MR and CT Image Fusion Using Nonlinear Anisotropic Filtering in PCA Domain

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Abstract: In medical science it has been commonly used for computer-aided brain surgery, Alzheimer's therapy, tumour identification & other medical assessment. Accurate fusion algorithms can be made to ensure proper detection of diseases. The mechanism of fusion is incredibly insightful, since it transforms information from a single picture from two or more pictures into a single picture. In addition, the most common application is the use of images of the magnet resonance (MR) & the computed tomography image (CT). The objects in the source images must be reduced. A new algorithm is introduced here for image fusion. In the principal component analysis (PCA) domain, the nonlinear anisotropic filtering (NLAF) most efficiently preserves texture features of the segmented image. The source images are broken down into estimation & information layers by NLAF. The PCA support is used to measure the actual detail & approximation layers. Fusioned images are eventually generated by last detail and approximation layers linear combination. The algorithm suggested efficiency & quantitative output is evaluated by image consistency parameters, including the PSNR, entropy (E), square-root root (RMS) & structural similitude (SSIM) indices. Compared with the conventional & recent image fusion algorithms, detailed simulation findings of the suggested hybrid technique. Evaluation of efficiency shows that the proposed fusion solution is beyond the actual fusion approach.

Keywords: MR and CT images, image fusion, edge preservation, texture preservation, nonlinear anisotropic filtering, principal component analysis and image quality metrics.

1. Introduction

Image fusion deals with the varying variations of images perceived from various cameras, including multi- & Views with many angles and multi-resolutions of high-spectrum. The ability to achieve continuity of the image. In certain fields, including artificial vision, remote sensing & medical imaging, multi-sensor images are used. The techniques of medical picture fusion have improved clinical assessment biomedical knowledge. Multimodalized photographs play a larger function than human photographs in medical diagnostics. The multi-Model Diagnostic Image Fusion incorporates complementary clinical imaging methods. Medical imagery multimodality, including Magnetic Resonance Imaging (MRI), Computed Tomography (CT), or Positron Emission Tomography (PET) [1]. is needed to help more detailed clinical knowledge for doctors who are interested in medical diagnosis & evaluation. For e.g., the CT image can have less distortion in thick but do not note physiological changes, such as bones & implants. However, MRI may offer normal & abnormal soft tissue information & may not endorse bone details [2]. In any case, a single picture is not ideal for supplying the doctors with complete clinical specifications. The merger of multimodal medical images is therefore important & has become in recent times a promising & challenging field of research [3].
Image fusion normally means that a single image combined without specifics or distortions is over one image with visual information [4]. Mixing many images reduces the complexity of an image to a minimum. In recent days, obtaining human’s anatomies and functions with high resolution and more instructive description becomes potential due to advancement in the imaging technology sector. The creation of medical pictures has had a straightforward influence on this area of research in clinical applications [5]. From there's been a last decades greater number of scientific research papers have been published on the topic of fusing the medical images. Essentially, three kinds of imaging fusion techniques were classified [6]. They are pixel level, level of operation and level of decision. Effective methods of fusion are addressed in [7] focused on morphological operators. Although these are easy ways, fused pictures cannot look fine. The fusion method is described as a Bayesian optimal solution in optimization-based approaches [8] and [9]. But ultimately it's hard to solve this dilemma. The random field of Markov [10] & widespread randomized methods [11] mitigate this issue by computation of edge weights. Cos of numerous tests, the merged picture may be over-smoothed. In addition, the inspiration of biological signal fusion has drawn a great deal of attention from ANN. This class addresses efficient approaches in [12]. Multi resolution systems have played a significant part in fragmentation of images in addition to the above fusion schemes. The reality that the human eye is susceptible to edge information creates these schemes [13]. In other words, even minor edge information shifts are interpreted by HVS. Multiresolution approaches include both image pyramid & wavelet decomposition. This allows domain interpretation to be converted. The picture pyramid splits each picture into a series of processed low-pass images. The data on the given image in various sizes is depicted in each filtered image. Fusion is used in gradient pyramid (Grad) [14], Laplacian pyramid [15], Low-Pass (Ratio) [16], Gaussian pyramid [17], contrast pyramid, philtre-decimal pyramid [18], etc. 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]. However, these techniques can incorporate fused objects. Fusion schemes are suggested to handle these issues. Many iterations are used to find the right solution (fused image) [20]. The primary analytical approach is one of the finest methodologies for acquiring fused images from provided MR and CT images [20], due to multiple Iterations. Furthermore, image fusion preservation schemes have now become common. These techniques are used to preserve the edge of the philtre / fusion smoothing operation [21]. Common picture philtre, weighted lowest square philtre, bilateral movable philtre, bilateral philtre cross, anisotropic 3-D diffusion , are the most popular techniques in that range. Some of these approaches are split into base & informative layers of each input images. The composite image may be produced by
either a modified Basic layer or manipulated layer of information or both layers changed. Bilateral filtering and bilateral philtre fusion processes generate reversed image gradients, while the directed image fusion technique creates fused image Halo effects. There should be 3 elements in an effective image fusion system.

