A NOVEL APPROACH FOR MULTI-MODAL MEDICAL IMAGE FUSION USING FUZZY TRANSFORM

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ABSTRACT

Multimodal medical image fusion has turned into an amazing asset in clinical applications. The primary point is to intertwine distinctive multimodal medical images, acquired from various imaging modalities, into a solitary melded image that is widely utilized by the doctors for unequivocal diagnosis and treatment of ailments. In this paper, an improved multimodal medical image fusion algorithm dependent on fuzzy transform (FTR) is proposed. The center thought behind the proposed algorithm is to improve the presentation of multimodal medical image fusion algorithm by thinking about the blunder images acquired utilizing FTR pair. Emotional just as target assessments show that the fusion quality as far as edge quality, standard deviation, include common data, fusion factor, highlight similitude and auxiliary closeness has altogether improved in the proposed algorithm when contrasted with other state-of-art multimodal medical image fusion algorithms.

I.INTRODUCTION

Medical imaging, diagnostics, and treatment arranging are in a progress stage. Present day prescription depends on data gave as images. Transverse cuts of the human body got from various modalities like Computed Tomography (CT), Magnetic Resonance Imaging(MRI), Positron Emission Tomography (PET), Single Photon Emission Computed Tomography (SPECT), and so on are generally utilized for the assessment of the patients' status. Distinctive imaging uncovers diverse data about a similar life structures and thus gives complimentary data to the clinicians. Medical imaging innovation has experienced huge improvement in the course of the most recent decades. Numerous modalities are currently ready to give three-dimensional and four-dimensional data (i.e.) 3D imaging extra time.

The manner in which the images are introduced and translated are additionally being changed. Despite the fact that 3D-and 4D-visualization methods are utilized for an expanding number of utilizations, the cross-sectional 2D cut images are still prevalently utilized in radiology. For legitimate diagnosis, medical images need to give two significant and interrelated snippets of data to radiologists: precisely what is happening and definitely where in the body. Anatomic imaging advancements like MRI and CT plainly demonstrate the morphological highlights like size enliven alone it is hard to decide if the suspicious mass is amalignant tumor or fibrosis. The useful imaging advancements like SPECT and PET utilize radio marked glucose or monoclonal antibodies to give the vital data on the cell movement, however it can't give the anatomical subtleties expected to correct restriction. From the useful data alone, it is hard to find precisely whether the metastatic hotspot is in the muscle or the close-by bone. Radiologists need both anatomic and useful information to make an authoritative diagnosis. High caliber advanced presentations are rising up out of radiology perusing rooms into interventional settings and even into versatile gadgets. Rather than seeing X-Ray movies and next to each other CT cut images on an illuminated board in the working room, specialists would now be able to picture live interventional imaging. Gone are where the medical images given by various modalities were considered as discrete wellsprings of data, coordinated just in the psyches of the physician.

Exact diagnosis and treatment arranging is conceivable by coordinating the medical images got utilizing distinctive imaging systems. The ongoing advances in the medical imaging innovation and the improvement of image handling algorithms give new methods for visualization. The converging of numerous imaging information of a similar patient, procured at various occasions and by various modalities, is named as multimodal fusion. Uniting anatomical and practical data with affectability and particularity gives the genuine estimation of multimodal fusion imaging. Blending the images got from various modalities with no artifacts is the focal point of this paper.

II.LITERATURE SURVEY

Kaur & Sharma (2013) proposed an improved contourlet transformation technique by modifying Directional Filter Banks (DFB) with log Gabor filters. It not only provides good quality of images but also localizes an image more accurately and minimizes the noise in the image .Singh & Goyal (2013) proposed the image fusion algorithm based on the contourlet transform. The basic drawbacks of the image fusion algorithms are that its basic images are not localized in the frequency domain and less regularity is seen in the spatial domain.

