MEDICAL IMAGE ANALYSIS USING MULTI RESOLUTION FUSION TECHNIQUES

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Abstract: In severe situations like accidents occur, majority of registered cases are for bone or head injury. For proper diagnosis, both CT scan and MRI scan are required to study the damage occurred for skull as well as for the internal organ injury of brain for the development of any brain tumors. If a combination of both images is present in a single image, then diagnosing the patient would be easier. Image Fusion is a method used to combine two input images to generate a combined complementary information contained image. For medical image processing, the resultant image is required to be highly reliable, low cost in terms of storage cost, uncertainty, etc. Also the information in both CT scan and MRI scan must be retained in the fused image for reliable study and assessment for diagnosis. This paper deals with pixel level fusion methods and their generic multiresolution fusion scheme. This scheme utilizes the low pass residuals and high pass residuals to segregate the information of two input images that are to be fused. The linear and nonlinear methods are used to develop the fused image. The fused image is evaluated in terms of fusion metrics such as standard deviation, entropy, fusion mutual information, etc. The methods like laplacian pyramid, ratio pyramid, principal component analysis, average methods prove to be better options for medical image fusion.
Keywords: Image Fusion, PCA, LUT, FPGA, Optimal filter, etc.

I. INTRODUCTION

With the advent of imaging sensors say in medical applications, the fusion of different images captured from different sources are necessary to develop a meaningful image for proper diagnosis. The captured images can be fused at different levels of information like at signal, pixel, feature, symbolic level, etc. The fusion of images at pixel level proves best for medical image processing. It undergoes the process of developing a composite image from different input images. Other applications where the image fusion is used are the fusion of images from an airborne sensor platform to help a pilot to navigate in poor weather conditions or darkness, i.e., to fuse forward looking infrared (FLIR) and low light visible images (LLTV).

In pixel-level image fusion, the basic constraints are that the fusion process should preserve all relevant information of the input imagery in the composite image called as pattern conservation, it should not introduce any artifacts or inconsistencies which would distract the human observer or following processing stages, the fusion process should be shift and rotational invariant, i.e. the fusion result should not depend on the location or orientation of an object the input imagery, combining out-of-focus images, remote sensing, etc.

But for the case of image sequence fusion, the additional problem of temporal stability and consistency arise. Temporal stability refers to the graylevel changes in the fused sequence caused by graylevel changes in the input sequences which must not be introduced by the fusion scheme. Temporal consistency refers to graylevel changes occurring in the input sequences that must be present in the fused sequence without any delay or contrast change. These are caused due to human visual system which is sensitive to moving light stimuli, so when artifacts move or time depended contrast changes, the fusion process will be highly distracting to the human observer.

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In medical imaging for diagnosis, majorly two scans are used to obtain the essential scan data of disease affected areas. They are CT (Computed Tomography) image and MRI (Magnetic Resonance Imaging) image. In cases where brain related images are to be studied these two images are considered for assessment. If there exists a solution to merge these two details without much loss, it would help doctor to assess the stage of disease correctly and help him to properly diagnose the patient to suggest medication or alternative surgery. The CT scan is used to observe the bone injuries whereas MRI Scan is used to observe the brain tumors. The combination of these two is evaluated for complete brain diagnosis, especially when a person has been injured in an accident.

This paper deals with the methods used for medical image fusion based on pixel level fusion. The metrics used for comparing fused images are standard deviation, entropy, PSNR, SNR and Mutual Information. These metrics prove whether the information in fused image is correct to utilize or not.

II. EXISTING METHODS

There exist several approaches to the pixel level fusion [1-7] of spatially registered input images, majority of them are developed for the fusion of stationary input images. Due to the static nature of the input data, temporal aspects arising in the fusion process of image sequences, e.g. stability and consistency need not addressed. The image fusion methods can comprise of linear superposition, nonlinear methods, optimization approaches, artificial neural networks, image pyramids, wavelet transform, generic multiresolution fusion scheme, etc.

Linear Superposition Method represents the straightforward method to build a fused image of several input frames is performing the fusion as a weighted superposition of all input frames. The optimal weighting coefficients, with respect to information content and redundancy removal, can be determined by a principal component analysis (PCA) of all input intensities. By performing a PCA of the covariance matrix of input intensities, the weightings for each input frame are obtained from the eigenvector corresponding to the largest eigenvalue.

