Multimodal Brain Images for Fusion Domains

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Abstract: ***The medical cases resulting due to neurological changes are dependent on imaging techniques for clinical assessment. The advent of diagnosis is dependent on the imaging modality and how the underlying organ is captured. Medical modalities can be divided into spatial and transform domain. Each includes a unlike lay down of medical information during capture. The content of diagnostic information captured from the neurological images is directly proportional to the strength and limitation of the selected medical modality. As per literature, only some diagnostic information is captured from one modality. Assimilating information from multiple modalities better reads and incorporates the clinical diagnostic data. This paper is designed to study and collaborate the study of neurological images from multiple modalities into a single fused image at multiscale. Neurological image fusion is aimed to encompass intricate diagnostic details in a single fused image to abet improved diagnosis.***

Keywords: Image fusion, Spatial Domain, Transform Domain, Multimodal Modality, fusion rules

1. Introduction

Medical imaging is the field of medicine also known as radiology. It is a non invasive technique to capture the underlying organ, bone, tissue and blood vessels in order to assess, diagnose and cure the patient. It plays a major role in modern imaging to show the interior of the body for analysis and treatment. The progression in imaging technology, revolutionaries all healthcare. The improved technologies provide high quality images with no interventions and reduced radiation. These modalities help accurately differentiate between the healthy and the diseased tissue. The innovation and accomplishment in medical image fusion research has enhanced due to the advancements in medical imaging equipments. The medical images are confined from different modalities as from anatomical, functional, tomography and projection. Each medical imaging modality consciously extracts the precise and detailed clinical features from the domain. Each modality only partially extracts medical information in order to differentiate disease from normal. Therefore with single modality it is hard to reveal structural tissue differences [1]. Scans from multiple modalities unveil additional clinical details for better diagnosis in a multidimensional manner. The aim is to extract and combine additional information in the fused image. This process of fusion must divulge information not achievable in single modality image scans. The structure and functional information is integrated for observation and diagnosis using image fusion [2]. The sections are as Section II gives the Levels of fusion, Section III illustrates the image fusion domains. Multiscale fusion framework is in section IV. The multiscale techniques from literature are given in section V, Conclusion in section VI.

2. Fusion Level Categories

Fusion can be performed at different levels of information representation as pixel level, feature level and decision level fusion [3]. Few authors have also worked on combined level to obtain fusion results [4]. Pixel level fusion combines original information from the source images. The spatial characteristics are preserved as the original pixel values are retained. The computational time is minimal in pixel level fusion. The simplicity in combining pixels from multiple medical images makes this as the preferred technique for fusion. Feature level fusion includes feature information and feature extraction from input images. Salient features are extracted. The size, shape, grey level, create a region map [5]. In Feature level fusion Mapping is conducted, but all features are not extracted. Decomposition, filtering, in feature fusion mechanism with PCA, with panchromatic and Multispectral images are proposed in literature [6]. Various schemes are proposed in literature with Each techniques aiming to extract specific image features to form the feature vector. Decision level fusion assimilates pixel intensities, texture information extracted in the form of features from the data [7] creating decision maps based on decision rules and classifiers.

3. Medical Image Fusion Domains

Image fusion methods are reported by researchers in literature in Spatial and Transform domains.

Spatial Domain Image

These techniques combine input images in either linear or non linear mode. In spatial domain the images can be directly combined at pixel level integrating the pixel intensities. The is given by p^i (m, n) where p^i is intensity value at pixel coordinates m, n. C_{m1} and C_{m2} are constants defining fusion. Medical images M1 and M2 are given by Im^{M1} and Im^{M2} in simple averaging function is given as

$$Im^{M1} = C_{m1.}p^i\,(m1, m2)\,.\,Im^{M1} \qquad (1)$$

$$Im^{M2} = C_{m2.}p^i\,(m1, m2)\,.\,Im^{M2} \qquad (2)$$

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$$Im^F(m1,m2) = (a.Im^{M1} + b.\ Im^{M2})/2 \quad (3)$$

The combination at each spatial position is given by

$$IM^F = \max\ [p^i(m1, m2)\ .\ Im^{M1},\ p^i(m1, m2)\ .\ Im^{M2}] \quad (4)$$

In spatial domain, have limitations of random noise, registration errors, deviation in results, and overlapping constraints.

