The main objective of medical image fusion is faithful integration of visual information observed from various input images into single image without any degradation and loss of information [1].Three major fusion methods have been dealt in the literature of image fusion – pixel level, feature level and decision level. Each method has its performance variability for various inputs. Pixel level fusion is carried out either in spatial domain or in trans-form domain. In spatial domain, relevant pixel values of source images contribute to the pixel value in the fused image. But spatial domain methods often lead to the absence of spectral information and introduce spatial distortions. Degradation in the form of poor perceptual quality is introduced by pixel level fusion methods such as averaging and weighted averaging. In transform domain, multi-resolution approaches have been proposed in the literature to overcome this problem.

Wavelet transforms based fusion is the alternative for this set-back, but often suffer from shift sensitivity, poor directionality and absence of phase information [8,9]. Dual tree complex wavelet transform (DTCWT) offers better directionality and shift invariance than wavelet transforms, hence suitable for wavelet based image fusion. But DTCWT is computationally costly and requires large memory.Principal component analysis (PCA) is an efficient method for feature extraction, dimensionality reduction and data representation. .Lot of algorithms has been proposed for fusion based on PCA because of its computation and realization. PCA is well known decorrelation method in statistical sense and preserves only the most significant principal components, thus lead to reasonably good image fusion. Principal components are derived from the covariance matrix and its diagonalization by finding its eigen vectors and eigen values. Largest principal components are the linear representation of most of the image details present in source images.These largest principal components corresponding to the largest eigen values of covariance matrix are the weights for the input images in the fusion rule [4].In this paper, a novel pixel level fusion algorithm called, Iterative block level principal component averaging (IBLPCA) has been pro-posed for fusion of noise free and noise filtered MR brain images.This algorithm evaluates principal components by splitting images into image blocks. Size of the image blocks are decided based on average mutual information (AMI) between fused image and source.

II. Literature Survey:

Zhigang Fenga, Tao Xua compared the fault diagnosis reliability and fault diagnosis efficiency (time consumption property) of PCASOM and SOM in liquid propellant rocket engine ground-testing bed, two types of ground-testing bed fault data are used. One is generated by the mechanism model of ground-testing bed. The other is generated according to the expert's experience and the statistical model of fault mode. The comparison results using these two types of fault data both indicate that the fault diagnosis reliability and fault diagnosis efficiency of PCA-SOM are better than SOM.[5]

Xiaoyan Luo a,n, JunZhang a,n, QionghaiDai proposed an image-driven regional fusion method based on a specific region partition strategy according to the redundant and complementary correlation of the input images. Different from the traditional regional fusion approaches dividing one or more input images, our final region map is generated from the similarity comparisons between source images. Inspired by the success of structural similarity index (SSIM), the similarity characteristics of source images are represented by luminance, contrast, and structure comparisons. To generate redundant and complementary regions, we over segment the

SSIM map using watershed, and merge the small homogeneous regions with close correlation based on the similarity components. In accordance with the concentrated similarity of different regions, the fusion principles for special regions are constructed to combine the redundant or complementary property. In our method, the redundant and complementary regions of input images are distinguished effectively, which can aid in the sequent fusion process. Experimental results demonstrate that our approach achieve superior results in the different fusion applications. Compared with the existing work, the proposed approach outperforms in both visual presentation and objective evaluation.[6]

Jae Ho Jang proposed a novel pixel-level multisensor image fusion algorithm with simultaneous contrast enhancement. In order to accomplish both image fusion and contrast enhancement simultaneously, we suggest a modified framework of the subband-decomposed multiscale retinex (SDMSR), our previous contrast enhancement algorithm. This framework is based on a fusion strategy that reflects the multiscale characteristics of the SDMSR well. We first apply two complementary intensity transfer functions to source images in order to effectively utilize hidden information in both shadows and highlights in the fusion process. We then decompose retinex outputs into nearly non-overlapping spectral sub-bands. The decomposed retinex outputs are then fused subband-by-subband, by using global weighting as well as local weighting to overcome the limitations of the pixel-based fusion approach. After the fusion process, we apply a space-varying subband gain to each fused SD retinex output according to the subband characteristic so that the contrast of the fused image can be effectively enhanced. In addition, in order to effectively manage artifacts and noise, we make the degree of enhancement of fused details adjustable by improving a detail adjustment function. From experiments with various multisensor image pairs, the results clearly demonstrate that even if source images have poor contrast, the proposed algorithm makes it possible to generate a fused image with highly enhanced contrast while preserving visually salient information contained in the source images.[7]

Alex Pappachen James , Belur V. Dasarathy has proposed medical image fusion is the process of registering and combining multiple images from single or multiple imaging modalities to improve the imaging quality and reduce randomness and redundancy in order to increase the clinical applicability of medical images for diagnosis and assessment of medical problems. Multi-modal medical image fusion algorithms and devices have shown notable achievements in improving clinical accuracy of decisions based on medical images. This review article provides a factual listing of methods and summarizes the broad scientific challenges faced in the field of medical image fusion. We characterize the medical image fusion research based on (1) the widely used image fusion methods, (2) imaging modalities, and (3) imaging of organs that are under study. This review concludes that even though there exists several open ended technological and scientific challenges, the fusion of medical images has proved to be useful for advancing the clinical reliability of using medical imaging for medical diagnostics and analysis, and is a scientific discipline that has the potential to significantly grow in the coming year.[8]

R. Vijayarajana, S. Muttan proposed a novel pixel level fusion called Iterative block level principal component averaging fusion is proposed by dividing source images into smaller blocks, thus principal components are calculated for relevant block of source images. Average of principal components of all the blocks provide weights for fusion rule, thus importance is given to blocks of source images. In this scenario, Iterations are incorporated in the form of size of blocks of source images which gives fusion results with maximum average mutual information.This algorithm is experimented for the fusion of noise free medical images and noise filtered of the same.The experimental results for both the cases show that the proposed algorithm performs well in terms ofaverage mutual information and mean structural similarity index.[4]

III. Comparison

Table 1 Performance of IBLPCA fusion of noise free images.[4]

Methods	MR & MR0	MR1 & MR2	MR 3 & MR 4
Average mutual information			
PCA	2.533853	2.22172	1.952471
IBLPCA	6.087183	2.368309	2.166826
DWT	1.570518	1.585696	1.456032
DTCWT	1.615786	1.616904	1.591223
Mean structural similarity index			
PCA	0.89534	0.950355	0.854088
IBLPCA	0.997192	0.989364	0.98074
DWT	0.920122	0.958164	0.903017
DTCWT	0.918625	0.940512	0.888479

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