Dammavalam et al (2013) proposed an iterative fuzzy logicapproach and utilized it to fuse the images obtained from different sensors, inorder to enhance visualization. This work further explores the comparisonbetween fuzzy based image fusion scheme and the iterative fuzzy fusiontechnique. The quality evaluation indices used for the analysis includes imagequality index, mutual information measure, Root Mean Square Error (RMSE),PSNR, entropy and correlation coefficient. Experimental results show that the iterative fuzzy fusion scheme can efficiently preserve the spectral information. It also has improved the spatial resolution of the remote sensing images and the medical images.

Nair et al (2013) demonstrated an image fusion algorithm known as fuzzy let that was developed by combining the features of Stationary Wavelet Transform (SWT) and fuzzy logic.

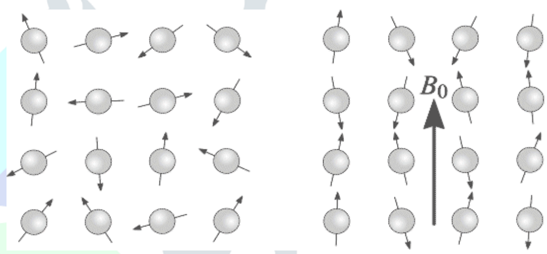
III.MEDICAL IMAGINGMODALITIES

Medical imaging is the procedure of making visual portrayals of the inside of a body for clinical investigation and medical mediation. It looks to uncover the inner structures covered up by the skin and bones, just as to analyze and treat sickness. Medical images are procured in different groups of the electromagnetic range. The wide assortments of sensors utilized for the procurement of the images and the material science behind them, make every methodology reasonable for a particular reason. Continu happen amid obtaining and to get data that is increasingly helpful from the images.

A.MAGNETIC RESONANCE IMAGING

Lauterbur (1973) who produced a 2D MR image of a phantom first illustrated the process of acquiring 2D and 3D images by nuclear magnetic resonance, known as MRI. Over the last 20 years, Fourier transform imaging techniques have tremendously accelerated the development of MRI (Kumar et al1978).

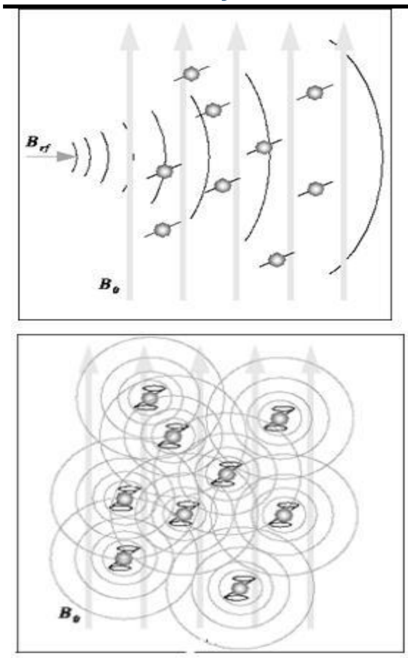
The premise of MRI is the directional magnetic field, or minute, related with the charged particles in movement. Cores containing an odd number of protons as well as neutrons have a trademark movement or precession. Since cores are charged particles, this precession creates a little magnetic minute. At the point when a human body is set in a huge magnetic field, huge numbers of the free hydrogen cores adjust themselves to the course of the magnetic field. The cores procedure about the magnetic field heading like gyrators. This conduct is alluded to as Larmor precession.



a)1H nucleiwithoutB_0 (b) 1H nuclei with B_0

Figure 1.Behavior of nucleus in the magnetic fieldB_0

Next, a radio-frequency pulse, B_{rf}, is applied perpendicular to B_0. When the frequency of this pulse equals the Larmor frequency, M tilts away from B_0. When the radio-frequency signal is evacuated, the nuclei realign themselves to such an extent that M, is again parallel with B0. This arrival to equilibrium is alluded to as unwinding. Amid unwinding, the nuclei lose vitality by producing their very own radio-frequency signal as appeared in Figure 2.2. This signal is alluded to as the Free-Induction Decay (FID) response signal. The FID response signal is estimated by a conductive field coil put around the item being imaged. This estimation is handled or recreated to acquire 3D dim scale MRI pictures.



