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Multimodal Medical Image Fusion Using DWT and SIDWT: A Wavelet-Based Approach for Enhanced Diagnostic Accuracy

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Abstract
The modalities of various medical images give only limited details corresponding to soft details like muscles or hard details like bones or skull, etc. Hence using a single modality, the prediction of diseases limits the diagnosis capability. This further results in compromise of accuracy. In the case of images, fusion methods enhance the accuracy by merging multimodality medical images like CT, MRI, PET, etc. This paper details about DWT and SIDWT techniques for fusion of images. In these techniques, wavelet transforms are used to cobineCT and MRI images. The DWT and SIDWT techniques are used with maximum and saliency features. The improvement in PSNR is atleast by 1%, MSE by 5.9%, Entropy by 29.37%, standarad deviation by 29.86% and mutual information by 11.8% when compared with input images.
METHODS:*DWT and SIDWT*
FINDINGS: *The improvement in PSNR is atleast by 1%, MSE by 5.9%, Entropy by 29.37%, standarad deviation by 29.86% and mutual information by 11.8% when compared with input images.*
NOVELTY: *fusion of images from different molarities.*
Keywords: *Diagnosis,Image Fusion,Modalities,Multisensory System,Wavelet Transform*

1. INTRODUCTION

Precision of the image produced by medical imaging modalities is crucial for the effective diagnosis of a disease. Fusing of Medical image is a "life saving instrument," hence currently, this area had become one of the promising areas of research. To goal of medical imaging is to get animage with better quality and good aount of information for diagnostic purposes. For multimodality medical pictures, the fusion method is employed. Anatomy provides structural information about bodily components using modalities like X-rays, CT scans, and MRIs. Physiology and Metabolism provides functional information about cell activity in an organ using modalities like SPECT and PET.

The process of developing visual representations of a body's interior for clinical and medical analysis, clear vision of human tissues and organs during surgeries is termed as medical imaging or scanning (physiology). Among the scan types are foetal ultrasound, PET/CT scanning, cardiac calcium scoring, MRI scanning, ultrasound scanning, CT scanning, X-ray scanning, and DXA scanning. The CT and MRI scans for fusion techniques are the main topic of this study. A CT scan is a different type of medical imaging where multiplex-rays are taken from different angles and combine them for producing fine grained images of the cross-sections of the internal body parts. This technique can be applied on most of the body arts like bones, soft tissues blood arteries, brain and lungs. Also, Computer Tomography (CT) is a choice for most of Tumors.

Image fusion is one of the methods for combining various images from various multi-modal sources effectively along with the available information to come out with a new image along with the required aspects from the obtained image [1][2]. The military, medical imaging, machine vision, and remote sensing are just a few of the fields that are rapidly adopting multisensory technologies. The field of image fusion provides a workable solution to the problem of handling the ever increasing data and information generated by processed source images. That being said, image fusion is a powerful tool for comparing and interpreting data from several sensors that provide supplementary information[3][4].

This data will have information about image fusion . The Image fusion [5] generates new images from the images produced by few applications such as medical imaging, remote sensingetc which are well suited for machine and human perception, for Image segmentation and Detection of Object etc.

It is necessary to translate the various geometric representations of the images from the various sensors into a single representation before fusing them. The sharpest resolution from either sensor should be preserved in this representation. Alignment of pictures from various sensors is the most crucial part of the pre-processing part in image fusion. The variances between the sensor pictures also have an impact on multi-sensor registration. Image fusion does not, however, automatically imply many sensor sources. In this research, both single-sensor and multi-sensor picture fusion have been thoroughly discussed.

Picture fusion often makes use of the same three stages of processing as other forms of information fusion: signal, features, and decision processing [6]. picture fusion at the pixel level occurs when numerous raw picture signals are fused at the signal level to produce a single fused image. Object level image fusion, also known as feature level image fusion, is the process of merging information from different input images with object names, features, and property descriptors. Information gathered from locally available decision makers based on the results of feature level information processing on images produced by individual sensors is fused at the highest level of image fusion, which is called decision or symbol level image fusion. Based on the calculation source, Figure 1 classifies some of the most popular image fusion approaches.

