Medical Image Fusion Approach using Machine Learning

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ABSTRACT

Fusion process gives highly informative image as it combines the information from two or more images into a single image. It has been utilizing widely in medical research field for computer aided brain surgery, Alzheimer’s treatment, tumour detection and other clinical diagnosis. Effective fusion algorithms are required to obtain accuracy of successful diagnosis of diseases. Magnetic resonance (MR) and computed tomography (CT) images are most widely utilized images for analysing the human body. The main objective of any fusion approach is to transfer maximum information from the source images to the fused image with minimum information loss. It must minimize the artifacts in the fused image. In this context, a novel medical image fusion algorithm is proposed. Nonlinear anisotropic filtering (NLAF) in principal component analysis (PCA) domain, which preserve the texture information of fused images most effectively. NLAF is utilized to decompose the source images into approximation and detail layers. Final detail and approximation layers are computed with the support of PCA. Finally, fused image is generated from the linear combination of final detail and approximation layers. Qualitative and quantitative performance of the proposed algorithm is assessed with the help of image quality metrics like peak signal-to-noise ratio (PSNR), correlation coefficient (CC), entropy (E), root mean square error (RMSE) and structural similarity (SSIM) index. Extensive simulation results of the proposed hybrid algorithm are compared with the traditional and recent image fusion algorithms. Performance evaluation discloses that the proposed fusion approach outperforms the existing fusion methods.

Keywords: Medical image fusion, machine learning, fusion algorithms.

1. INTRODUCTION

Image fusion treats the different combinations of images sensed from different sensors which include multi-spectrum and high-spectrum, multi-angle viewing and multi-resolutions. This enhances the scope for accomplishing the quality of images. Multi-sensor images are used in several fields such as machine vision, remote sensing, and medical imaging. Medical image fusion techniques provide better biomedical information for clinical evaluation. In medical diagnosis multimodal fused images has more significant role than individual image. The multi model medical image fusion is the process of combining compliment fusion techniques for clinical analysis. To support more accurate clinical information for physicians to deal with medical diagnosis and assessment, multimodality medical images are required such as Computed Tomography (CT), Magnetic Resonance Imaging (MRI), or Positron Emission Tomography (PET) [1,2] etc. For example, the CT image can provide dense structures like bones and implants with less distortion but cannot detect physiological changes. But the MRI can provide information of normal and pathological soft tissues and it cannot support the bone information. In this circumstance, a single image cannot be appropriate to deliver perfect clinical requirements for the physicians. Hence the fusion of the multimodal medical images is essential, and it has become a promising and very challenging research area in recent years [3].

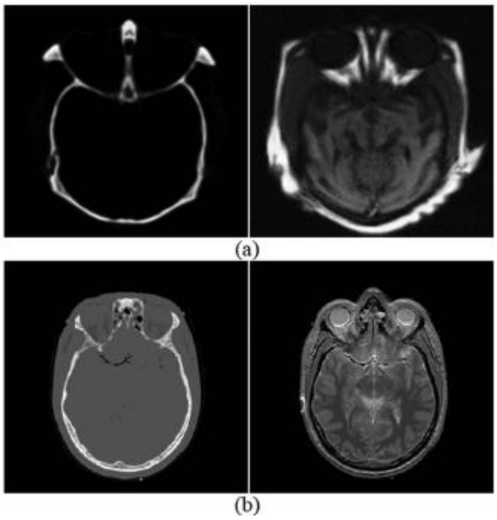


Fig. 1: CT and MR images (a) dataset 1 (b) dataset 2.

Image fusion broadly defined as the representation of the visual information with more than one input image, as a single fused image without the introduction of distortion or loss of information [4]. The fusion of different images can reduce the ambiguity related to a single image. In recent days, obtaining human's anatomies and functions with high resolution and more instructive description becomes potential due to advancement in the field of medical imaging technology. The encouragement for the research in the analysis of medical images has been done by such development. In addition, the development of medical images vitality in the clinical applications rendered a straight effect on this field of research [5].

