Medical Image Fusion Based on Retina Model

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Abstract: Image fusion is a process of combining two or more images into an image. It can extract features from source images, and provide more information than one image can. In this research, we propose a novel method for multimodality medical image fusion. Low spatial resolution limits the diagnostic potential of brain positron emission tomography (PET) imaging. As a possible remedy for this problem we propose a technique for the fusion of PET and MR images, which requires for a given patient the PET data and the T1-weighted MR image. Basically, after the registration steps, the high-frequency part of the MR, which would be unrecoverable by the set PET acquisition system is extracted and added to the PET image. This paper introduces new application of the human vision system model in multispectral medical image fusion. The methodological approaches proposed in this paper result in merged images with improved quality with respect to those obtained by HSI, DWT, wavelet à trous algorithm and wavelet based sharpening methods. Results show proposed method preserves more spectral features with less spatial distortion.

Keywords: Fusion, Retina based, Multi-resolution, MRI, PET.

1 Introduction

Noninvasive technologies that image various aspects of the disease process for clinical diagnosis are divided into two types—structural and functional images. Magnetic resonance imaging (MRI) and X-ray computed tomography (CT) provide mainly high-resolution images with anatomical information, whereas positron emission tomography (PET) and single-photon emission computed tomography (SPECT) provide functional information, but with coarser resolution. Fusing these two types of images solves the problem of the insufficiency of the information provided by a single modality. Image fusion is the process of combining information from two or more images of a scene into a single composite image that is more informative and is more suitable for visual perception or computer processing. The objective in image fusion is to reduce uncertainty and minimize redundancy in the output while maximizing relevant information particular to an application or task. There are many algorithms for spatially enhancement of low-resolution images by combining high and low resolution data. Recently, the wavelet transform has been used for merging multi-resolution images. Normally, the objective of these procedures is to create a composite image of enhanced interpretability, but, those methods can distort the spectral characteristics of the multispectral images and the analysis becomes difficult [1-2].

It is desirable that procedure for merging high-resolution panchromatic data with low-resolution multispectral data should preserve the original spectral characteristics of the later as much as possible. The procedure should be optimal in the sense that only the additional spatial information available in higher resolution data is imported into the multispectral bands. This paper presents a retina based multi-resolution data fusion procedure, allowing the use of high-resolution MRI image while conserving the spectral properties of the original low-resolution multispectral PET images.

2 Retinal Model

Our image fusion architectures are motivated by the biological computational processes of the human
The three different cone cells in the retina are sensitive to the short, medium, and long wavelengths of the visible spectrum. The outputs from these photoreceptors are then contrast enhanced within band by center-surround spatial opponent processes at the bipolar cells. In later stages (ganglion cells in retina and VI) these signals are contrast enhanced by center-surround processes between the different bands. This opponent-color processing separates (i.e. de-correlates) the complementary information that each band contains. This insight into how the visual system contrasts and combines information from different spectral bands provides one example of a working multi-spectral fusion system [3].

Image fusion can incorporate the processing principles of human vision system. In this paper we present a multisiresolution data fusion scheme, based on retinal visual channels decomposition, motivated by analytical results obtained from "retina based image analysis, or multiscale image decomposition incorporates the visual channels phenomena": the energy packing the spectral features are distributed in the lower frequency subbands, and the spatial features, edges, are distributed in the higher frequency subbands. By adding the high-scale spatial features (extracted from MRI image) to the low-scale spatial features (extracted from PET image), the visual-channels procedure enhances the multispectral images.