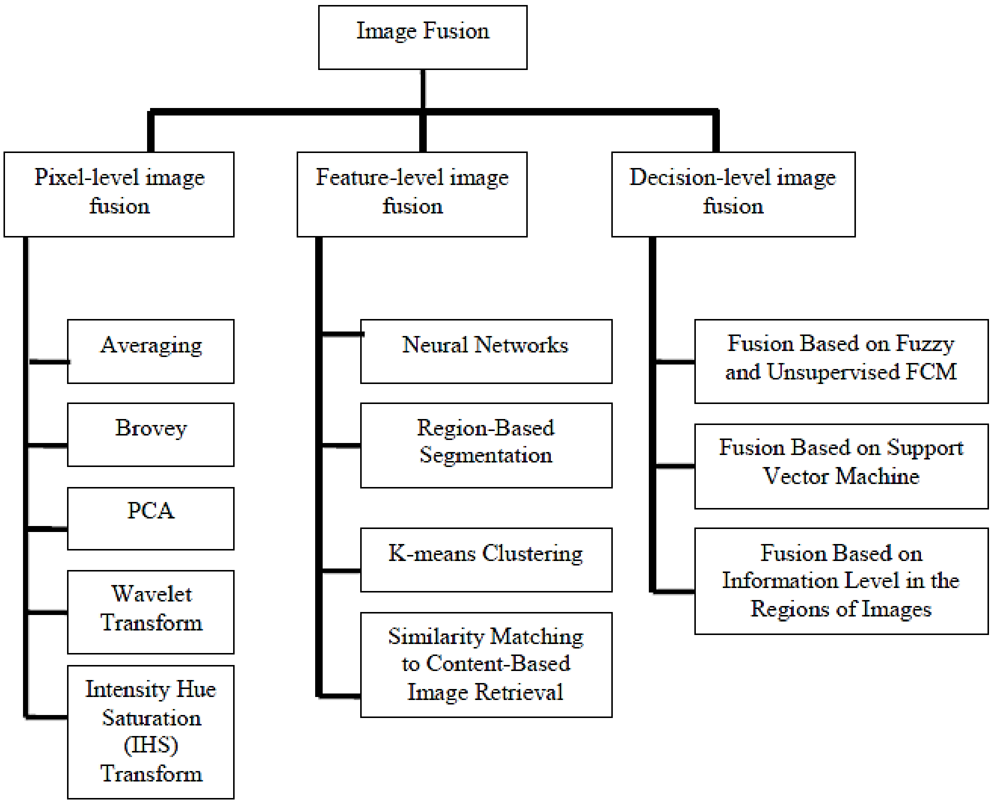

Figure 1. Classification of different popular image fusion techniques based on the computation source

As compared to just one of the separate image sources, the combined image has more information about the scene. The incorporation of similar and complimentary information improves the image's consistency and overall detail. Images must be registered before they may be merged in image fusion. Fusion falls under three primary categories:

A. fusion of pixels and data
B. fusion of pixels and data
C. Decision-level Fusion.

The straightforward method of fusion of Images, called "pixel level image fusion," creates a single output image by averaging the values and intensities of two input images. The primary benefit of pixel level fusion is that the fusion procedure directly utilises the original measured data.Where as the fusion at decision level involves the integration of decisions from multiple sources as well as feature level fusion with the fusing of features like edges or texture. To put it another way, the fusion at feature level necessitates the drawing out of various features from the source information prior to the merging of features. The decision-level fusion involves fusing sensor data that the sensors have already predetermined.Here, few examples are presented based on the decision level Fusion techniques like inference techniques, decision-making techniques, classical and Dempster-Shafer Bayesian technique.

2 METHODOLOGY

Data appear as arrays of integers that represent brightness, colour, temperature, distance, and other scene features in the process of image fusion which is a subset of data fusion. Such information can take the shape of two-dimensional and (for still photos), three-dimensional (for volumetric video clips and images), or higher-dimensional data. The earliest image fusion research dates to the middle of the 1980s. By applying the Laplacian pyramid technique, Burt had fused a picture from Binocular with the image from another application for the firs time.

Later, Burt along with Adelson unveiled a fresh method for fusing images based on hierarchical picture decomposition.The Laplacian technique was used to generate an image from the collection of photographs with the depth of the field which are recorded with fixed and still camera. The same work was repeated by Adelson with different focal lengths around the same time. Different pyramid systems were later employed in image fusion by Toet and Toet et al. For surveillance purposes, these approaches were mostly used to combine visible and infrared images.