IMAGE FUSION

In computer vision, Multi sensor Image fusion is the process of combining relevant information from two or more images into a single image. The resulting image will be more informative than any of the input images.

In remote sensing applications, the increasing availability of space borne sensors gives a motivation for different image fusion algorithms. Several situations in image processing require high spatial and high spectral resolution in a single image. Most of the available equipment is not capable of providing such data convincingly. The image fusion techniques allow the integration of different information sources. The fused image can have complementary spatial and spectral resolution characteristics. But, the standard image fusion techniques can distort the spectral information of the multispectral data, while merging.

In satellite imaging, two types of images are available. The panchromatic image acquired by satellites is transmitted with the maximum resolution available and the multispectral data are transmitted with coarser resolution. This will be usually, two or four times lower. At the receiver station, the panchromatic image is merged with the multispectral data to convey more information.

Many methods exist to perform image fusion. The very basic one is the high pass filtering technique. Later techniques are based on DWT, uniform rational filter bank, and Laplacian pyramid.

Medical Image Fusion

Image fusion has become a common term used within medical diagnostics and treatment. The term is used when multiple patient images are registered and overlaid or merged to provide additional information. Fused images may be created from multiple images from the same imaging modality, or by combining information from multiple modalities, such as magnetic resonance image (MRI), computed tomography (CT), positron emission tomography (PET), and single photon emission computed tomography (SPECT). In radiology and radiation oncology, these images serve different purposes.

2. DESIGN OF AN IMAGE FUSION SYTEM

Image fusion can be carried out at three different levels:

- Pixel level
- Feature level
- Decision level

Pixel Level Image Fusion

Pixel-level image fusion is the information fusion that is implemented directly using the basic data of the images needed to be fused.

This kind of image fusion integrates the information of multi-source images on the premise of strict registration.

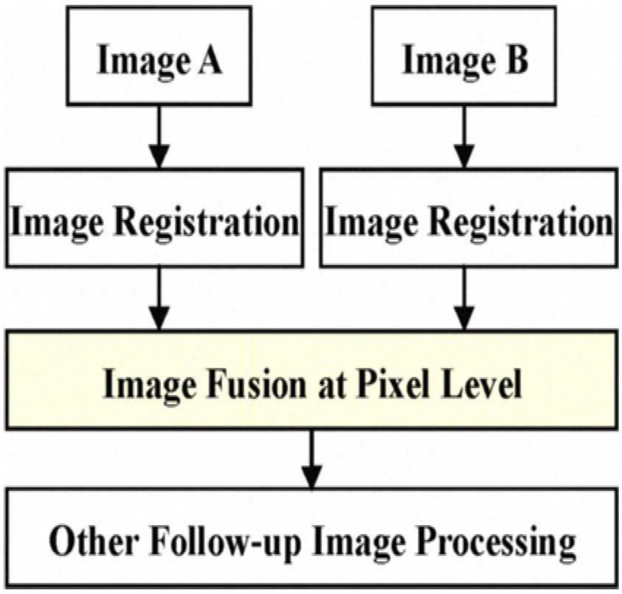


Fig. 2: Structure of image fusion system at pixel level.

3. LITERATURE SURVEY

From the past decades, there has been a greater number of scientific research papers have been published on the topic of fusing the medical images. Essentially, image fusion techniques have been classified into three sorts. They are pixel level, feature level and decision level. Successful fusion methods based on morphological operators are discussed in [6-7]. Even though these methods are simple, fused image may not look good. In optimization-based approaches [8] and [9] fusion process is expressed as Bayesian optimization problem. But in general, this problem is difficult to solve. Markov random field [10] and generalized random walk [11] methods solve this problem by computing edge aligned weights. Fused image may be over smoothened because of multiple iterations. In addition, artificial neural networks have gained a lot of interest in image fusion by the inspiration of biological signal fusion. Successful methods in this class are discussed in [12-13].

