

Hybrid Image Fusion Algorithm using DWT Maximum Selection Rule and PCA

Surya Prasada Rao Borra, Rajesh K Panakala, P.Rajesh Kumar

Abstract— The main objective of medical imaging is to obtain a highly informative image for better diagnosis. A single modality of medical image cannot provide accurate and complete information in many cases. In brain medical imaging, Magnetic Resonance Imaging (MRI) image shows structural information of the brain without any functional data, where as Computer Tomography (CT) image describes functional information of the brain but with low spatial resolution especially with low dose CT scan, which is useful to reduce the radiation effect to human body. In the field of medical diagnosis, Image fusion plays a very vital role. Fusing the CT and MRI images gives a complete information about both soft and hard tissues of the human body. This paper proposes a two stage hybrid fusion algorithm . First stage deals with the enhancement of a low dose CT scan image using different image enhancement techniques viz., Histogram Equlaisation and Adaptive Histogram Equalization. In the second stage, the enhanced low dose CT scan image is fused with MRI image using different fusion algorithms viz., Discrete Wavelet Transform (DWT) and Principal Component Analysis (PCA). The proposed algorithm has been evaluated and compared using different quality metrics.

Index Terms— Image fusion, Image Enhancement, MRI Imaging, Low dose CT, DWT, PCA

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1 INTRODUCTION

IN medical imaging, different modalities replicate different details of human organs and tissues. For example, Magnetic Resosance Imaging(MRI) provides low density soft tissues such as blood vessels, where as Computed Tomography(CT) provides clear detail about bone tissue and also provides the reference for location of the lesion[1]. As it is known, dose reduction lowers the radiation exposure risks, but at the same time decreases the image quailty. By its nature, CT involves larger radiation doses than the more common, conventional x-ray imaging procedures[2]. We briefly discuss the nature of CT scanning and its main clinical applications, both in symptomatic patients and, in the screening of asymptomatic patients. We focus on the increasing number of CT scans being obtained, the associated radiation doses, and the consequent cancer risks in adults and particularly in children. Although the risks for any one person are not large, the increasing exposure to radiation in the population may be a public health issue in the future. The use of CT has increased rapidly since 1980's, according to recent surveys, it is showing that more than 62 million CT scans are currently obtained ever year in the United States, as compared with about 3 million in 1980's. The largest use of CT scan, however, have been in the categories of pediatric diagnosis and adult screening, and these trends can be expected to continue for the next few years. The increase in use of CT scan in children has been driven primarily by the decrease in the time needed to scan, which is less than a second, and also eliminating the need for anesthesia to prevent the child from moving during image ac-quisition process. The major growth area in using CT scan for children has been presurgical diagnosis of appendicitis, for which CT appears to be both accurate and cost-effective.

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The radiation doses from CT scanning are considerably larger than those from corresponding conventional radiography. Michael F. McNitt-Gray [3] discussed that the radiation doses to a particular organ from any given CT scan depends on number of factors, such as number of scans, the tube current and scanning time in milliampseconds (mAs), the size of the patient, the axial scan range, the scan pitch (the degree of overlap between adjacent CT slices), the tube voltage in the kilovolt peaks (kVp), and the specific design of the scanner being used. Patient dosimetry and evaluation of image quality are basic aspects of any quality control program in diagnostic radiology. Image quality must be adequate for diagnosis and obtained with reasonable patient doses [5]. As per the recommandations of International Commission on Radiological Protection, No dose limit applies to medical exposure to patients, but diagnostic reference levels or reference values have been proposed by the International Commission on Radiologic Protection [6]. Thomas Lehnert et al. said that it is always the relative noise in CT images will increase as the radiation dose decreases, which means that there will always be a tradeoff between the need for low-noise images and the desirabilityof using low doses of radiation[4]. The low dose CT scan image usually suffers from serious noise and artifacts by using analytical reconstruction methods. It is always preferable to have standard imaging techniques that diminish the patient dose with reasonable image quality [7]. As part of implementation efforts, an important clinical requirement has been addressed that low-dose CT (LDCT) images need to be improved in the Electronic Health Records(EHR). Khalid et. al., proposed an enhanced dynamic quadrant equalization for image contrast enhancement, in which input image histogram is divided into 8 subhistograms by using median values. For individual subhistograms, clipping of histogram is done by the average pixels. New dynamic range is assigned to each subhistograms and HE is done separately. This approach preserves the mean brightness[8]. As there is no guarantee that the contrast will always be increased by the histogram equalization[1], Aaptive HistogramEqualisation has been applied on low dose CT scan imageto improve the contrast.