Nonlinear Methods are developed based on simple nonlinear operator such as max or min. If in all input images the bright objects are of interest, a good choice is to compute the fused image by a pixel-by-pixel application of the maximum operator. Basically these use morphological operators such as opening or closing, the actual fusion process is performed by the application of conditional erosion and dilation operators. In high-level algebraic extension of image morphology, the basic types defined in image algebra are value sets, coordinate sets which allow the integration of different resolutions and tessellations, images and templates. For each basic type binary and unary operations are defined which reach from the basic set operations to more complex ones for the operations on images and templates. Image algebra has been used in a generic way to combine multisensor images.

Artificial Neural Networks are used to fuse different sensor signals in biological systems. For example, Rattlesnakes (and the general family of pit vipers) possess so called pit organs which are sensitive to thermal radiation through a dense network of nerve fibers. The output of these pit organs is fed to the optical tectum, where it is combined with the nerve signals obtained from the eyes. Newman and Hartline distinguished six different types of bimodal neurons merging the two signals based on a sophisticated combination of suppression and enhancement.

Optimization Approaches use bayesian optimization problem. Using the multisensor image data and an a-prori model of the fusion result, the goal is to find the fused image which maximizes the a-posteriori probability. Due to the fact that this problem cannot be solved in general, some simplifications are introduced: All input images are modeled as markov random fields to define an energy function which describes the fusion goal. Due to the equivalence of of gibbs random fields and markov random fields, this energy function can be expressed as a sum of so-called clique potentials, where only pixels in a predefined neighborhood affect the actual pixel. The fusion task then consists of a maximization of the energy function. Since this energy function will be non-convex in general, typically stochastic optimization procedures such as simulated annealing or modifications like iterated conditional modes will be used.

Image pyramids have been initially described for multiresolution image analysis [8-10] and as a model for the binocular fusion in human vision. A generic image pyramid is a sequence of images where each image is constructed by lowpass filtering and subsampling from its predecessor. Due to sampling, the image size is halved in both spatial directions at each level of the decomposition process, thus leading to an multiresolution signal representation. The difference between the input image and the filtered image is necessary to allow an exact reconstruction from the pyramidal representation. The image pyramid approach thus leads to a signal representation with two pyramids: The smoothing pyramid containing the averaged pixel values, and the difference pyramid containing the pixel differences, i.e. the edges. So the difference pyramid can be viewed as a multiresolution edge representation of the input image. The actual fusion process can be described by a generic multiresolution fusion scheme which is applicable both to image pyramids and the wavelet approach.

There are several modifications of this generic pyramid construction method described above. Some authors propose the computation of nonlinear pyramids, such as the ratio and contrast pyramid, where the multiscale edge representation is computed by a pixel-by-pixel division of neighboring resolutions. A further modification is to substitute the linear filters by morphological nonlinear filters, resulting in the morphological pyramid. Another type of image pyramid - the gradient pyramid - results, if the input image is decomposed into its directional edge representation using directional derivative filters.

Wavelet Transform is a signal analysis method similar to image pyramids, called as discrete wavelet transform. The main difference is that while image pyramids lead to an overcomplete set of transform coefficients, the wavelet transform results in a nonredundant image representation. The discrete 2-dim wavelet transform is computed by the recursive application of lowpass and highpass filters in each direction of the input image (i.e. rows and columns) followed by subsampling. One major drawback of the wavelet transform when applied to image fusion is its well known shift dependency, i.e. a simple shift of the input signal may lead to complete different transform coefficients. This results in inconsistent fused images when invoked in image sequence fusion.

To overcome the shift dependency of the wavelet fusion scheme, the input images must be decomposed into a shift invariant representation. There are several ways to achieve this: The straightforward way is to compute the wavelet transform for all possible circular shifts of the input signal. In this case, not all shifts are necessary and it is possible to develop an efficient computation scheme for the resulting wavelet representation. Another simple approach is to drop the subsampling in the decomposition process and instead modify the filters at each decomposition level, resulting in a highly redundant signal representation.

III. PROPOSED METHODS

The Generic Multiresolution Fusion Scheme develops a local contrast change i.e., at edges as both image pyramids and the wavelet transform result in a multiresolution edge representation. The input images are decomposed into their multiscale edge representation, using either any image pyramid or any wavelet transform. The multiscale resolute images are combined using the high pass residuals and low pass residuals by using wavelets by the process of pixel-by-pixel selection of the coefficients with maximum magnitude. Finally the fused image is computed by an application of the appropriate reconstruction scheme. The corresponding figure is shown in figure 1.