In addition to the above fusion schemes, multiresolution schemes have played a great role in image fusion. These schemes are motivated by the fact that human visual system (HVS) is sensitive to the edge information. That is, HVS can perceive even small changes in edge information. Both image pyramid and wavelet decomposition belong to multiresolution methods. These approaches require transform domain analysis. Image pyramid decomposes each given image into set of low pass filtered images. Each filtered image represents the information of the given image in different scales. Gradient pyramid (Grad) [14], Laplacian pyramid [15], ratio of low-pass pyramid (Ratio) [16], Gaussian pyramid [17], contrast pyramid, filter-subtract-decimate pyramid, and morphological pyramid [18] methods are used for fusion. Wavelet transform based fusion algorithms have tremendous performance over the algorithms presented in the literature. Recent years, many extended versions of wavelet transform have done to improve the fusion performance further [19-20].

4. PROPOSED METHODOLOGY

This section describes the brief explanation of our proposed fusion framework. Fused output image is obtained by implementation of NALF process to obtain the approximate and detail layers with PCA fusion rule. Proposed NLAF-PCA fusion methodology shown in fig. 5.

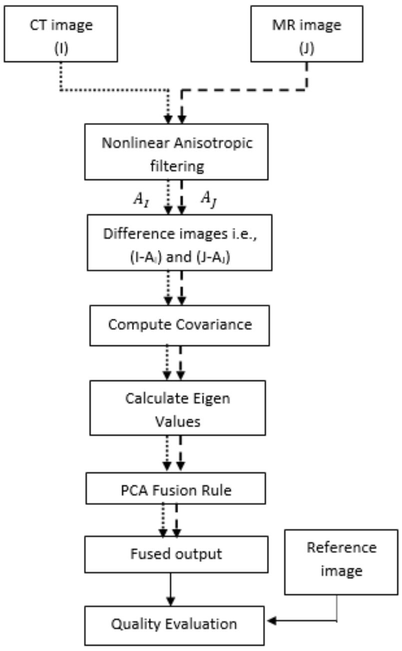


Fig. 3: Proposed NLAF-PCA fusion process flow.

Non-Linear Anisotropic Filtering

The NLAF process will smooth a given image at homogeneous regions while preserving the nonhomogeneous regions (edges) using partial differential equations (PDE). It overcomes the drawbacks of non-linear isotropic filtering, which uses inter-region smoothing. So, edge information is lost. In contrast, NLAF uses intraregional smoothing to generate coarser resolution images. At each coarser resolution edges are sharp and meaningful. The NLAF equation uses flux function to control the diffusion of an image I as,

$$I_t = \mathbb{F}(x,y,t)\Delta I + \nabla\mathbb{F}\cdot\nabla I \tag{1}$$

Where $\mathbb{F}(x,y,t)$is flux function, Δ is a Laplacian operator, $\nabla$is a gradient operator and $t$is time or scaling constant.

We can also term (1) as heat equation. Forward-time-central space (FTCS) scheme is used to solve this equation. The solution for this PDE is

$$I_{i,j}^{t+1} = I_{i,j}^{t} + \beta\left[\mathbb{F}_N\cdot\overline{\nabla}_N I_{i,j}^{t} + \mathbb{F}_S\cdot\overline{\nabla}_S I_{i,j}^{t} + \mathbb{F}_E\cdot\overline{\nabla}_E I_{i,j}^{t} + \mathbb{F}_W\cdot\overline{\nabla}_W I_{i,j}^{t}\right] \tag{2}$$

