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Survey Of Data Fusion And Tumor Segmentation Techniques Using Brain Images

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ABSTRACT

Medical image fusion combines several medical images from different modalities to a single image. It gives more quality image and clinical information dropping redundancy. The fusion methods have proved better information accuracy and thereby increase clinical applicability like diagnosis, segmentation, surgery planning etc. MRI has gained wide acceptance due to its ability to provide tissue details. This survey article provides list of methods for the image fusion and MRI brain segmentation. The image fusion review is mainly based on three levels 1) pixel level, feature level and decision level. 2) Widely used techniques for image fusion. 3) Techniques for MRI brain segmentation. This paper concludes that these methods will help physician in medical diagnosis and analysis within short span of time.

Keywords: Image fusion, image segmentation, brain tumor.

1. INTRODUCTION

Development of high-modernized technology and instruments has drastically paved the way for many treatments, diagnosis, research applications in medical fields. Medical imaging was revolutionized when X-ray and CT were introduced and it provided clear cross sectional image of human body. Later on tomography, MRI, ultrasound, FMRI gained wide acceptance. Physicians and researchers were able to provide more accurate information from image fusion. It's all about integrating information in the images from different sources. Medical Images acquired from different viewpoint, sources and sensors provides useful details about human body. MRI depicts about soft tissues whereas CT provides details about hard tissues. So fusion of multimodal, monomodal images can provide more clinical information's and became very challenging and promising research area in recent. The imaging modalities can be classified into two, structural and functional modalities. Structural modalities depict morphology, including X-Rays, CT, Ultrasound, and MRI so on. Functional modality represents metabolism includes FMRI, PET, SPECT and EEG [1]. The initial stage of image integration is registration. Image registration is the process of bringing different images in same spatial alignment. Different combinations of component choice can be used for registration. The components are search space, feature space, search strategy, similarity metrics [2]. The modalities in image registration can be further categorized as

i. Monomodal
ii. Multimodal
iii. Modality to model
iv. Patient to modality

Though multimodal images signify important information, it also complicates extraction of diagnostic information. This difficulty can be simplified using multispectral analysis (MSA). Tissue properties can be extracted automatically from unrestricted number of image combination. Multi-spectral images are monochrome images of same picture which is taken from different sensors, where every image refers to as band. Fusion of multispectral image provides information to make decision on location, extension, prognosis and diagnosis of tumor. MR image encodes different pulse sequences. PD (Proton Density), T1 and T2 are two relaxation times that are susceptible to local environment which are used to illustrate different tissue type. T1 (Short T1 relaxation) characterize Fat, Lipid containing molecules, fluid, Gadolinium. Long T1 relaxation gives information about Neoplasm, Edema, inflammation, Pure fluid. PD high proton density depicts information concerning fats and fluids whereas PD low proton density gives Calcium, Air, Fibrous tissues, cortical bone. Short T2 relaxation contains blood break down products and Long T2 relaxation gives Neoplasm, Edema, inflammation, pure fluid [3]

This paper presents an outline of some of image data fusion techniques in section 2. Tumor Comparison and analysis of image fusion techniques are discussed in section 3. In section 4 the segmentation techniques for multispectral MR images has been described.

2. IMAGE FUSION

Image fusion can be performed in both spatial domain and frequency domain. It is categorized into three level, pixel level, feature level and decision level. In some papers it is also referred as low level, mid level and high level.

2.1 *Pixel Level*

Local operation is done in pixel level, but fused images are fashioned by applying transform domain algorithms. Pixel based image fusion can be processed as multi-transform based and multi-geometry analysis. Former one is frequently used technique; later one creates misrepresentation in images by adding artifacts in some area of image. There are different methods applied for image fusion in pixel level. An algorithm was described by Zheng et.al for this problem by reducing the spatial frequency error by focusing on desired image area. Averaging method is the simplest of image fusion. Averaging each pixel of input images gives the resulting image. laplacian pyramid[1] [5], gradiant pyramid [1] [7], morphological pyramid [1] [6], stationary wavelet transform (SWT) [8], FSD pyramid, DWT pyramid, SIDWT pyramid, IHS, contrast pyramid, ridglet transform, curvelet transform, non-subsampled counterlet transform, PAN sharpened ,DT-CWT [1] are the other methods. Table 1 is the comparison table of some image fusion techniques.