- Much of the critical data must be passed to the image fused from source images.
- In the fusion process, valuable origin picture details should not be loosened.
- No objects or external material should be inserted into the fused image.

It has been suggested to fix the issue of current methods & to take the above properties into account a novel nonlinear, anisotropic filtering image fusion (NLAFF) in the PCA region. Estimated & informative layers are removed by NLAF method for each input images. The fused image is combined with valuable details from preliminary & detailed layers. The novel this work's contributions can be summarised as follows:

- A Novel utilization of non-linear anisotropic filtering in PCA domain for extracting the features from the input MR and CT images to be fused. As per the author’s best knowledge, this combo hasn’t utilized in image fusion applications yet.
- A Fully new fusion frame work is introduced based on proposed hybrid methodology. We mainly focused on the retaining of texture even after fusion process. Algorithms presented in the literature like stationary wavelet transform (SWT) , Discrete Wavelet Transform (DWT), Principal Component Analysis (PCA), DWT+PCA, SWT+PCA and fast discrete curvelet transform (FDCT) aimed at enhancement in the performance of fusion process only. These methodologies haven’t concentrated on the visual texture of fused medical images.
- We considered several quality indexes to disclose the quality and power of the plan NLAF-PCA fusion model.

The rest of the paper is: Section II explains the NLAF briefly. The following hybrid approach NLAF-PCA is found in Section III. Section V contained the findings and future improvements. The results and discussions are discussed in Section IV.

2. Non-Linear Anisotropic Filtering

In homogeneous regions, the NLAF method smooths a particular picture thus retaining regions with Partial Differential Equations (PDE). Edge data is then destroyed. NLAF, on the other hand, created grosser resolution of images using intra-regional smoothing. Each rib is sharp and significant at a grosser level. The flux function of the NLAF equation governs the spread of a image $I$ as,

$$I_t = \nabla \cdot \nabla F (x, y, t) + \nabla \cdot \nabla I $$ (1)

Where, $F(x, y, t)$ is a flux function, $\Delta$ is a Laplacian operator, $\nabla$ is a gradient operator and $t$ is time or scaling constant. Even (1) can be called the heat equation. The Central Space Future Time (FTCS) is used to overcome this equation. The solution is this PDE,

$$I_{i,j}^{t+1} = I_{i,j}^t + \beta [F_N \cdot \nabla_N I_{i,j}^t + F_S \cdot \nabla_S I_{i,j}^t + F_E \cdot \nabla_E I_{i,j}^t + F_W \cdot \nabla_W I_{i,j}^t] $$ (2)

In above eq., $I_{i,j}^{t+1}$ is the grosser image resolution at $t + 1$scale which depends on the previous coarser scale image $I_{i,j}^t$. $\beta$ is a stability constant satisfying $0 \leq \beta \leq 1/4$. The nearest north, south, east and west neighbour discrepancies denoted as $\nabla_N I_{i,j} = I_{i-1,j} - I_{i,j}$, $\nabla_S I_{i,j} = I_{i+1,j} - I_{i,j}$, $\nabla_E I_{i,j} = I_{i,j+1} - I_{i,j}$, $\nabla_W I_{i,j} = I_{i,j-1} - I_{i,j}$,
\[ \nabla_E I_{i,j} = I_{i,j+1} - I_{i,j} \]
\[ \nabla_W I_{i,j} = I_{i,j-1} - I_{i,j} \]

Similarly, the flux functions are denoted as \( F_N, F_S, F_E \) and \( F_W \) respectively.