In above eq., $I_{i,j}^{t+1}$is the coarser resolution image at $t+1$scake which depends on the previous coarser scale image $I_{i,j}^{t}$. $\beta$is a stability constant satisfying $0 \leq \beta \leq 1/4$. Nearest neighbour differences in north, south, east and west directions denoted as $\overline{\nabla}_N, \overline{\nabla}_S, \overline{\nabla}_E, \overline{\nabla}_W$ respectively. They are defined as

$$\begin{aligned} \overline{\nabla}_N I_{i,j} &= I_{i-1,j} - I_{i,j} \\ \overline{\nabla}_S I_{i,j} &= I_{i+1,j} - I_{i,j} \\ \overline{\nabla}_E I_{i,j} &= I_{i,j+1} - I_{i,j} \\ \overline{\nabla}_W I_{i,j} &= I_{i,j-1} - I_{i,j} \end{aligned} \tag{3}$$

Similarly, the flux functions are denoted as $\mathbb{F}_N$, $\mathbb{F}_S$, $\mathbb{F}_E$ and $\mathbb{F}_W$respectively.

$$\begin{aligned} \mathbb{F}^t{}_{N_{i,j}} &= g\left(\left\|(\nabla I)^t{}_{i-1/2,j}\right\|\right) = g\left(\left|\overline{\nabla}_N I_{i,j}^t\right|\right) \\ \mathbb{F}^t{}_{S_{i,j}} &= g\left(\left\|(\nabla I)^t{}_{i+1/2,j}\right\|\right) = g\left(\left|\overline{\nabla}_S I_{i,j}^t\right|\right) \\ \mathbb{F}^t{}_{E_{i,j}} &= g\left(\left\|(\nabla I)^t{}_{i,j+1/2}\right\|\right) = g\left(\left|\overline{\nabla}_E I_{i,j}^t\right|\right) \\ \mathbb{F}^t{}_{W_{i,j}} &= g\left(\left\|(\nabla I)^t{}_{i,j-1/2}\right\|\right) = g\left(\left|\overline{\nabla}_W I_{i,j}^t\right|\right) \end{aligned} \tag{4}$$

In eq. (4), g (·) is a monotonically decreasing function with g (0) = 1. Different functions can be used for g (·). But Perona and Malik [36] suggested two functions as mentioned below

$$g(\nabla I) = e^{-\left(\frac{\|\nabla I\|}{k}\right)^2} \tag{5}$$

$$g(\nabla I) = \frac{1}{1+\left(\frac{\|\nabla I\|}{k}\right)^2} \tag{6}$$

These functions offer a trade-off between the smoothing and texture preservation. First function is useful if the image consists of high-contrast edges over the low-contrast edges. Second function is useful if the image consists of wide regions over the smaller regions. Both functions consist of a free parameter k. This constant k is used to decide the validity of a region boundary based on its edge strength.

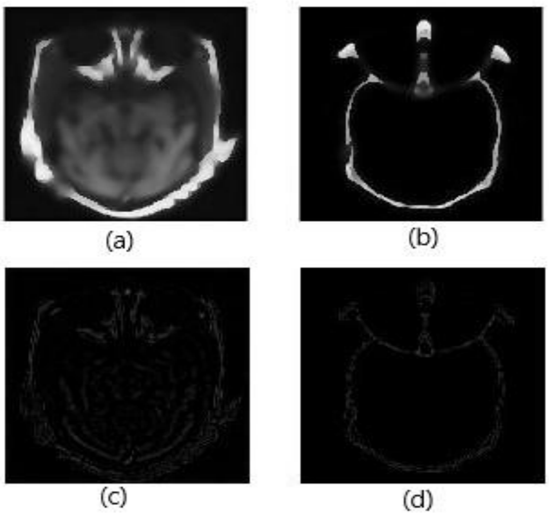


Fig. 4: (a) approximate layer of MR image (b) approximate layer of CT image (c) detail layer of MR image (d) detail layer of CT image.

