**基于IHS变换参数自适应稀疏表示医学图像融合算法研究**

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**摘要：**

**关键词：**

**A novel method for medical image fusion**

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**Abstract:**Image fusion combines multiple images to incur a single image with excellent quality, retaining the features of original images.

In parallel, the introduction of the matching pursuit, and the basis pursuit denoising gave rise to the ability to address the image denoising problem as a direct sparse decomposition technique over redundant dictionaries.

**Keywords:**

## 1 引言

随着医学影像技术的发展，衍生出多种成像方式用在临床以提供诊断信息，如核磁共振成像（MRI）、电子计算机断层扫描成像(CT)、单光子发射计算机断层成像(SPECT)、正电子发射型计算机断层成像(PET)等。但由于其各自成像机理的不同，导致各种成像技术各有优缺点[1]（如SPECT能够显示细胞和分子的生物学活动，但是缺乏组织结构信息，MIR则相反，见图1）。医学图像融合技术能够将多幅不同成像模式的图像融合成为一幅，融合图像能够提供丰富的互补诊断信息，提高疾病诊断精度[2]。同时，图像融合技术的使用，能够使医生对病情的研判不再需要分别参考不同成像模式的病理图像，大大提高诊断效率[3]。

近年来，为了提高图像融合质量，同时减少算法时间复杂度，许多医学图像融合方法被提出。总的来说，医学图像融合方法可以分为三大类：特征级融合、决策级融合、像素级融合[4]，其中像素级融合方法是使用最为广泛，由于其直接对原始数据进行处理，对原图像信息失真度最小。像素级融合方法可以分解为三个步骤：一是对两张原图像做相同变换后获取两组系数(下称图像分解)、二是对已获取两组系数进行处理合成为一组系数（下称融合规则）、三是对合成后系数进行反变换获取融合图像（下称图像重构）[5]。

像素级融合方法三个步骤中，图像分解和融合规则对融合图像质量及时间复杂度的影响最为关键。图像分解方法有如下几类：基于空间变换域的方法（如IHS空间变换和PCA变换[6]）;空间变换域方法能够减少算法时间复杂度，但是其提供的细节有限，为了提高对细节信息的表示能力，后来发展出基于多尺度变换的方法（如拉普拉斯金字塔（LP）[7]、形态学金字塔[8][9]、基于局部拉普拉斯滤波器（LLF）的多尺度分解[10]、基于拉普拉斯金字塔和卷积神经网络的医学图像融合方法[11]）；多尺度的方法只是单单对图像进行多个尺度分解，但是无法获取每个尺度上信息，因此，基于多尺度几何分析的方法被提出（如基于小波变换的图像融合[12][13][14],小波擅长对点的表示，但是对图像的线的奇异性表示能力较弱、脊波变换通过radon变换将线的奇异性转化为点的奇异性，应用于图像融合中一定程度上提高了成像质量[15]、为了对每个尺度进行多方向分解，达到更精细表示的目的，曲波变换[16][17]、轮廓波变换[18][19][20]和剪切波变换[21][22]应用于图像融合、为了解决轮廓波变换和剪切波变换不具有平移不变性的问题，非下子采样轮廓波变换（NSCT）[23]和非下子采样剪切波变换（NSST）[24][25][26]被提出应用于图像融合）;多尺度几何分析方法只是通过固定基函数（相当于固定的原子）去捕获图像几何结构，对于图像中复杂部分而言，并不具备较好的适应性，稀疏表示的方法通过基于目标图像预先建立字典，字典中由若干个原子组成，通过字典去表示目标图像，能够大大提高对图像的表示能力，同时具有平移不变性，在图像融合中应用取得较好效果[27]-[36]。

基于稀疏表示的方法中，融合规则有两种：一种是系数最大值原则[27][30][31][33]，在医学图像融合中，系数最大值原则会导致融合图像不够平滑，造成信息严重丢失；另一种是加权平均的方式[29][32][36]，能够解决信息丢失的问题，但是获取加权平均参数方式的合理性决定着成像质量，传统加权平均方法没有充分考虑原图像自身特征去获取最佳加权参数，难以获得最优参数，同时缺乏自适应性。

为了减少对图像表示失真，本文采用

## 2 方法原理

### 2.1 自适应稀疏表示

##### 2.1.1 稀疏表示基础理论

稀疏表示理论基础是目标图像能够被完备字典D线性组合来表示[37][38]，完备字典包含K个n维信号原子，通过窗移动将目标图像Y截取成M个小块，即，进一步地，图像Y可以表示为，误差

##### 2.1.2 自适应系数表示

### 2.2 IHS变换

### 2.3 自适应加权算法

## 3 实验和结果

### 3.1 实验设置

### 3.2 评价指标

#### 3.2.1 主观评价指标

#### 3.2.2 客观评价指标

### 3.3 与其他融合算法对比

### 3.4 进一步讨论

## 4 结论

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