\[
F^t_{N,i,j} = g \left( \left\| (\nabla I)^t_{i-1/2,j} \right\| \right) = g(\nabla N I_{i,j})
\]
\[
F^t_{S,i,j} = g \left( \left\| (\nabla I)^t_{i-1/2,j} \right\| \right) = g(\nabla S I_{i,j})
\]
\[
F^t_{E,i,j} = g \left( \left\| (\nabla I)^t_{i+1/2,j} \right\| \right) = g(\nabla E I_{i,j})
\]
\[
F^t_{W,i,j} = g \left( \left\| (\nabla I)^t_{i,j-1/2} \right\| \right) = g(\nabla W I_{i,j})
\]

In eq. (4), \( g (\cdot) \) is a structure that monotonously decreases \( g (0) = 1 \). Various functions for \( g \) can be used (\( \cdot \)). But Perona and Malik [36] mentioned below,

\[
g(\nabla I) = e^{-\left( \frac{\|\nabla I\|}{k} \right)^2} \quad (5)
\]
\[
g(\nabla I) = \frac{1}{1 + \left( \frac{\|\nabla I\|}{k} \right)^2} \quad (6)
\]

Both functions make a distinction between the maintenance of smoothing & texture. First feature is helpful if the picture leads to high rims over low rims. If the picture involves large parts over smaller areas, the second function is useful. A free parameter \( k \) consists of all functions.

3. Proposed Frame Work

This section describes the brief explanation of our proposed fusion frame work. 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 Figure 2.

3.1. Extraction of approximated and the use of layers of information from sources NLAF

Let the source MR and CT images as shown in Figure 1 are denoted as \( I_n(x,y) \), \( J_n(x,y) \) respectively witha size of \( p \times q \) and these two images are co-registered images. These two source images are passed through the NLAF block to obtain the approximate layers.

\[
A_{I_n}(x,y) = nla f(I_n(x,y)) \quad (7)
\]
\[
A_{J_n}(x,y) = nla f(J_n(x,y)) \quad (8)
\]

Where \( A_{I_n}(x,y) \) and \( A_{J_n}(x,y) \) are \( n^{th} \) approximate layers and \( nla f \) is a sub function that process the Source picture (see Section II for details). Now, by retiring the NLAF production using eq the informative textures are received. (7) and (8), respectively.

\[
D_{I_n}(x,y) = I_n(x,y) - A_{I_n}(x,y) \quad (9)
\]
\[
D_{J_n}(x,y) = J_n(x,y) - A_{J_n}(x,y) \quad (10)
\]

The Figure 3 demonstrates that the output layers obtained from NLAF process i.e., approximation and detail layers of MR and CT images.

**Algorithm: NLAF-PCA based fusion process**

**Step1:** Select and read MR and CT source images from the MATLAB current directory (data set2 shown in Figure 1).

**Step2:** Convert the source images into gray scale in case of RGB images.

**Step3:** 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.

Figure 2: Proposed NLAF-PCA fusion process flow

3.2. Principal Component Analysis
The challenge of visualising data with several variables is among the complexities inherent in multivariable statistics. Happily, classes of variables also travel together during data sets of several variables. One explanation is that more than one variable will calculate the behaviour of the device by the same guiding theory. Just a few such driving forces remain in many systems. However, a vast number of instruments allow you to calculate hundreds of device variables. This continuity of information should be used as this occurs. This issue can be simplified by replacing a number of variables with one new variable.
3.3. Definition
A quantitatively robust method of simplification is primary component analysis. A new number of samples is created, known as key elements. A linear combination of the original versions is any principal part. There is no redundant knowledge for all the principal components orthogonal to each other. The main components form an orthogonal base for the data space.

3.4. Definition
A single axis in the space is the first major part. The measured value form a new variable as each observation is projected on that axis. And this variable's variation is the largest of all possible options in the first dimension. The second main factor is a separate dimension, based on the first axis. Another new variable is created by projecting the measurements on this axis. The variation of this equation is the peak of all alternatives in this second axis. The entire range of key components is as large as the initial set. But it is normal for 80 % of the overall variation of the original information to surpass the quantities of discrepancies of the first few key components.