a)When B_{rf} is applied(b) When B_{rf} is removed

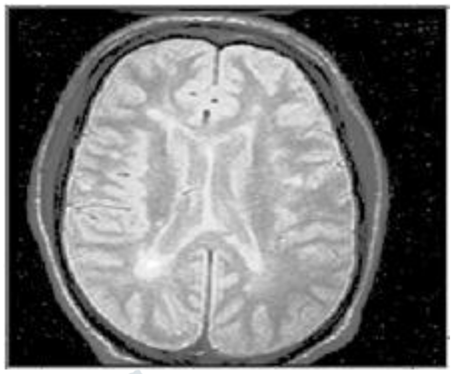
Figure 2. Net magnetic moment of the nuclei

The 2D spatial reconstruction with each pivotal cut is practiced utilizing frequency and stage encoding. A gradient in the y-heading, Gy, is connected making the thunderous frequencies of the nuclei change as per their situation in the y-bearing. Gy is then expelled and another gradient in the x-course, Gx, is connected opposite to Gy. Thus, the full frequencies of the nuclei shift in the x-heading due to Gx, and have a stage variety in the y-course because of the recently connected Gy. Along these lines, x-course tests are encoded by frequency and y-bearing examples are encoded by stage. A 2D Fourier transform is then used to transform the encoded picture to the spatialdomain.

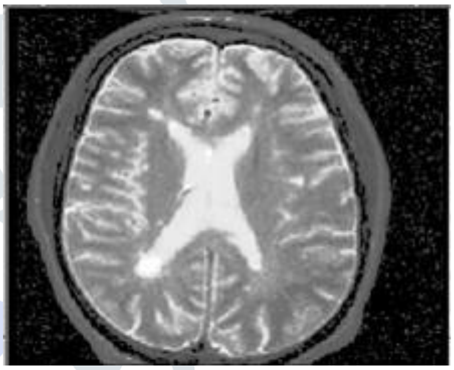
The voxel power of a given tissue type relies upon the proton thickness of the tissue; the higher the proton thickness, the more grounded theFID response signal. The MR picture differentiate additionally relies upon two other tissue-explicit parameters:

1. The longitudinal relaxation time, T1 2. The transverse relaxation time, T2 When MRI images are acquired, the radio-frequency pulse, B_{rf}, is repeated at a predetermined rate. The period of the radio-frequency pulse sequence is the repetition time, TR. The FID response signals can be measured at different instant of times within the TR interval. The time between which the radio-frequency pulse is applied and the response signal is measured is the echo delay time, TE. By adjusting TR and TE, the acquired MRI image can be made to contrast different tissuetypes.

Figure 4 shows 2D slices from the weighted MRI volumes. The TR and TE are adjusted such that tissues with a high proton density appear bright in the first image and tissues with a long T2 appear bright in the second image. The two images are said to be proton density-weighted and T2-weighted respectively.



a)PDweighted



(b) T2 weighted

Figure 4. MRIimages

III.PROPOSED SYSTEM

In the course of the most recent couple of years, medical imaging has created from a stateof infancy to a condition of development. Different imaging modalities, for example, CT,MRI, PET and SPECT have empowered radiologists to investigate the perplexing body parts situated in the inside of human body .However, extraordinary imaging modalities give exceptionally corresponding data. For instance, CT and MRI furnish images with superb anatomical in-arrangement and exact confinement yet can't give utilitarian data. Though, PET and SPECT give images containing exceedingly useful data that is required for recognizing metabolic variations from the norm however can't give the anatomical subtleties required to exact restriction. Along these lines, so as to get a solitary medical image that can give both the anatomical data just as the useful data, medical images of various modalities are required to be intertwined. This prerequisite, of getting a solitary melded medical image that has the vast majority of the applicable data, has attracted the consideration of analysts towards multimodal medical image fusion.