The metrics used to evaluate the fused image can be based on whether a reference image is available or not. If the reference image is available, the SNR and PSNR can be used. Where SNR is signal to noise ratio and is used to measure the ratio between information and noise of the fused image and PSNR is Peak Signal to Noise Ratio and it represents the number of gray levels in the image divided by the corresponding pixels in the reference and the fused images. The higher values corresponding to these metrics represent the similarity of reference image and fused image and superior fusion of images respectively.

If only the fused image is available then the metrics used for evaluation are Standard deviation, entropy, fusion mutual information, etc. The standard deviation is used to measure the contrast in the fused image, a high value indicates high contrast fused image. Entropy is used to measure the information content of a fused image; a high entropy value indicates the fused image as rich information content. Fusion Mutual Information is used to compute the degree of dependency between the input images and fused image, a large value indicates a better quality of fused image.

IV. RESULTS AND DISCUSSION

The table 1 shows the corresponding metric based evaluation of different methods of image fusion. The figures 2 and 3 represent the actual images of CT Scan and MRI Scan images respectively. The figures from 4 to 23 represent the corresponding fusion methods by generic mutliresolution fusion scheme.

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

Parameters	Standard Deviation	Entropy (image2= 444448.574) (image1= 648124.289)	PSNR (image1=20.1649, image2= 21.0347)	SNR (image1= 626.0273, image2= 512.4001)	Mutual Information (image1 and image2 0.1725) between image1 and	Mutual Information between image 2 and
Average	34.0804	2069700.681	20.9237	525.6619	0.1147	0.2958
Contrast Pyramid	48.1575	1162126.860	19.9601	656.2479	0.0661	0.1633

(maximum)					
Contrast pyramid (Saliency)	47.2929	1146609.768	20.0799	638.3911	0.0670	0.1641
DWT using DBSS (Maximum)	37.1452	839303.601	20.8134	539.1833	0.1218	0.2702
DWT using DBSS (Saliency)	37.0829	839269.800	20.9596	521.3401	0.1220	0.2729
FSD Pyramid (Maximum)	43.2201	837938.882	20.9577	521.5643	0.1284	0.2857
FSD Pyramid (Saliency)	36.7677	840820.493	20.6955	554.0292	0.1215	0.2772
Gradient Pyramid (Maximum)	39.5550	832587.729	20.6679	557.5622	0.1266	0.2726
Gradient Pyramid (Saliency)	43.5495	846456.187	20.7819	543.1076	0.1245	0.2773
Laplacian Pyramid (Maximum)	62.1221	899659.270	20.7366	548.8037	0.1577	0.3738
Laplacian Pyramid (Saliency)	53.5563	818760.516	20.8820	530.7338	0.1395	0.2990
Morphological Pyramid (Maximum)	55.9516	804734.901	20.8583	533.6404	0.1519	0.2958
Morphological Pyramid (Saliency)	55.7033	811536.554	20.9759	519.3899	0.1459	0.2954
PCA	51.8598	794921.564	21.1138	503.1590	0.1771	0.4293
Ratio Pyramid (Maximum)	64.2068	796933.194	20.8718	531.9905	0.1655	0.3660
Ratio Pyramid (Saliency)	43.5821	856597.571	20.6487	560.0331	0.1336	0.3064
Maximum	59.4959	784228.514	21.1938	493.9709	0.1842	0.4367
Minimum	17.2288	1173396.461	20.0271	646.2020	0.0448	0.0919
SIDWT using HAAR (Maximum)	46.3233	842871.565	20.6006	566.2631	0.1325	0.2683
SIDWT using HAAR (Saliency)	47.6470	851213.480	20.6088	565.2031	0.1249	0.2669

From the table 1, it is clear that the fused images are better in terms of SNR when fused by using Contrast Pyramid with Maximum as Highpass combination and average as low pass combination, Morphological Pyramid with Saliency/Match Measure as Highpass combination and average as low pass combination for PSNR, Ratio or Laplacian Pyramid with choose maximum as Highpass combination and average as low pass combination for standard deviation, Average method for Entropy and by Principal Component Analysis or Select Maximum Method for Mutual Information. Hence based on the requirement, the choice of fusion method can be done to assess medical images.

V. CONCLUSION

In severe situations like accidents occur, majority of registered cases are for bone or head injury. For proper diagnosis, both CT scan and MRI scan are required to study the damage occurred for skull as well as for the internal organ injury of brain for the development of any brain tumors. If a combination of both images is present in a single image, then diagnosing the patient would be easier. Hence a generic mutliresolution fusion scheme is used to evaluate the fused image by various linear and nonlinear techniques. Among them contrast or morphological pyramid prove to be better methods if good SNR and PSNR are required respectively. Also Ratio or Laplacian Pyramid for standard deviation, Average method for Entropy and by Principal Component Analysis or Select Maximum Method for Mutual Information proved to be better choices. Hence based on the requirement i.e., the choice of features like similarity, contrast, rich information and better quality of fused images, the choice of fusion method can be done to assess medical images for proper immediate diagnosis.