This paper gives a comparative study related to performance of the image fusion techniques. Organization of this paper is as follows; Section 2 explains the image enhancement techniques. The principle of PCA and DWT image fusion techniques are discussed in section 3. In section 4, fusion performance assessment techniques are explained. In section 5, the results of fused images for two different data sets are compared with PCA and DWT applied to medical images by implementing in MATLAB.

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2 Image Enhancmement

The goal of an image enhancment is to improve the visual effects of the entire image or to enhance the certain information in accordance with specific needs [14]

2.1 Histogram Equalization

Histogram equalization is a global processing technique used to spread the pixel values over the dynamic range of image and the equalized histogram must be approximately uniformly distributed in the dynamic range [1]. It is a distribution function transformation method based on histogram modification.

Characteristics of Histogram of a digital image:

1. The frequency of the histogram reflects only the pixels in the image of a certain grey level values but not reflects the position of each pixel.

2. Histogram of an image doesn't overlap each sub section of an image.

It is not sure that the contrast will always be increased by the histogram equalization. There may be some cases in which histogram equalization can be worse. In that cases the contrast may be decreased. In general, ordinary histogram equalization uses the same transformation which is derived from the image histogram to transform all pixels. This works well when the distribution of pixel values is similar throughout the image. However, when the image contains regions that are significantly lighter or darker than most of the image, the contrast in those regions will not be sufficiently enhanced. Adaptive histogram equalization (AHE) improves in this aspect by transforming each pixel with a transformation function derived from its neighbourhood region.

2.2 Adaptive Histogram Equalization

Adaptive Histogram Equalization (AHE) is a computer image processing technique used to improve the contrast in images. It differs from ordinary histogram equalization in the respect that the adaptive method computes several histograms, each corresponding to a distinct section of the image, and uses them to redistribute the brightness values of the image. In its simplest form, each pixel is transformed based on the histogram of a square surrounding that pixel. The transformation functions derived from the histograms is exactly the same as for ordinary histogram equalization. The transformation function is proportional to the cumulative distribution function (CDF) of pixel values in the neighbourhood. Pixels near the image boundary have to be treated specially, because their neighbourhood would not lie completely within the image. It is therefore suitable for improving the local contrast and enhancing the definitions of edges in each region of an image. However, AHE has a tendency to over amplify noise in relatively homogeneous regions of an image.

Properties of Adaptive Histogram Equalisation:

- The size of the neighbourhood region is a parameter of the method. It improves the contrast at smaller scales and reduces the contrast at larger scales.
- Due to the nature of histogram equalization, the resultant value of a pixel under AHE is proportional to its rank among the pixels in its neighbourhood. This allows an efficient implementation of hardware that can compare the center pixel with all other pixels in the neighbourhood[3]. An unnormalized result value can be computed by adding 2 for each pixel with a smaller value than the center pixel, and adding 1 for each pixel with equal value.
- When the image region containing a pixel's neighbourhood which is homogeneous, its histogram will be strongly peaked, and the transformation function will map a narrow range of pixel values to the whole range of the resultant image. This causes AHE to over amplify the small amounts of noise in largely homogeneous regions of the image.[4]

3 Image Fusion

3.1 DWT Image Fusion

Image fusion process is used to associate the two or more images in to a single image. The resultant fused image obtained will be more explanatory than the distinct source images. The wavelet transform is a mathematical tool that can be used to detect local features in a signal process. It also can be used to decompose two-dimensional (2D) signals such as 2D grayscale image signals into different resolution levels for multiresolution analysis. Wavelet transform has been greatly used in many areas, such as data compression, texture analysis, feature detection, and image fusion.