Multimodal medical image fusion intends to consolidate data, from numerous medical images of same methodology or of various modalities, to give a solitary melded image. The melded image so obtained provides data that is progressively exact to the doctors for express analysis and treatment of ailments. Multimodal medical image fusion has wide scope of utilizations because of its reduced and exact portrayal of data. For example, fusion of CT and PETimages not just assistance oncologists to plan and screen malignancy treatmentbut additionally help cardiologists to survey the nearness and degree of coronaryartery illness [1]. Fusion of SPECT and CT images give upgraded confinement and organizing of neuro endocrine tumor [2]. Fusion of MRI and CT is utilized for neuron route in skull-base medical procedure [3]. Further, fusion of PET and MRI images can be utilized to identify and pursue assortment of sicknesses from neurodegenerative clutters to cardiovascular diseases[4].

Many image fusion calculations have been created in literature[5,6]. These calculations can be comprehensively gathered into three categories[7]: pixel-level, include level and choice dimension. Pixel-level calculations can protect the vast majority of the first data when contrasted with highlight level and choice dimension calculations [8,9]. Further, pixel-level calculations are anything but difficult to actualize, are computationally increasingly proficient, and are hence favored for multimodal medical image fusion. The generally utilized pixel-level image fusion calculations [10] are average based fusion calculation and select maxima based fusion algorithm. However, these calculations regularly lead to unfortunate reactions such as reduced differentiate [11]. Other pixel-level image fusion calculations are principal part examination (PCA), power tone immersion (IHS) and Brovey transform (BT). Be that as it may, the intertwined image acquired utilizing these algorithms experience the ill effects of high spatial contortion and low SNR [12] and are therefore not favored for medical image fusion. To defeat these disadvantages, multimodal medical image fusion calculations based on multi resolution transforms have been created by numerous scientists.

The most commonly used multi resolution transforms include pyramid transforms and wavelet transforms. Pyramid transforms include Laplacian pyramid, Gaussian pyramid, contrast pyramid, ratio of low pass pyramid and morphological pyramid. However, pyramid transforms fail to introduce spatial orientation selectivity in the decomposition process and occasionally introduce many undesired edges in the fused image. Wavelet transforms include discrete wavelet transform(DWT), lifting wavelet transform (LWT), Daubechies complex wavelet transform (DCxWT) and dual tree complex wavelet transform(DTCWT).

In order to take into account the intrinsic geometrical structure of images, several multiscale geometric analysis tools such as curvelet transform [16], ripplet transform [17], contourlet transform, non-subsampled contourlet transform (NSCT) [18] and shearlet transform [19]have been used by many researchers for fusion of multiple images. Moreover, artificial neural networks based image fusion algorithms alsoexist in literature. However, the performances of neural network based algorithms depend upon the number of neurons in the hidden layer[20–22].

Researchers have successfully used FTR in developing image fusion algorithms [26,27] as FTR possesses various important properties such as ability to provide better approximation, ability to preserve image edges, noise removing capability and smoothing ability. Multimodal medical image fusion algorithm base on FTR has already been proposed in [26] and produced good fusion results. However, the algorithm presented in [26] does not take into account the loss of information that is contained in the error images, obtained using FTR pair (i.e. FTR and its inverse transform). The errorimage is the difference between the original image and the reconstructed image obtained using FTR. Considering the accuracy required in medical field, the loss of information contained in error image cannot be neglected. Thus, in order to produce a highly informative fused medical image that takes into account the error images, an improved multimodal medical image fusion algorithm based on FTR is proposed in the paper.