The spatial alignments of features from complementary images suffer from registration errors and posses a limitation in obtaining accurate fusion results. Certain vital details from the fused image are smoothened due to combination resulting from overlap of the images.

Transform Domain Image Fusion

In this the intensity pixel values are changed governed by multiscale principle. Transform domain techniques have three broadly classifications. Pyramid transforms, basic wavelet transforms and advance wavelet transforms are multi scale transforms. Filter subtract decimate pyramid, Laplacian pyramid, morphological pyramid, ratio to low pass pyramid, contrast pyramid and gradient pyramid technique are pyramid multiscale techniques [8]-[10]. The basic wavelets are Discrete Wavelet Transform (DWT), Stationary Wavelet Transform (SWT), Lifting Wavelet transform (LWT) , Dual Tree Complex Wavelet Transform (DTCWT) and Discrete Fractional Wavelet transform. (DFRWT). The complex wavelets as Ripplet Transform (RT), Curvelet Transform (CVT), the Contourlet Transform (ConT), Non-subsampled Contourlet Transform (NSCT) [11],[12] and Discrete Fractional Wavelet Transform [13]. These are depicted in Fig. 1.

These transforms better signify the edges, boundaries and discontinuities parallel to human visual system. Pyramids endure blocking effects and the heterogeneous aspects are represented inadequately. The complex wavelets give image details with stability and phase information. The fractional wavelet transform (FRWT) are capable of capturing both frequency and time location to represent the input [13][14]

Fusion Framework

The multiscale fusion perform decomposition of original images. This is performed at different resolutions. [15]. Literature provides categorization of image fusion methods at multi scale [16]. Comparison of different multi-resolution techniques was performed in literature [17].

Analysis section and synthesis block formulate the multiscale fusion. In a generalized fusion mechanism as depicted in fig 2, the inputted medical images from two modalities are decomposed in the analysis section. Fusion rules combine images in synthesis section. The inverse transform forms the final fused image.

The evaluation of the fusion mechanism is metric based. includes objective and subjective metrics. The Subjective evaluation does visual image assessment and objective metrics from literature are Mean square error, Shannon's Entropy, Structural Similarity Index, Mutual information, Standard Deviation etc [18]-[21].

Results from a Fusion mechanism using Neuro medical images are acquired from multiple modalities for the clinical cases is given in fig 3. The medical images are pre processed to remove noise and impurities.