Wavelet transforms provide a framework in which an image is decomposed, with each level corresponding to lower frequency band and higher frequency bands. The DWT is a spatial-frequency decomposition which provides a flexible multiresolution analysis of an image. In general, the basic idea of image fusion based on wavelet transform is to perform a multi-resoltion decomposition on each source image; the coefficients of both the low-frequency band and high-frequency bands are then performed with a certain fusion rule [13]. The widely used fusion rule is maximum selection rule. This simple scheme just selects the largest absolute wavelet coefficient at each location from the input images as the coefficient at that location in the fused image. After that, the fused image is obtained by performing the inverse DWT (IDWT) for the corresponding combined wavelet coefficients. The detailed fusion steps based on wavelet transform can be summarized below.

Step 1. The images to be fused must be registered to assure that the corresponding pixels are aligned.

Step 2. These images are decomposed into wavelet transformed images, respectively, based on wavelet transformation. The transformed images with K-level decomposition will include one low-frequency portion (low-low band) and 3 high-frequency portions (low-high bands, high-low bands, and high-high bands).

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Step 3. The transform coefficients of different portions or bands are performed with a certain fusion rule.
Step 4. The fused image is constructed by performing an inverse wavelet transform based on the combined transform coefficients from Step 3.
The overall fusion processing goes through the preprocessing and image registration followed by wavelet decomposition. The input images must be of same size for fusion. For easy computation and to abstract information, the image has to be converted into a gray scaled image from color image. Histogram normalization provides tonal distribution of the entire image. Preprocessed images are split in to four frequency sub bands such as LL, LH, HL and HH. A general fusion rule is to select, the coefficients whose values are higher and the more dominant features at each scale are preserved in the new multi-resolution representation. The fused image is constructed by performing an inverse wavelet transformation. The main objective of an image fusion is combining complimentary, as

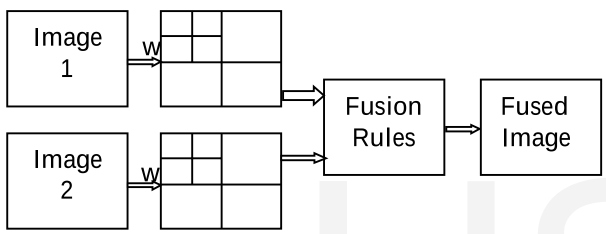

Fig1. Fusion Process using Wavelet transforms

well as redundant information from multiple images to create a single image which provides more complete and accurate description. This fused image is more suitable for human visual, machine perception or further image processing and analysis tasks. Another advantage of image fusion is that it decreases the storage space and cost by storing only the single fused image, instead of storing different modality images. In the area of medical imaging, combining the images of different modalities of same scene gives so many advantages it may be fusion of image taken at different spatial resolution, intensity and by different methods helps physician / Radiologists to easily extract or recognize the features or abnormalities that may not be usually visible in single image.

3.1.1 Simple Averaging Rule

In transform based fusion algorithm a simple “averaging rule” is adopted to fuse the low frequency coefficients. Low-frequency coefficients contain outline information related to the image instead of specific major details, and thus an averaging method is applied to produce the compositelow-frequency coefficients [18]. The computation is performed as follows:

$$F(x,y) = \frac{F_1(x,y)+F_2(x,y)}{2} \qquad \text{………(1)}$$

where F(x, y) are the low frequency coefficients of the fused image IF , $f_1(x, y)$ and $f_2(x, y)$ are the low frequency coefficients of the source images.