Contribution: Considering the accuracy required in medical field, an improved multimodal medical image fusion algorithm based on fuzzy transform is proposed in the paper. The proposed algorithm produces highly informative fused medical images by taking into account the loss of information that is contained in the error images obtained using FTR pair. The proposed algorithm has been performed on different datasets of medical images. Results obtained using the proposed algorithm has been compared, subjectively as well as objectively, with recent state-of-art multimodal medical image fusion algorithms.

The fused images obtained using proposed algorithm have better visual quality with sharp and smooth edges, fine texture and high clarity and these images are also free from the problem of artifacts.

The human in most of the applications observes the results of the fusion algorithms and therefore the human perception of the fused image is of significant importance. The performance of fusion algorithms is mainly evaluated subjectively. The subjective evaluation involves a number of human observers to judge the quality of fused image. Since such an evaluation depends highly on psycho-visual characteristics and specialized knowledge of the observer, and therefore, subjective tests are difficult to reproduce and are time consuming as well as expensive. Therefore, objective evaluation is equally important for evaluating the performance of fusion algorithms. Thus, alongwith subjective evaluation, objective evaluation has also been performed using various performance measures to evaluate the performance of the proposed algorithm. Researchers have proposed as well as used various performance measures to evaluate the quality of fused images. Some of these measures are: 1. Edge strength (Q) [42] measures the relative amount of edge information that is transferred from the input images X and Y into the fused image Z.

IV.RESULTS AND DISCUSSION

The performance of proposed fusion algorithm is evaluated on different datasets of multimodal medical images. In order to verify the operational effectiveness of the proposed system, the proposed system is designed, coded, developed, implemented and tested in the Mat lab Environment and the simulation results are presented as follows.

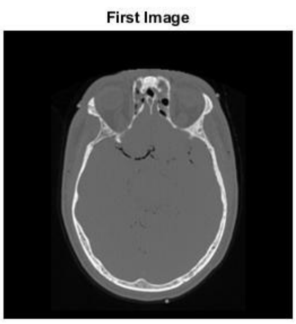


Fig 4:First Image

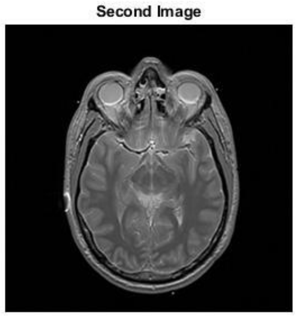


Fig 5:Second Image

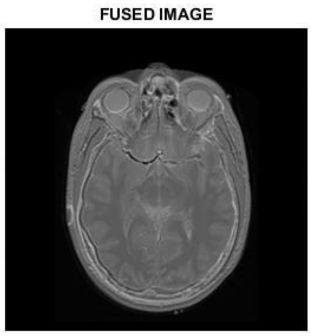


Fig 6:Fused Image

TABLE I:

PERFORMANCE COMPARISON

S.NO	EXISTING METHODS	PROPOSED METHODS
PSNR	26.5248	32.8756
RMSE	21.8436	17.5474
MAXERR	158	119
L2RAT	1.1256	0.8286

V.CONCLUSION

Multimodal medical image fusion algorithms fuse complementary information contained in multiple medical images in a single fused image, which is extensively used by clinical practitioners for quick diagnosis and treatment. Considering the accuracy required in medical field, an improved multimodal medical image fusion algorithm based on fuzzy transform is proposed in the paper. The proposed algorithm produces highly informative fused medical images by taking into account the loss of information that is contained in the error images obtained using FTR pair. The proposed algorithm has been performed on eight different datasets of medical images. Results obtained using the proposed algorithm has been compared, subjectively as well as objectively, with recent state-of-art multimodal medical image fusion algorithms. The fused images obtained using proposed algorithm have better visual quality with sharp and smooth edges, fine texture and high clarity and these images are also free from the problem of artifacts. Thus, the proposed multimodal medical image fusion algorithm promises improved information to clinical professionals that is bound to facilitate them in better diagnosis and treatment.

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