Ajjimarangsee, Huntsberger suggested the application of neural networks in the visible and infrared image fusion.Nandhakumar, Aggarwal had came out with Sceme interpretation using integrated analysis of visual and thermal images. Rogers et al. explained about the fusion of passive infrared images with LADAR for segmentationof target . These are some other early image fusion works. Li et al., Chipman et al. had almost simultaneously proposed the Discrete Wavelet Transform method (DWT) for fusion of pictures [7]. Koren et al. had demonstrated steerable dyadic wavelet transform for fusion of pictures during the same time. Later, Waxman with his associates created a computational method for image fusion technology at roughly the same time based on biological colour vision models and fused visible and infrared images via adversarial processing. Further study into image fusion was spurred by the requirement of combiningrange data along with the visual data in robot navigations . The Images taken from various locations and to blend images and modes for the localization of target and tracking of targets in defence applications [12-15].

Over the past ten years, numerous other fusion procedures have been created. These days, applications that call for the utilisation of numerous photographs of a scene include those in medicine, remote sensing, industry, surveillance, and military.Readers can witness the article written by Smith, Heather and also can look into the series of papers published by Blum, Liu for latest assessments of the applications of picture fusion. Allen Waxman and his colleaguesgave special session about Image Fusion at the Information Fusion Conferences during 2000-2004 which wasan other outstanding resources that track the development of image fusion systems over the past few years[16].

2.1 EXISTING METHOD

The output picture whose quality surpasses all of the input photographs in every current method. Spatial fusion and transform domain fusion are the two basic categories of image fusion techniques.Direct use of the image pixels in the spatial domain was made.Achieving the best possible outcome involves adjusting the pixel values.The first step is to use frequency domain algorithms to transform the image into frequency domain.Therefore, the image's Fourier transform is applied initially [17]. Afterwards, the picture undergoes all the Fusion procedures before being transformed using an Inverse Fourier transform to obtain the final image. Applications of fusion methods like as averaging and principal component analysis (PCA) as well as IHS-based methods are subsequently made in the spatial domain. The distortion caused spatially in the merged image is a drawback of spatial domain techniques. The discrete wavelet transform, which offers adecomposition of a multi-resolution image is done by dividing the image into a good number of segments [8]. Each segment corresponds to a unique frequencyslot which is a major transform domain fusion technique used in image fusion[18].

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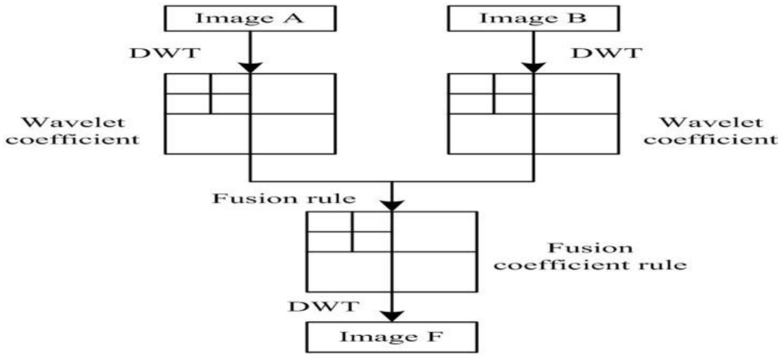

Figure 2. Fusion of images by DWT

An image is broken down using Laplacian image pyramid along with 2-D DWT. After this, multiscale edge representations are formed [9]. The following fusion technique can be created from the observations of the visual system of human being. The Human visual system is basically sensitive to shifts in local image contrast contrast like edges: All input photos are subjected to DWT decomposition in the first stage, generating the edge representation of multiscale imagery. Later, creation of multiscale edge is done by choosing the coefficients of wavelet from images. A straightforward method which is a more complex method is chosen. This new method is Energy computation based on area. Choose-max of the absolute values or a more complex area-based energy computation might be used as the selection strategy. Final step: An algorithm is employed to compute the Applying the inverse of DWT to the composite wavelet method results in the computation of the fused image[19-21].

The shift-variant signal representation produced by the DWT, which results in a shift-dependent fusion method, is widely known. The following is how we looked into the wavelet fusion method's shift dependency: Using the investigational approach, a fused image of the two input photographs was created and used as a reference image[10]. Both input images were moved horizontally before being fused and returning to their original positions. In the region unaffected by the shift operation, the root mean square error (RMSE) of the reference image from the backshifted fused image is shown in figure 3.