3.1.2 Maximum Selection Rule

Maximum selection rule is used in high frequency coefficients. Two images wavelet coefficients are compared and select the maximum value coefficient for fusion process as shown in equation (2)

$$W(x,y) = \begin{matrix} W_1(X,Y) & if & I_1(x,y) > I_2(x,y) \\ W_2(X,Y) & if & I_1(x,y) < I_2(x,y) \end{matrix} \qquad \text{……..…(2)}$$

W_1 (x, y) – Image I wavelet coefficient
W_2 (x, y) - Image 2 wavelet coefficient

3.2 Principal Component Analysis

Principal component analysis is performed which aims at decreasing a large set of variables into a small set that still containing most of the information that was existing in the large set. As medical image data is bulky, to reduce these data PCA method is essential. The method of principal component analysis enables us to create and use a decreased set of variables, which are called principal vectors. A reduced set is much easier to analyze and interpret. The most straight forward way to build a fused image of several input images is performing the fusion as a weighted superposition of all input images[17]. 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 computing PCA of the covariance matrix of input intensities, the weights for each input image are obtained from the eigenvector corresponding to the largest Eigen value. PCA is the simplest of the true eigenvector-based multivariate analysis. Often, its operation can be thought of as revealing the internal structure of the data in a way which best explains the variance in the data. If a multivariate dataset is visualized as a set of coordinates in a high-dimensional data space (1 axis per variable), PCA can supply the user with a lower-dimensional picture, a "shadow" of this object when viewed from its most informative viewpoint. This is done by using only the first few principal components so that the dimensionality of the transformed data is reduced. The number of principal components is less than or equal to the number of original variables.

PCA Algorithm:

- Transform the data into column vectors. Determine the mean along each column
- Subtract the empirical mean vector.
- Compute the covariance matrix C of X i.e. $=XX^T$
- mean of expectation = covariance(X).
- Compute the eigenvectors V and Eigen value D of C and sort them by decreasing Eigen value
- Consider the first column of V which corresponds to larger Eigen value to compute P_1 and P_2 as

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- $P_1=V(1)/\Sigma V$ and $P_2=V(2)/\Sigma V$

The input images (images to be fused) $I_1(x, y)$ and $I_2(x, y)$ are arranged in two column vectors and their empirical means are subtracted. From the resulting vector, compute the eigenvector and Eigen values and the Eigenvectors corresponding to the larger eigen value are obtained. The normalized components P_1 and P_2 (i.e., $P_1 + P_2 = 1$) are computed from the obtained eigenvector. The fused image is

$$I_F(x,y) = P_1 * I_1(x,y) + P_2 * I_2(x,y) \qquad \text{.......(3)}$$

Where P1 and P2 are the principal components

4. PERFORMANCE ANALYSIS

In this, the outcome of fusion transformation is evaluated with different parameter, may be quantitatively & qualitatively and compared the results with the other algorithms, to check efficiency of the hybrid algorithm. Some of the quantitative parameters are listed below:

Entropy: Entropy is a measure of the information content in an image. An image with high information will have high entropy.

$$H = -\sum_{i=0}^{L-1} p_i \log(p_i) \qquad \text{........ (4)}$$

Where L is the number of grey levels in an image.
P_i is t eprobability of occurring ith gery level

Standard Deviation: Standard Deviation is used to measure the contrast in the fused image. It consists of both signal and noise, an image with more information would have high standard deviation.

$$\sigma = \sqrt{\sum_{i=0}^{L-1} (i-\bar{i})^2 h_{If}(i)} \qquad \text{.......... (5)}$$

Where $h_{If}(i)$ is the normalized histogram of the fused image
L is the number of grey levels in an image

Mean Squared Error:

$$MSE = \frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[R(i,j)-F(i,j)]^2}{MXN} \qquad \text{........... (6)}$$

Root Mean Square Error(RMSE): The error between fused image F and reference image R .is given by,

$$RMSE = \sqrt{\frac{\sum_{i=0}^{M-1}\sum_{j=0}^{N-1}[R(i,j)-F(i,j)]^2}{MXN}} \qquad \text{........... (7)}$$

Where R is reference image and F is fused image.