6. ACKNOWLEDGEMENTS

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FIGURES

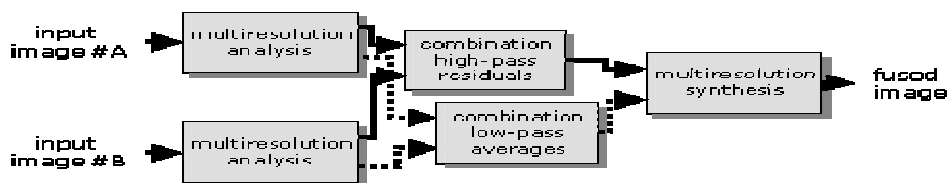Figure 1: Generic Multiresolution Fusion Scheme
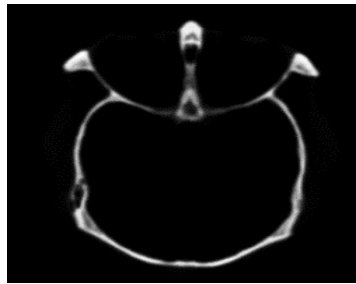

Figure 2: Medical Image1
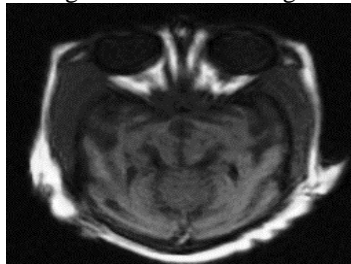
Figure 3: Medical Image2

Figure 4: Fused image by AverageFusion Method

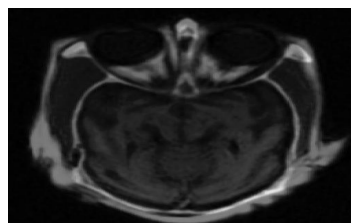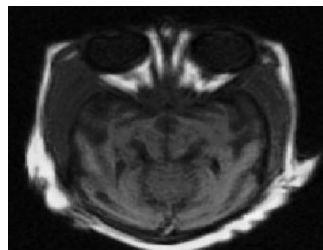Figure 5: Fused Image by PCA Method
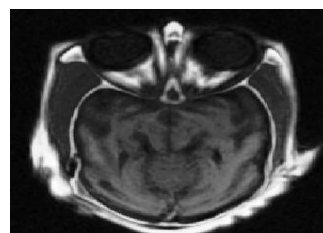

Figure 6:Fused Image by Select Maximum Method

Figure 7: Fused Image by Select Minimum Method

Figure 8: Fused Image by laplacian Pyramid with choose maximum as Highpass combination and average as low pass combination
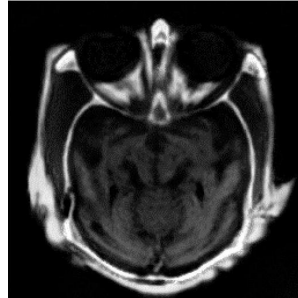

Figure 9: Fused Image by laplacian Pyramid with saliency/MatchMeasure as Highpass combination and average as low pass combination
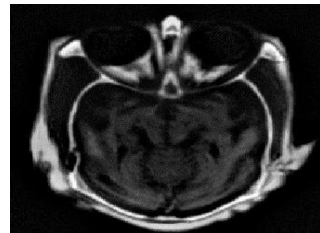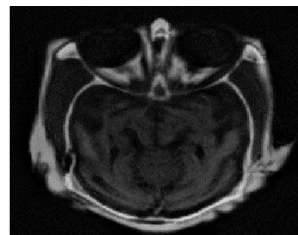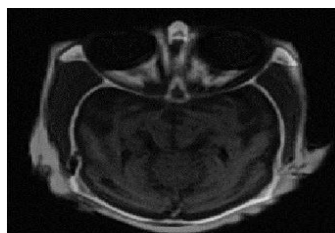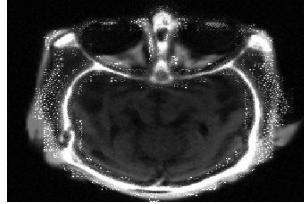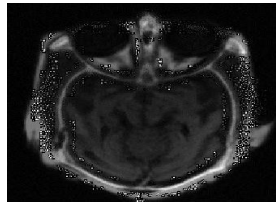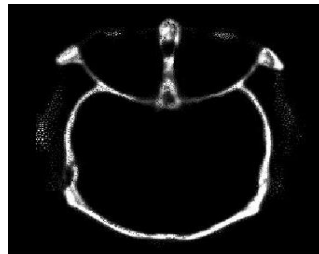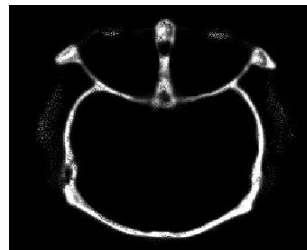