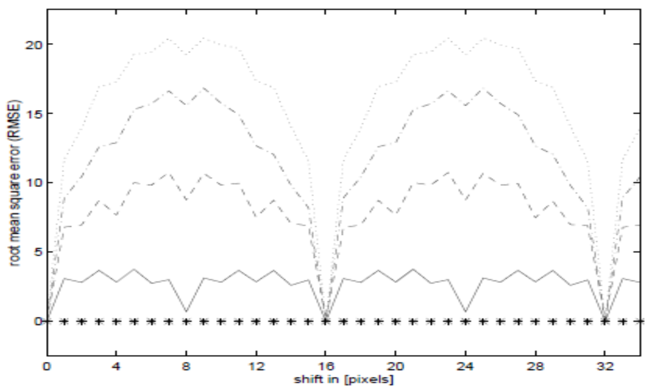

Figure 3. Shift dependency of DWT Fusion Method

When Haar wavelet is applied, the shift error is shown by the dotted line. Better wavelet selection (dashed line of a spline wavelet) and use of an algorithm based on area selection can both lessen this shift dependency (dashed line). The solid line represents the shift error of Laplacian pyramid method is displayed by the bold line. The error signal is produced by image fusion when a subsampling signal is decomposed asthe input signal. The decomposition depth in our experiment was 4, producing a shift dependence signal with a period of 24 = 16 [pixels].

2.2 PROPOSED METHOD

All the source images have to be distributed to shift invariant form of wavelet to be around shift reliance on the wavelet fusion approach. There are numerous methods to accomplish this: Considering each feasible (circular) shift of the input images by calculating the wavelet transform is the simplest method.Noting that not all shifts are required, Beylkin created an effective computing strategy for the overcomplete wavelet representation that resulted. Unser suggested a different strategy based on the idea of wavelet frames. We provide a convenient summary of this method for 1D input signal cases.The input sequence is representedtwo sequences. One is wavelet sequence $w_i(n)$ and the other is scale sequence $s_i(n)$.The Wavelet sequence and the scale sequence stored in each stage of the shift invariant DWT (SIDWT) are shown below.

$$w_i(n) = \sum_k g(2^i \cdot k) \cdot s_i(n-k)$$

$$s_{i+1}(n) = \sum_k h(2^i \cdot k) \cdot s_i(n-k)$$

The entire SIDWT decomposition scheme is defined by equalling the zeroth level scale sequence to the input sequence. i.e. $s_0(n) = f(n)$. In contrast to typical DWT decomposition approach, the subsampling is deleted, producing a wavelet form that is extremely redundant. Inbetween the taps of the filter prototypes g(k) and h(k), the sufficient count of zeros are inserted.Thus, it creates g(2i • k) and h(2i • k) at level i which is called as analysis filters. The inverse SIDWT reconstructs the input sequence by convolution of the scale and shift invariant wavelet sequences with the necessary reconstruction filters, g(2ik) and h(2ik):

$$s_i(n) = \sum_k \tilde{h}(2^i \cdot n - k) \cdot s_{i+1}(n) + \sum_k \tilde{g}(2^i \cdot n - k) \cdot w_{i+1}(n)$$

The standard tensor product formulation comes next, followed by an expansion of the decomposition strategy to 2D pictures. In the SIDWT scenario, the actual fusion procedure is the same as it is in the general wavelet fusion case: When an appropriate selection strategy is used, a composite shift invariant wavelet representation is created by decomposing the input images into their shift invariant wavelet representation. For this purpose, we developed two selection schemes for evaluating fusion algorithms: one based on points and the other on areas, with the latter including a consistency check. The shift error signal for the SIDWT fusion technique is shown by the crosses in Figure 3, since this fusion method does not rely on shifts. Figure 4 shows the process of implementing the SIDWT to fuse two images.

