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硕士学位论文

图像稀疏表示的自适应多原子匹配追踪算法研究

Research on structure adaptive multi-atoms matching pursuit algorithm of image sparse representation

吴颢

指导教师：李翠华

专业名称：计算机技术

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摘　要

图像内容的有效表示是图像处理领域的基本问题。图像的稀疏表示是指用相对较少的数据来表示出目标图像的主要信息。稀疏表示能够更有效地对图像建模，已成为带动压缩感知与图像处理、信号处理、通信等领域发展的核心技术之一，是当前图像处理领域的研究热点与难点，受到国内外学者的广泛关注。本文主要围绕图像稀疏表示理论中过完备字典设计和快速稀疏分解算法两个方面进行了详细和深入的研究，取得的主要研究成果及创新点如下：

1）根据图像的几何结构特性，参考哺乳类动物的视觉系统感知特性，选取二维Gabor函数作为过完备字典的生成函数，建立了可以匹配多种图像结构的Gabor多成分过完备字典。该字典包含平滑、边缘轮廓与纹理三种结构类型的子成分字典，同时依据图像几何结构特征来调整生成函数中自由参数，大幅缩减了原子个数。实验结果表明Gabor多成分过完备字典对图像中平滑、边缘轮廓与纹理结构具有自适应性，与Anisotropic Refinement-Gauss过完备字典相比能够以较少的原子实现对图像更为高效的稀疏分解。

2）提出了一种图像结构自适应的多原子匹配追踪分解算法，首先对待分解图像进行结构自适应的四叉树区域划分，并将划分后的每一子块分类为平滑、边缘轮廓或纹理三种结构类型之一，进一步将每一子块只在与其结构类型一致的单一子成分字典中进行稀疏分解。在进行稀疏分解时使用了基于过完备字典非相干分解的多原子匹配追踪分解算法。多原子匹配追踪算法每次迭代选取若干个匹配度最高的原子，从而实现图像的快速稀疏分解。使用多原子匹配追踪算法使得本文算法在保证稀疏分解有效性的同时，降低了图像维数与字典搜索的复杂度，大幅度提高了稀疏分解效率，为基于过完备图像稀疏表示的实际应用奠定了基础。

关键词：稀疏表示；多成分过完备字典；多原子匹配追踪；压缩感知

Abstract

Efficient representation of image is the basic problem in digital image processing. Image sparse representation can capture significant information of the original image with relatively less data. Because sparse representation model can effectively represent the image, it becomes one of the core technologies which drive the development of many subjects, such as Compressed Sensing, Signal Processing, Communication and so on. In recent years, parse representation theory has already attracted large numbers of international and domestic scholarsAt present it is a research hotspot and difficult problemThis thesis mainly revolves around the two aspects of sparse representation theory, which are the design of overcomplete dictionary, sparse decomposition (approximation) algorithms. The main contributions and innovation points of the thesis are as follows:

1) Based on the geometric properties of the image structures and the perception characters of mammal's visual system, we choose two dimensional Gabor function as the generating function of the dictionary. In this way, a multi-component Gabor perception dictionary matching various image structures is constructed, which includes smooth, edge and texture sub-dictionariesMeanwhile, the value of all free parameters in the Gabor function are allocated according to the geometric characters of the image structuresThus, the number of atoms in the dictionary is reduced dramaticallyThe experimental results indicate that the Gabor multi-component perception dictionary can adaptively provide a precise and complete characterization of local geometry structures, such as plain, edge and texture structures in imagesIn comparison with the anisotropic refinement-Gaussian (AR-Gauss) mixed dictionary, our dictionary has a much sparser representation of images

2) A structure adaptive multi-atoms matching pursuit algorithm is proposed to

obtain effective sparse representations of imagesFirstly, images are adaptively segmented into quad-tree blocks in terms of geometrical structure characterThen each block is classified as one of smooth, edge or texture structure typesWhen seeking for sparse decomposition of every quad-tree block, it is only to search in subspace of single component sub-dictionary with the same structure type as current blockThe multi-atom matching pursuit method based on incoherent decomposition of redundant dictionary is proposed. In this method, the image is decomposed by several the best matching atoms selected at each iteration. The performances of the proposed method are comparable with the traditional matching pursuit. Due to the reduction of dimension of image and complexity of search in the dictionary, our algorithm for sparse decomposition is effective and fast. It will be help to the research of applications based on overcomplete sparse representation.

Keywords: Sparse Representation; Multi-Component Overcomplete Dictionary; Multi-Atoms Matching Pursuit; Compressed Sensing

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