Extraction of approximated and detail layers from source images using NLAF

Let the source MR and CT images are denoted as $I_n(x,y)$, $J_n(x,y)$ respectively with a size of $p \times q$ and these two images are co-registered images. As shown in figure 4.1, these two source images are passed through the NLAF block to obtain the approximate layers.

$$A_{In}(x,y) = nlaf\big(I_n(x,y)\big) \tag{7}$$

$$A_{Jn}(x,y) = nlaf\big(J_n(x,y)\big) \tag{8}$$

Where $A_{In}(x,y)$ and $A_{Jn}(x,y)$are n^{th}approximate layers and $nlaf$is a sub function that process the source image (refer section II for more information). Now, the detail layers are obtained by subtracting the output of NLAF by utilizing eq. (7) and (8).

$$D_{In}(x,y) = I_n(x,y) - A_{In}(x,y) \tag{9}$$

$$D_{Jn}(x,y) = J_n(x,y) - A_{Jn}(x,y) \tag{10}$$

Algorithm: NLAF-PCA based fusion process

Step 1: Select and read MR and CT source images from the MATLAB current directory (data set2 shown in figure 1).

Step 2: Convert the source images into gray scale in case of RGB images.

Step 3: Apply NLAF process to obtain approximate layers of MR and CT images as described in section II.

Step 4: Subtract the source images from the obtained approximate layers to get the detail layers of MR and CT images.

Step 5: Compute the covariance of detail layers obtained from step 4.

Step 6: Calculate the Eigen vectors for step 5 output.

Step 7: Now, apply PCA fusion rule to obtain final fused output of MR and CT images.

Principal Component Analysis

Principal component analysis is a quantitatively rigorous method for achieving this simplification. The method generates a new set of variables, called principal components. Each principal component is a linear combination of the original variables. All the principal components are orthogonal to each other, so there is no redundant information. The principal components form an orthogonal basis for the space of the data.

Fusion Rule

After obtaining the approximate and detail layers from the source MR and CT images PCA is applied to find out principal components (as described in section III) for getting better analysis over conventional fusion algorithms presented in the literature. Now, to get a fused output image a rule must be utilized to obtain optimum output from the proposed NLAF-PCA fusion process. We first combine the approximate layers of MR and CT images. Then sum the detail layers by multiplying with the principal components denoted as $\mathfrak{p}$ obtained by PCA algorithm. Finally, integrate these two process outputs to obtain fused image.

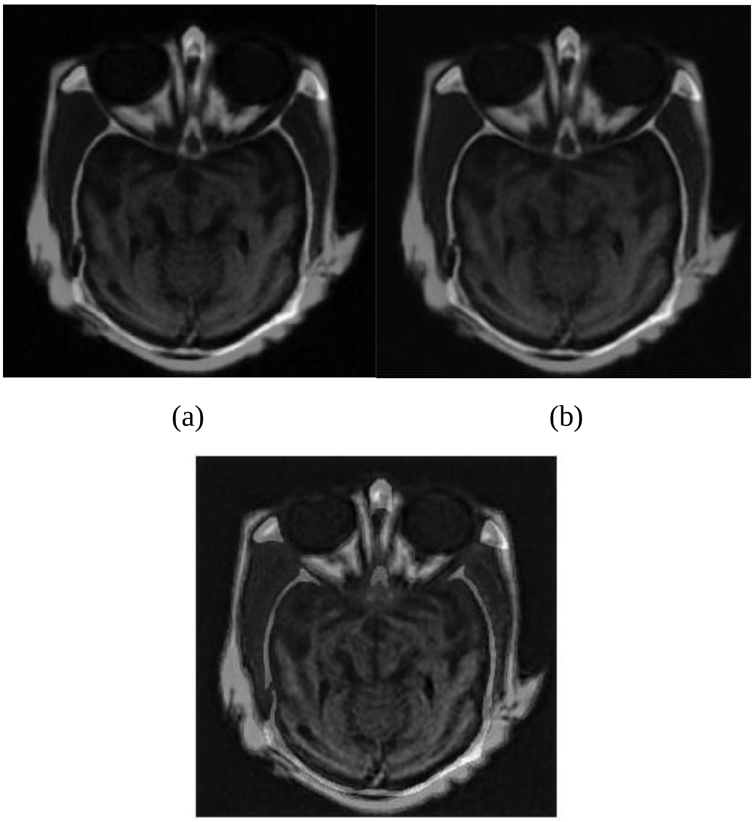
$$D(x,y) = \mathfrak{p}(1) * D_{In}(x,y) + \mathfrak{p}(2) * D_{Jn}(x,y)$$