Table 1- comparison of image fusion techniques in pixel level

Technique	Modalities	Advantage	Disadvantage
Simple average	MRI,CT.PET	Simplest method.	No assurance of clear object from the image. Less quality
PCA	MRI,CT,PET	Redundancy in images are reduced	Contrast of image can be affected, occurrence distortion of spatial features are high
HIS	PET	Low resolution intensity component	Color distortion occurs. noise ,artifacts causes high contrasts
IHS+PCA	PET+MRI	Preserve more spectral features, reduced redundancy, high quality fused image	
Brovey method	CT, MRI	Efficiency of fused image spatial resolution, simple method.	Spectral distortion

2.2 *Feature Level*

Feature level image fusion, fuse images based on feature properties like regions and edges. Images are fused based on salience measure which helps to incorporate most important features. Salience matching helps in determining the method selection or averaging , local deviation, convolution method, local gradient, gradient match, fusion based on edge are few of them [9]. The improvement in feature level image fusion can be seen when wavelet methods combined with other technique. Fusion of wavelet technique and neural network is one of the most significant approaches in feature level. Wavelet image act as fusion operator whereas neural network performs feature processing. The other methods in feature level image fusion are wavelet–SVM method, self organizing map (SOM) –wavelets transform [10], texture-wavelet [11], lifting wavelets [12], self adaptive-wavelet operator [13], entropy-wavelet resolution [14], ICA –wavelet [15], wavelet –genetics [16], wavelet-neuro fuzzy.

2.3 Decision Level

Decision fusion can be categorized as hard and soft fusion. Fuzzy logic, voting, statistical are some of decision methods. Fuzzy integral, confidence fusion, separation index, position index are soft fusion whereas hard fusion represents logical information [17]. Table 2 provides the advantages of some of the feature based fusion techniques.

Table 2- Advantages of feature based image fusion

Technique	**Advantages**
Fusion on salience measure (Burt and koylensky)	Most dominant features are incorporated in fused image
Salience match measure	Determine selection or averaging to be used.
Convolution	Extraction of edge information from sub images based on direction(horizontal , vertical, diagonal)
Local gradient	Preserve edge information, so quality of fused image is high
Lifting wavelet	Information can be retrieved at different level and direction, reveals prominent features
Wavelet –entropy	Slight variations in signals are disclosed, provide details of minute region, pathological changes can be detected in the early stage
Wavelet-ICA	Integrate accurate information about soft tissues
Maxima /modulus transform	Edge and image information are conserved, high density of pixel

3 COMPARISON ANALYSIS AND DISCUSSION FOR IMAGE FUSION TECHNIQUES

3.1 Quantitative Comparison

In addition to the hypothetical analysis quantitative analysis is performed based on the table given below. The comparison is mainly performed only for the CT and MRI fusion for the dataset http://www.med.harvard.edu/aanlib/home.html, based on the parameters, standard deviation and $Q^{AB/F}$

Standard Deviation:

The contrast in the fused image or brightness probability distribution is estimated as standard deviation. High contrast image will have high standard deviation.

$$SD = \sqrt{\left(\frac{1}{M \times N}\sum_{m=1}^{M}\sum_{n=1}^{N}(I(m,n) - \mu\right)^2}$$

I(m,n) is an image of size M,N, μ is mean value [22].

Edge preservation Measure $\boldsymbol{Q^{AB/F}}$
This is edge retention measure, as the value increases better the result.

$$Q^{AB/F} = \frac{\sum_{n=1}^{N}\sum_{m=1}^{M}\left(Q^{AF}\,(n,m)w^{B} + Q^{BF}\,(n,m)w^{B}(n,m)\right)}{\sum_{n=1}^{N}\sum_{m=1}^{M}\left(w^{A}(n,m) + w^{B}(n,m)\right)}$$

$$Q^{AF} = Q_g^{AF}(n,m)Q_\alpha^{AF}(n,m)$$

$$Q^{BF} = Q_g^{BF}(n,m)Q_\alpha^{BF}(n,m)$$

$\boldsymbol{Q_g}$**= edge strength**
$\boldsymbol{Q_\alpha}$ **= orientation retention value** w is important factor, $Q^{AB/F}$ value ranges from 0-1. $Q^{AB/F} = 1$, represents no loss of information while fusion [18].