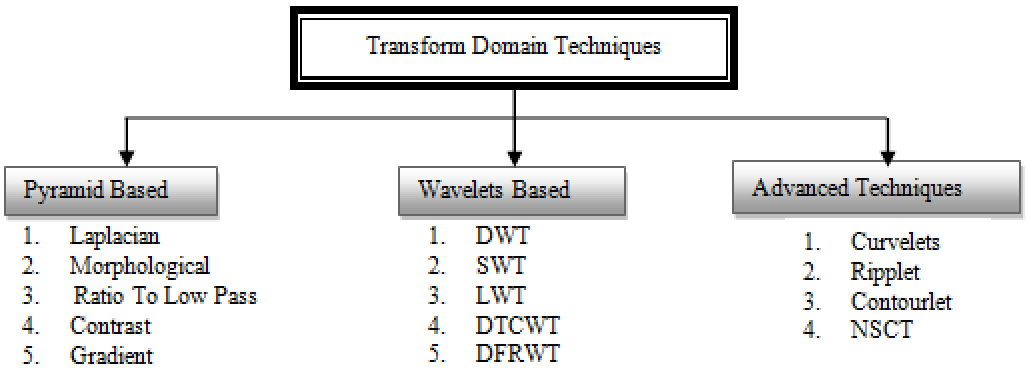

Figure 1: Transform Domain Fusion Techniques

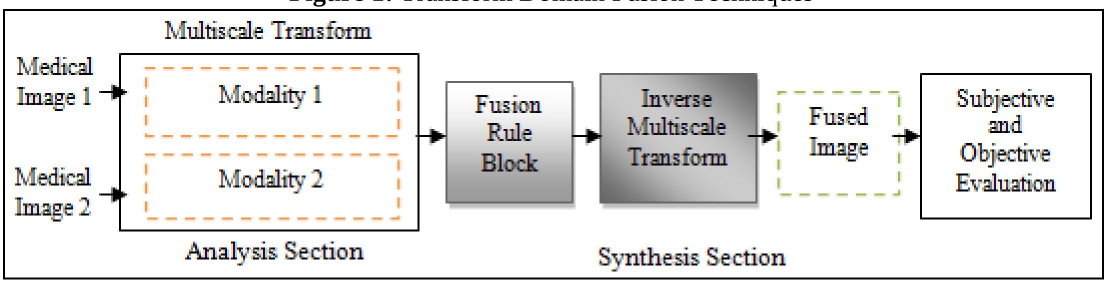

Figure 2: Multiscale Medical Fusion Method

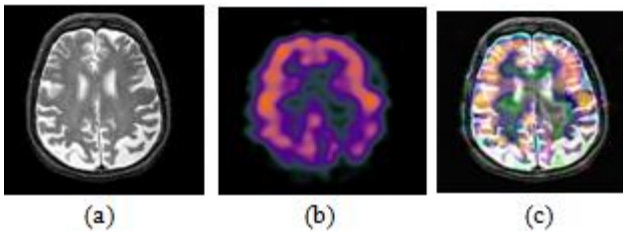

Figure 3: Image Fusion (a) MRI (b) SPECT (c) Fused Image

When complementary medical images are fused, they superior diagnostic information is congregated.

4. Medical Modality based Literature

The literature is presented with respect to medical modalities.

Lot of work is done in literature to fuse anatomical modalities using brain images. The Mexican hat wavelets is used with a multiscale transform to decompose the images into various coefficients at multiple scales[22]. Meaningful results are obtained with whole anatomical structure preservation using hierarchical scheme and morphological filters [23]. Images CT and MRI are fused using different wavelets DWT, Dual Tree Complex Wavelet Transform (DT-CWT) and Discrete Dyadic Wavelet Transform (DDWT) [24]. DT-CWT preserved regions better, and improved outputs in association to PCA and shift invariant DWT. MRI, CT brain image are combined with wavelets, with human visual system [25]. CT/MRI, T1-MR/ MRA, CT/ T1-MR images used Sub sampled Contourlet transform and pulse coupled neural network to fuse [26]. Multiscale transform and sparse representation were used to fuse CT with MRI and Gd-DTPA-MR with MR-T2 pairs. [27]. CT and MRI were fused using Curvelets and Wavelet [28]. Another Multimodal model was projected to fuse MRI and CT cerebral infraction images [29]. The image fusion techniques have been discussed from literature for anatomical-anatomical images.

Multiple literature deals with anatomical-functional fusion. Reference [30] MRI and PET images are fused using DWT technique. Anatomic markers with respect to the functional information were presented. PET and MRI brain image wavelet decomposition was presented in [31]. Reference [32] proposed MR and SPECT multiscale variable weight fusion. The idea to reduce the tremendous increase in volume of data was advanced to achieve superior results for further processing using multiple modalities [33].

A multimodal image fusion improves diagnosis on MRI and SPECT combines structural and functional data from multimodal anatomical and functional input [34]-[35]. The multimodal anatomical and functional based fusion techniques in literature are conferred.

5. Conclusion

Widespread research has been completed in medical image fusion. Various algorithms have been proposed in literature, for improving the diagnostic value from fusion. Medical images are difficult to interpret and encompass ambiguous diagnostic information. In this paper medical fusion framework, fusion mechanisms and techniques with respect to modalities are discussed from literature. The transformations, the modalities, the organ, together form the fused image.

Anatomical and functional modalities, have higher diagnostic assessment in previous work. Fractional wavelet transforms characterize in time-fractional-frequency domain. From it is learn that existing methods have a greater potential of progression.

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