The computer retina model presented here is based on *Difference-Of-Gaussian* operator, which describes some of the receptive field properties of the ganglion cells. The building block of this operator is given below [4-5]:

\[
\text{DOG}(r, \sigma) = \alpha \cdot \text{g}(r, \sigma) - \alpha \cdot \text{g}(r, \sigma)
\]

(1)

Our model, shown in Fig.1 - consists of five layers. The first layer represents an array of high resolution receptors. The second layer is high-scale spatial feature extractor. We represent the function of this layer by the following operator:

\[
h_t(r) = \frac{\Delta_1^2}{2\pi} \exp\left(-k\Delta_1^2 r^2\right) - \frac{\Delta_2^2}{2\pi} \exp\left(-k\Delta_2^2 r^2\right)
\]

(2)

where \( r = \sqrt{x^2 + y^2} \), \( \Delta_1 \) is the low-resolution pixel size, \( \Delta_2 \) is the high-resolution pixel size. Third layer is the array of low resolution (\( \Delta_1 \)) receptors (horizontal cells). The fourth and the fifth layers consist of bipolar and ganglion cells, we can represent the function of these layers by:

\[
f(x, y) = h_1(x, y) \otimes f_1(x, y) + h_2(x, y) \otimes f_2(x, y)
\]

(3)

where \( f_1(x,y) \) is the high resolution image, and \( f_2(x,y) \) is the low resolution image. This allows to generate a spatially enhancing multispectral images \( f(x,y) \), by adding the high resolution spatial features to \( f_2(x,y) \). The proposed method in this paper is a feature level image fusion technique. At this level, image fusion requires a robust feature selection scheme for the multi-sensor images and a sophisticated feature extraction technique.

### 3 Experimental Results

The widespread use of multi-sensor and multispectral images in medical diagnostics has increased the importance of assessing the quality of different fusion techniques and relating it to human or computer performance when using the fused images. Better quality assessment tools are needed to compare results obtained by different fusion techniques and to derive the optimal parameters of these techniques.

Often the ideal fused image is not known or is very difficult to construct. This makes it impossible to compare fused images to a gold standard. In applications where the fused images are for human observation, the performance of fusion algorithms can be measured in terms of improvement in user performance in tasks like detection, recognition, tracking, or classification. This approach requires a well defined task for which quantitative measurements can be made to characterize human performance. However, this usually means time...
consuming and often expensive experiments with human subjects.

In recent years, a number of computational image fusion quality assessment metrics have been proposed. Metrics that accurately relate to human observer performance are of great value but are very difficult to design and, thus, are not yet available at present. In order to objectively compare different image fusion algorithms, what we also need is publicly available multi-spectral or multi-sensor data sets that can be used to benchmark existing and new algorithms.

In this experiment, multispectral PET image is fusing with the MRI data. The test images are 256×256 pixels. The PET image consists of three multispectral bands (red, green, blue) and MRI image has a bond. The retina based method is compared with the HSI, DWT, wavelet-based sharpening and à trous wavelet transform methods. Visual evaluation of the color composite images indicates that the HSI, DWT, Wavelet-based sharpening and à trous wavelet transform methods change color of the composite images, which means that the spectral features are distorted by these methods. The image fusion algorithms should not distort the spectral characteristics of the original multispectral data.

A good fusion scheme should preserve the spectral characteristics of the source multispectral image as well as the high spatial resolution characteristics of the source panchromatic image. In this paper, two evaluation criteria are used for quantitative assessment of the fusion performance [6]. The spectral quality of a P · Q fused image can be measured by the discrepancy $D_k$ at each band:

$$D_k = \frac{1}{P \cdot Q} \sum_{x=1}^{P} \sum_{y=1}^{Q} |F_k(x,y) - L_k(x,y)| \quad k = R, G, B$$

(4)

where $F_k(x,y)$ and $L_k(x,y)$ are the pixel values of the fused and original multispectral images at position $(x,y)$, respectively, in this paper $P=256$, $Q=256$. A small discrepancy implies a good fusion result. For the spatial quality, we use the average gradient to evaluate the performance of the fused image $F$. That is:

$$a_{g_k} = \frac{1}{(P-1)(Q-1)} \times \sum_{x=2}^{P-1} \sum_{y=2}^{Q-1} \left( \frac{\partial F_k(x,y)}{\partial x} \right)^2 + \left( \frac{\partial F_k(x,y)}{\partial y} \right)^2$$

$$\quad k = R, G, B$$

(5)
where $F_k(x,y)$ is the pixel value of the fused image at position $(x,y)$. The average gradient reflects the clarity of the fused image. It can be used to measure the spatial resolution of the fused image, i.e., a larger average gradient means a higher spatial resolution.