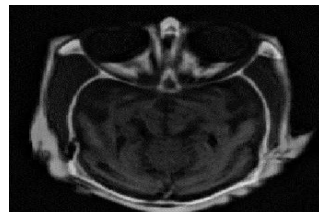Figure 10: Fused Image by FSD Pyramid with maximum as Highpass combination and average as low pass combination

Figure 11: Fused Image by FSD Pyramid with saliency/Match Measure as Highpass combination and average as low pass combination

Figure 12: Fused Image by Ratio Pyramid with Maximum as Highpass combination and average as low pass combination

Figure 13: Fused Image by Ratio Pyramid with saliency/MatchMeasure as Highpass combination and average as low pass combination
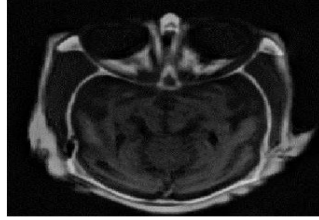

Figure 14: Fused Image by Contrast Pyramid with Maximum as Highpass combination and average as low pass combination

Figure 15: Fused Image by Contrast Pyramid with Saliency/MatchMeasureas Highpass combination and average as low pass combination

Figure 16: Fused Image by Gradient Pyramid with Maximum as Highpass combination and average as low pass combination

Figure 17: Fused Image by Gradient Pyramid with Saliency/Match Measure as Highpass combination and average as low pass combination

Figure 18: Fused Image by DWT with DBSS(2,2) with Maximum as Highpass combination and average as low pass combination
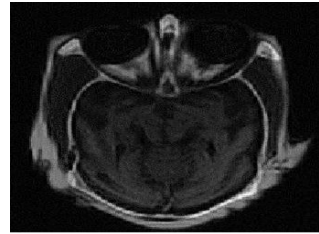

Figure 19: Fused Image by DWT with DBSS(2,2) with Saliency/Match Measure as Highpass combination and average as low pass combination
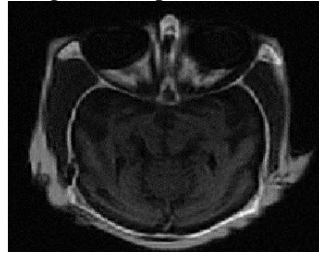

Figure 20: Fused Image by SIDWT with Haar with Maximum as Highpass combination and average as low pass combination
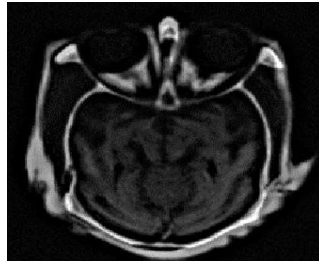

Figure 21: Fused Image by SIDWT with Haar with Saliency/Match Measure as Highpass combination and average as low pass combination
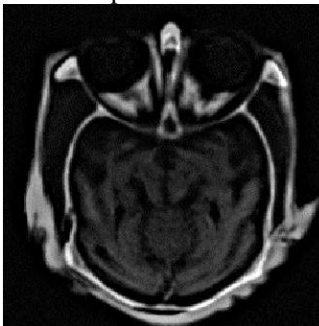

Figure 22: Fused Image by Morphological Pyramid with Maximum as Highpass combination and average as low pass combination
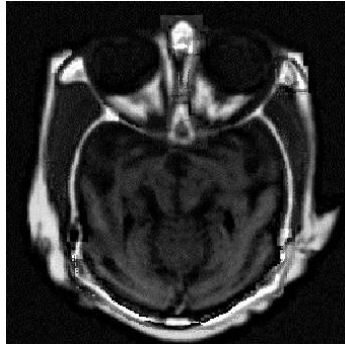
Figure 23: Fused Image by Morphological Pyramid withSaliency/Match Measure as Highpass combination and average as low pass combination