In Fig 2 and Table 3 four techniques Averaging, PCA, Laplacian Pyramid and DWT results are compared based on the parameter $Q^{AB/F}$, Edge similarity measure. As the $Q^{AB/F}$ value is high edge details are more preserved. From the above table and graph $Q^{AB/F}$ value is high for Laplacian Pyramid. In Fig 3 and Table 4 the comparison is done for three techniques Averaging, PCA and DWT with parameter Standard Deviation. Here it can be observed that the SD value is high for the PCA. As standard Deviation is high, it provides better result. From the above result we can infer that for high contrast image PCA gives the enhanced result and Laplacian Pyramid and DWT provides improved results. The above table values are assessment of $Q^{AB/F}$ from two papers [21] [20] respectively and Standard deviation from [19][20][21].

Table 3 – Edge preservation measure of various image fusion techniques Of various image fusion techniques

Techniques	$\boldsymbol{Q^{AB/F}}$	
Averaging	0.4264	0.4186
PCA	0.6549	0.6481
Laplacian Pyramid	0.7442	0.7296
DWT	0.6339	0.6167

Table 4 – Standard Deviation measure of various image fusion techniques Of various image fusion techniques

Techniques	Standard Deviation		
Averaging	34.95	34.9509	7.8904
PCA	54.16	54.1586	8.425
DWT	46.62	46.6236	7.9004

4 SEGMENTATION TECHNIQUES ON MRI BRAIN IMAGES

Segmentation is the process of segmenting the images and choosing the segment is performed based on region of interest and functional area. Segmentation methods plays vital role in medical imaging. Brain tumor segmentation is one of the major recent research areas, as it helps in diagnosis, treatment planning, surgery and radiotherapy. In clinics the segmentation is still a manual process, which is tedious and time consuming [23]. The major issue in manual segmentation is accuracy. The segmentation process can be broadly classified into manual segmentation, semi automatic segmentation and fully automatic segmentation. The Table 5 comprises the various segmentation techniques performed in MRI brain images.

Table 5- Segmentation techniques in MRI brain images

Author	Segmentation Technique	Modality	Type	Disease
Prastawa, Marcel, et al(2004) [24]	outlier detection	T1,T2	Automatic	Edema
Clark, Matthew C., et al(1998) [25]	knowledge based	T1,T2,PD	Automatic	glioblastoma-multiforme
Cobzas, Dana, et al(2007) [26]	tumor segmentation using a high dimensional feature set	T1,T2,T1c	Automatic	grade 2 astrocytoma, an anaplastic astrocytoma , glioblastoma multiforme

Shen, Shan, et al(2005) [27]	extension to the traditional fuzzy c-means (FCM) clustering algorithm	T1,PD	Semi-Automatic	
Wang, Jianzhong, et al(2008) [28]	modified FCM algorithm (BCFCM Algorithm)	T1	Semi-Automatic	
Ho, Sean, Elizabeth Bullitt et.al(2002) [29]	Level-set evolution	T1	Automatic	meningioma and glioblastoma
Yeh, Jinn-Yi, and J. C. Fu(2008) [30]	hierarchical genetic algorithm	T1,T2,PD	Automatic	meningioma
Corso, Jason J., et al(2008) [31]	Weighted aggregation algorithm	T1,T2	Automatic	glioblastoma multiforme brain tumor
Zhang, Nan, et al(2011) [32]	Kernel feature selection+SVM	T1,T2,PD	Automatic	
Nie, Jingxin, et al(2009) [33]	tumor segmentation using spatial accuracy-weighted hidden Markov Random Field	T1,T2,FLAIR	Automatic	Edema

Kaus, Michael R., et al(2001) [34]	Adaptive template	T1	Automatic	low-grade glioma,meningioma
Cai, Hongmin, et al(2007) [35]	Probabilistic	T1,T2,FLAIR,DW1	Automatic	Glioma