3.5. 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 p obtained by PCA algorithm. Finally, integrate these two process outputs to obtain fused image.

\[ F(x, y) = A(x, y) + D(x, y) \]  
Where, \( A(x, y) = A_{in}(x, y) + A_{jn}(x, y) \) 
\( D(x, y) = p(1) \ast D_{in}(x, y) + p(2) \ast D_{jn}(x, y) \)

4. Results and Discussion
In the MATLAB 2016b version all tests were carried out for faster running time, under the high-speed CPU conditions. Table 1 indicates research findings on the medical images based shown in Table 1. Dataset 1 & dataset 2, respectively. Any fusion algorithms are expected to provide the information needed in the output image from both input image. The graphic display and the objective use of fusion
metrics shall be measured qualitatively. In this section, both visual and quantitative analyses of different algorithms are presented such as, Wavelet based methods DWT, SWT, DWT+PCA, SWT+PCA and Fast Discrete Curvelet Transform (FDCT). 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.

![Image](http://example.com/image.jpg)

**Figure 4:** (a) Fused performance image visualisation with data set 1 (a) PCA (b) DWT (c) SWT (d) FDCT (e) SWT+PCA and (f) Our method

The best performance fusion metric is seen in bold letter. The fused images obtained using state-of-art algorithms such as PCA, DWT, SWT, FDCT, SWT+PCA and our method has demonstrated in Figure 4 and Figure 5 with data set 1 and data set 2. It clearly observe that the perceptual quality of fused output using PCA, shown in Figure 4(a) looks low resolute image and the gray levels hasn’t up to the mark. Other transformation methods like the methodology proposed in, SWT and the algorithm demonstrated and shown in Figure 4(b-d) respectively, which performed superior to the PCA method in terms of visual perception, however these methods suffer from lack of contrast and edge preservation. Figure 4 (e) shown that the fused output of the method presented, which was far better than the above-mentioned algorithms. However, all the existing fusion methods outputs not good at visual perception, lack of contrast with edge information and texture preservation. Our proposed method which is presented in Figure 4(f), which looks more quality in visualization, good contrast with proper edge information and excellent texture preservation as the value of entropy is much higher.
Figure 5: Fused performance image visualisation with data set 2 (a) PCA (b) DWT (c) SWT (d) FDCT (e) SWT+PCA and (f) Our method

Table 1: Fusion approaches for Dataset Quantitative Analysis 1

| Methodology | PSNR (in dB) | RMSE | CC   | SSIM  | Entropy |
|-------------|--------------|------|------|-------|---------|
| PCA         | 60.595       | 0.16 | 0.888| 0.9989| 6.09    |
| SWT         | 62.253       | 0.1967| 0.7928| 0.986 | 6.11    |
| DWT         | 62.257       | 0.1966| 0.7935| 0.986 | 6.099   |
| FDCT        | 65.156       | 0.146 | 0.9  | 0.9983| 5.963   |
| DWT+PCA     | 63.159       | 0.165 | 0.895| 0.9987| 6.12    |
| SWT+PCA     | 64.96        | 0.143 | 0.9  | 0.997 | 6.19    |
| Our method  | **65.06**    | **0.142** | **0.913** | **0.997** | **6.24** |

| Methodology | PSNR (in dB) | RMSE | CC   | SSIM  | Entropy |
|-------------|--------------|------|------|-------|---------|
| PCA         | 69.937       | 0.056 | 0.87 | 0.999 | 4.637   |
| SWT         | 68.95        | 0.0909| 0.933| 0.988 | 0.9684  |
| DWT         | 68.98        | 0.0906| 0.934| 0.988 | 0.9683  |
| FDCT        | 70.215       | 0.140 | 0.9206| 0.9983| 5.05    |
| DWT+PCA     | 71.159       | 0.0486| 0.9  | 0.999 | 5.09    |
| SWT+PCA     | 72.932       | 0.047 | 0.96 | 0.999 | 4.9     |
| Our method  | **74.18**    | **0.049** | **0.973** | **0.999** | **5.16** |
Figure 5 (a-f) demonstrated that the PCA, DWT, SWT, FDCT, SWT+PCA and our proposed method fused outputs with data set 2. The same analysis which we have discussed above has applicable for this also. Quantitative analysis with IQA sown in Table 1 for the test results presented in Figure 4, which gives the analysis of dataset 1. Table 1 consists of various fusion metric parameters such as PSNR, RMSE, CC, SSIM and entropy. The best values are highlighted in bold letters. Our proposed method obtained far better values over all the existing fusion methods discussed in the literature. We also tested the qualitative analysis of dataset 2 with the similar fusion metric parameters considered for dataset 1.

5. Conclusion
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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