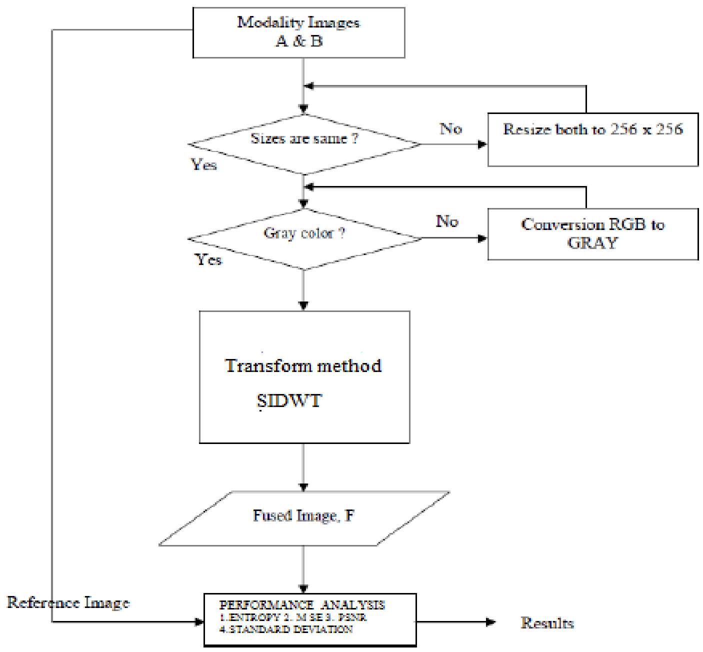

Figure 4. Procedure for implementing SIDWT Fusion Method

3. RESULTS AND DISCUSSION

The brain CT and MRI images are used for fusion and comparion with existing method [11]. The matlab codes are developed and the results are as obtained as shown in figures below.

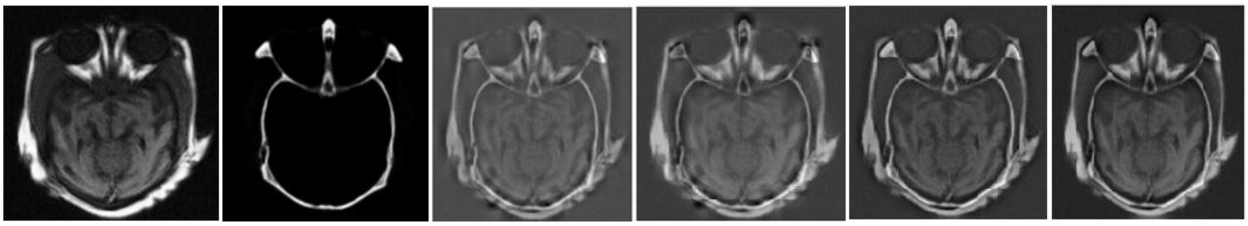

Figure 5. (a) Brain CT Scan Image (b) Brain MRI Scan Image (c) DWT/DBSS(2,2) Fused Image with Maximum as Highpass and Average as Low Pass (d) DWT/DBSS(2,2) Fused Image with Saliency/Match Measure as Highpass and Average as Low Pass (e) SIDWT merged image using Haar with Maximum as highpass and average as low pass (f) SIDWT merged image using Haar with Saliency/Match Measure as highpass and average as low pass

Table 1 shows that when pictures are fused using SIDWT employing HAAR with saliency as the high pass combination and average as the low pass combination, the resulting merged images perform better in terms of standard deviation, entropy, and mutual information between image 2 and the merged image. When fusing by DWT using DBSS with saliency as high pass combination and average as low pass combination, it proves better for SNR, PSNR, and mutual information between image1 and fused image. Therefore, the choice of fusion method can be made to evaluate medical pictures depending on the demand [9]. SIDWT turns out to be a superior option over the other combinations. PSNR has improved by at least 1%, MSE by 5.9%, Entropy by 29.37%, standard deviation has decreased by 29.86%, and mutual information has increased.by 11.8%.

Table 1. Comparison Table for various metrics of fused images by different fusion methods

Parameters	Standard Deviation	Entropy	PSNR	MSE	Mutual Information
DWT with DBSS (Maximum)	104.8709	3.4118	24.8509	214.4816	0.6464
DWT with DBSS (Saliency)	104.8709	3.4118	24.8684	213.6211	0.8477
SIDWT with HAAR (Maximum)	73.5535	4.8310	24.9526	209.5191	0.9478
SIDWT with HAAR (Saliency)	73.5535	4.8310	25.1185	201.6648	1.0749

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5. CONCLUSION

The multimodalities can be fused to accurately obtain the features of medical images. The basic modalities like CT, MRI, PET, etc as scan images. This paper details the usage of wavelet transforms for fusion of CT and MRI images to improve the accuracy of the image details and enhance the ease in diagnosis of diseases in critical cases. The DWT and SIDWT techniques are used with maximum and saliency features. The improvement in PSNR is atleast by 1%, MSE by 5.9%, Entropy by 29.37%, standarad deviation by 29.86% and mutual information by 11.8% when compared with input images.

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