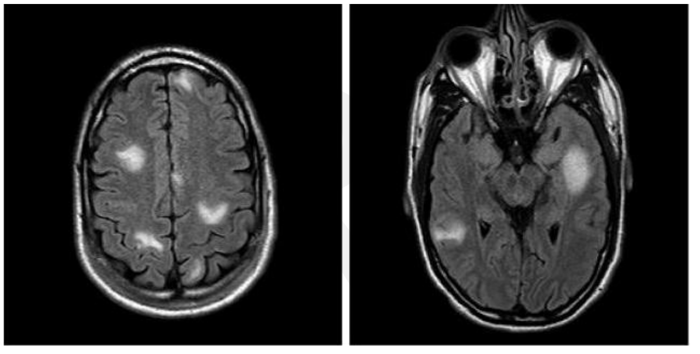
Peak-to-Peak Signal-to-Noise Ratio (PSNR):
PSNR is the ratio between the maximum possible power of a signal and the power of corrupting noise that affects the fidelity of its representation.
The PSNR measure is given by

$$PSNR = 10 * \log_{10} \frac{(L-1)^2}{MSE} \qquad \text{....... (8)}$$

The higher the PSNR value, better the fusion process.

5. RESULTS AND DISCUSSION

The proposed algorithms are tested and compared with different fusion techniques. The testing data sets are of two medical modality images like, CT and MRI of size 480X403. The original MRI image of set1 is shown in figure 2(a) and also the CT image of set1 is shown in figure 2(b).



(a) MRI scan image (b) CT scan image
Fig. 2: Date set-1of the brain

Table 1: Comparison pameters of the output images of fusion algorithm of Dataset-1

	DWT Simple Averaging				
	Entropy	Standard Deviation	MSE	RMSE	PSNR
CT	4.5208	74.0343	--	--	--
MRI	5.6829	73.4328	--	--	--
DWT Simple Average	5.8438	71.2463	91.2320	9.5515	47.38
DWT Maximum Selection Rule	6.2348	69.3433	94.0791	9.6994	53.39
PCA	7.0439	67.3869	95.2059	9.7573	58.64

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Fig.3 shows an image resulting from DWT simple averaging fusin technique. DWT maximum selection rule is applied on data set 1 and resulting image is shown in fig.4. and fig.5 shows animage which is obtained from PCA fusion method.