$$A(x,y) = A_{In}(x,y) + A_{Jn}(x,y)$$

$$\mathcal{F}(x,y) = A(x,y) + D(x,y)$$

4. RESULTS AND DISCUSSION

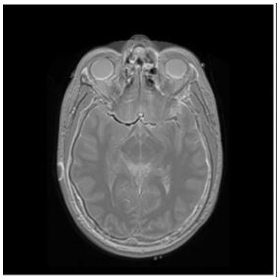
All the experiments have been done in MATLAB 2016b version under the high-speed CPU conditions for faster running time. Aim of any fusion algorithm is to integrate required information from both source images in the output image. Fused image cannot be judged exclusively by seeing the output image or by measuring fusion metrics. It should be judged qualitatively using visual display and quantitatively using fusion metrics. In this section, we are presenting both visual quality and quantitative analysis of proposed and existing algorithms such as, Wavelet based methods discrete wavelet transform (DWT), stationary wavelet transform (SWT). Analysis of fusion metrics along with image quality assessment (IQA) metrics such as peak signal-to-noise ratio (PSNR), structural similarity index (SSIM), correlation coefficient (CC), root mean square error (RMSE) and entropy (E) are considered to verify the effectiveness of the proposed algorithm. The objective of any fusion algorithm is to generate a qualitative fused image. For better quality, fused image should have optimal values for all these metrics.



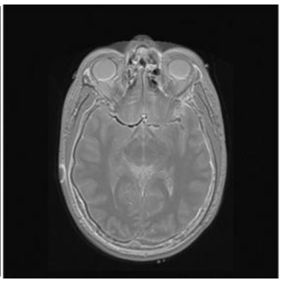
(a) (b)

(c)

Fig. 5: Visualization of fused output images with data set 1 (a) DWT (b) SWT and (c) Proposed method.



(a)



(b)

(c)

Fig. 6: Visualization of fused output images with data set 2 (a) DWT (b) SWT and (c) Proposed method.

Table 1: Quantitative Analysis of Fusion Methods For Dataset 1.

Methodology	PSNR (in dB)	RMSE	CC	SSIM	Entropy
SWT	62.253	0.1967	0.7928	0.986	6.11
DWT	62.257	0.1966	0.7935	0.986	6.099
Proposed method	65.06	0.142	0.913	0.997	6.24

Table 2: Quantitative Analysis Of Fusion Methods For Dataset 2.

Methodology	PSNR (in dB)	RMSE	CC	SSIM	Entropy
SWT	68.95	0.0909	0.933	0.988	0.9684
DWT	68.98	0.0906	0.934	0.988	0.9683
Proposed method	74.18	0.049	0.973	0.999	5.16

5. CONCLUSIONS

A new texture preserving fusion approach is proposed for MR and CT images by utilizing NLAF-PCA methodology. NLAF has utilized to extract the approximate and detail layers from the MR and CT source images. Then the principal components computed according to the PCA algorithm. Finally, fusion is applied to obtain a fused image with texture preservation. Performance of proposed NLAF-PCA fusion process is assessed with several medical image fusion methodologies presented in the literature. Comparative analysis is done according to the image quality metrics and shown that the proposed NLAF-PCA fusion process performed superior to the conventional medical fusion algorithms.

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