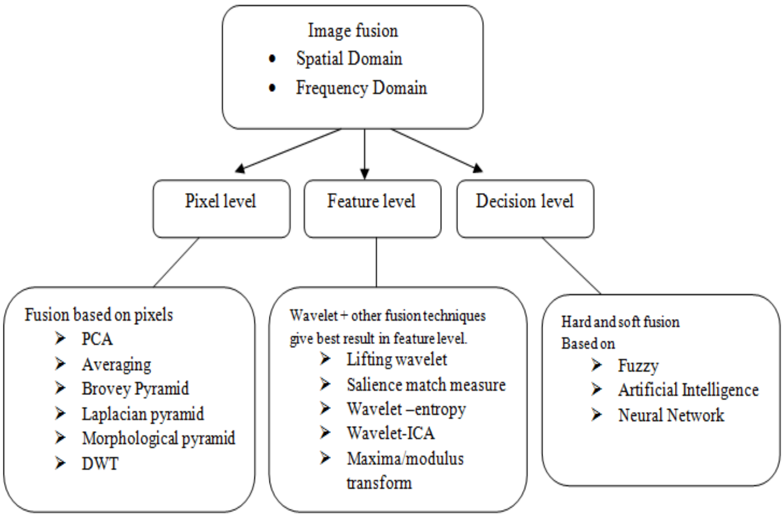

Fig 1 Classification of Image Fusion

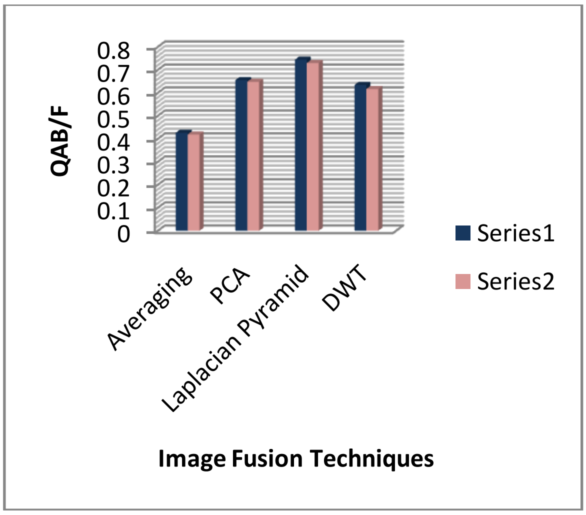

Fig 2 – Graph analysis of image fusion techniques for Edge similarity measure

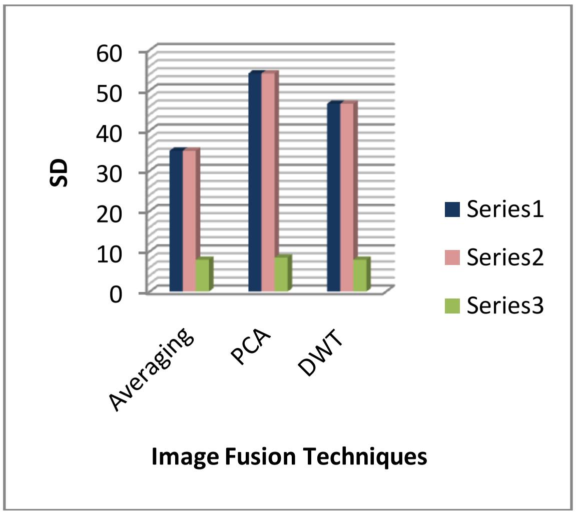

Fig 3 – Graph analysis of image fusion techniques for standard deviation.

5 CONCLUSION

In this review paper we have mainly discussed about the various image fusion and segmentation techniques. From the above study we can conclude that due to the rapid growth in technology, medical imaging applications are extensively used in both research and medical field. Several algorithms and techniques have come up with better results that gains clinical reliability. It also helps medical expert in diagnosing, tumor treatment, analysis and radiotherapy. Wavelet techniques are observed to be most relevant technique. Combining wavelet techniques with other methods also gives better results. Various fuzzy, neural networks, machine learning techniques are used for brain tumor segmentation. Though semi automatic and fully automatic segmentation provides good result, it is not widely accepted in clinic. Even though we have remarkable improvement in medical field, efficiency of image fusion, time complexity, computation complexity, availability of medical images is still a challenge.

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