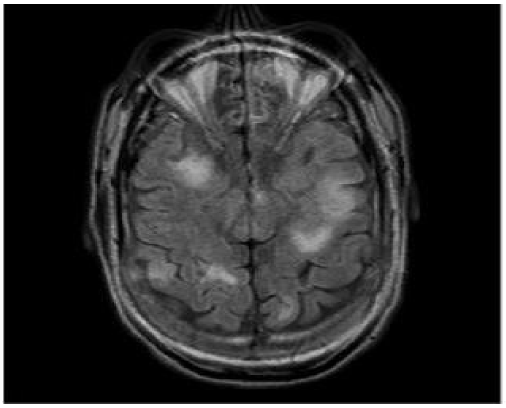


Fig. 3. Fused image of date set 1in DWT Maximum selection Rule method

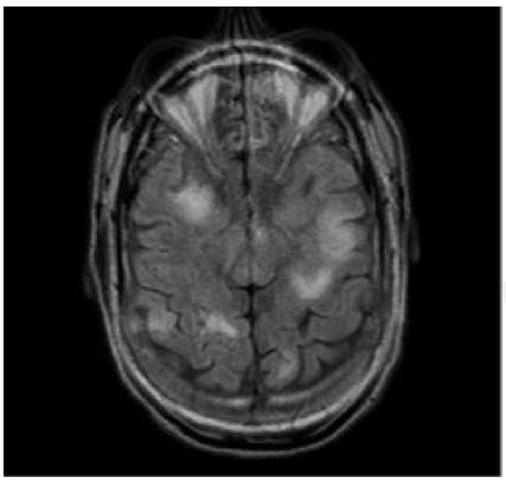


Fig. 4. Fused image of date set 1in DWT Maximum selection Rule method

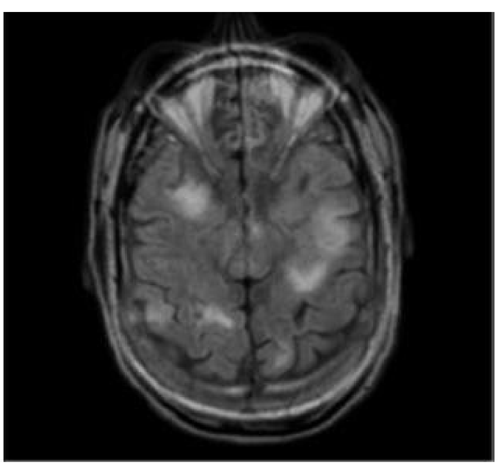
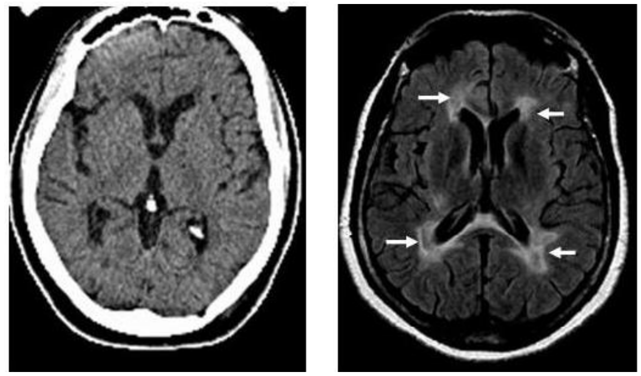


Fig. 5. Fused imageof data set-1 in PCA

The table.1 shows, the values of different quality parametric measures like Entropy, Standard Deviation, Mean Squared Error and Root Mean Squared Error for various fusion algorithms. Values for the proposed PCA is resulted better than other w.r.t the quality parametric measures.



(a) MRI scan image (b) CT scan image

Fig. 6: Date set-2of the brain

Table 2: Comparison pameters of the output images of fusion algorithm of Dataset-2

	DWT Maximum Selection Rule				
	Entropy	Standard Deviation	MSE	RMSE	PSNR
CT	6.3425	81.1017	--	--	--
MRI	5.6423	53.3808	--	--	--
DWT Simple Average	6.6093	73.5183	99.8073	9.9904	28.1394
DWT Maximum Selection Rule	6.6746	72.3431	78.7480	8.8740	29.1684
PCA	6.6921	70.2923	72.0784	8.4899	29.5528

The testing data sets are of two medical modality images i.e., CT and MRI of size 410X388. The original MRI image of set 2 is shown in figure 6(a) and the CT image of set1 is shown in figure 6(b).

Fig. 7: Fused image of Date set-2 in DWT Simple Averaging Method

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Fig.8. Fused image of date set 2 in DWT Maximum selection Rule method

Fig. 9. Fused image of data set-2 in PCA

Fig.7 shows an image resulting from DWT simple averaging fusin technique. DWT maximum selection rule is applied on data set 2 and resulting image is shown in fig.8. and fig.9 shows animage which is obtained from PCA fusion method.
The table.2 shows, the values of different quality parametric measures like Entropy, Standard Deviation, Mean Squared Error and Root Mean Squared Error for various fusion algorithms. Values for the proposed PCA is resulted better than other w.r.t the quality parametric measures.

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