Table 1 shows the spectral discrepancies between the images obtained by different fusion algorithms and the source multispectral image. The average gradients of the images obtained by different fusion algorithms are shown in Table 2. From these two tables, we can conclude that the proposed algorithm can preserve high spatial resolution characteristics of the source panchromatic image. In addition, the spectral distortion introduced to the proposed fusion method is less than the traditional algorithms based on the HSI, DWT, Wavelet-based Sharpening and à trous wavelet transform methods. Results show that it preserves more spectral features with less spatial distortion.

4 CONCLUSION

In this paper we present a multiresolution image fusion scheme, based on retinal visual channels decomposition. Basically, after the registration steps, the high-frequency part of the MR, which would be unrecoverable by the set PET acquisition system is extracted and added to the PET image. This paper introduces new application of the human vision system model in multispectral medical image
**Table 1:** Spectral discrepancies between the fused images and the source multispectral image

<table>
<thead>
<tr>
<th></th>
<th>R</th>
<th>G</th>
<th>B</th>
<th>Aver.</th>
</tr>
</thead>
<tbody>
<tr>
<td>The IHS trans. based algorithm</td>
<td>18.38</td>
<td>16.72</td>
<td>9.41</td>
<td>14.84</td>
</tr>
<tr>
<td>The DWT based algorithm</td>
<td>18.59</td>
<td>13.78</td>
<td>30.12</td>
<td>20.83</td>
</tr>
<tr>
<td>The Wavelet-based Sharpening</td>
<td>17.75</td>
<td>12.61</td>
<td>29.34</td>
<td>19.90</td>
</tr>
<tr>
<td>The Wavelet-à trous algorithm</td>
<td>15.87</td>
<td>15.91</td>
<td>10.89</td>
<td>14.22</td>
</tr>
<tr>
<td>The proposed algorithm</td>
<td><strong>13.60</strong></td>
<td><strong>12.16</strong></td>
<td><strong>14.11</strong></td>
<td><strong>13.29</strong></td>
</tr>
</tbody>
</table>

**Table 2:** Average gradients of the fused images

<table>
<thead>
<tr>
<th></th>
<th>R</th>
<th>G</th>
<th>B</th>
<th>Aver.</th>
</tr>
</thead>
<tbody>
<tr>
<td>The IHS trans. based algorithm</td>
<td>5.00</td>
<td>5.45</td>
<td>4.96</td>
<td>5.14</td>
</tr>
<tr>
<td>The DWT based algorithm</td>
<td>4.20</td>
<td>5.03</td>
<td>5.56</td>
<td>4.93</td>
</tr>
<tr>
<td>The Wavelet-based Sharpening</td>
<td>4.16</td>
<td>5.09</td>
<td>5.88</td>
<td>5.04</td>
</tr>
<tr>
<td>The Wavelet-à trous algorithm</td>
<td>4.09</td>
<td>4.47</td>
<td>4.60</td>
<td>4.39</td>
</tr>
<tr>
<td>The proposed algorithm</td>
<td><strong>5.24</strong></td>
<td><strong>5.23</strong></td>
<td><strong>5.08</strong></td>
<td><strong>5.18</strong></td>
</tr>
</tbody>
</table>

fusion. The presented computer retina model is based on Difference-Of-Gaussian operator. The proposed method is compared with the HSI, DWT, Wavelet-based Sharpening and à trous wavelet transform methods. Results show retina based image fusion method preserves more spectral features with less spatial distortion than others.

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**Reference**


