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Guest Editorial: Sparse Coding

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1 Introduction

Sparse models have gained a tremendous success during the past two decades in various scientific fields. In statistics and machine learning, the sparsity principle is used to perform model selection—that is, selecting a simple model among a large collection of them. This is interpreted as automatically selecting a few predictors that explain the observed data. In signal processing, sparsity is used for approximating signals as a linear combination of a few dictionary elements, imposing a union-of-subspaces model on the true data. Not surprisingly, similar formulations and algorithms have been developed in both these fields, which are now extremely popular in both disciplines. The image processing and computer vision communities have a dominant part in this trend, and we have seen a growing interest in sparse models and their deployment to applications in these fields. In particular, methods where the dictionary is learned from data have been successfully used for a wide range of computer vision and image processing tasks, such as feature and codebook learning, image restoration, super-resolution, compression, visual tracking, and many others.

The goal of this special issue is to present the most recent sparse coding techniques dedicated to computer vision and image processing problems, novel applications of sparse coding, as well as theoretical contributions that are relevant to computer vision.

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2 Overview of the Papers from this Special Issue

A total of 12 papers were accepted, which we have organized into three clusters representing three main trends. The first group presents novel sparse image models or new algorithms, the second is dedicated to image processing applications, and the last set refers to classification tasks.

New dictionary learning and sparse transforms algorithms. The five papers below make fundamental contributions to the sparse coding literature by introducing new image models, or new algorithms.

- The paper "Learning Sparse FRAME Models for Natural Image Patterns" (doi:10.1007/s11263-014-0757-x) by Xie et al. bridges the gap between the literature of sparse models and Markov random fields, and proposes an elegant generative model of natural images. As described by one reviewer, the paper is "conceptual in nature"; it presents significantly novel ideas and differs from classical sparse coding contributions, which makes it particularly interesting to read.
- The paper "Extrinsic Methods for Coding and Dictionary Learning on Grassmann Manifolds" (doi:10.1007/s11263-015-0833-x) by Harandi et al. extends the traditional concept of dictionary learning to Grassmann manifolds, via an embedding to the space of positive definite matrices, and proposes efficient algorithms to learn the dictionary. Finally, kernelized variants are also proposed to deal with non-linear data structures.

- The paper "Structured Overcomplete Sparsifying Transform Learning with Convergence Guarantees and Applications" (doi:10.1007/s11263-014-0761-1) by Wen et al. revisits the sparse analysis principle with a union of sparsifying transforms model. The proposed approach is appealing from a computational point of view and yields competitive performance for several applications, incuding image denoising.
- The paper "Efficient Dictionary Learning with Sparseness-Enforcing Projections" (doi:10.1007/s11263-015-0799-8) by Thom et al. proposes efficient projection algorithms to deal with the sparsness measure introduced in the pioneer work of P. Hoyer. These projection tools are shown to be fast and flexible, allowing the authors to learn dictionaries efficiently with a topographic structure.
- Finally, the paper "Toward Fast Transform Learning" (doi:10.1007/s11263-014-0771-z) of Chapiron et al. is an interesting contribution that may also by qualified as "conceptual". This work addresses the important problem of learning an optimal non-stationary filter bank. This is related to different scientific topics such as dictionary learning, filter bank design, and convolutional neural networks.

Sparse representations for image processing. The following second cluster's papers make significant contributions in image processing. Even though they propose novel sparse models, which may justify their place in the first part, they also achieve outstanding results for concrete image processing tasks.

- The paper "Image Restoration via Simultaneous Sparse Coding: Where Structured Sparsity Meets Gaussian Scale Mixture" (doi:10.1007/s11263-015-0808-y) by Dong et al. proposes a hybrid approach that combines ideas from non-local sparse models and from the Gaussian scale mixture model. The proposed approach consists of finding a pointwise estimate of the parameters of the Gaussian scale mixture model by MAP estimation. The global optimization problem is nonconvex, but an approximate solution is obtained by alternating minimization. The method is evaluated on image denoising and deblurring and achieves outstanding results.
- The paper "A Bimodal Co-Sparse Analysis Model for Image Processing" (doi:10.1007/s11263-014-0786-5) by Kiechle et al. proposes a new co-sparse analysis model that is able to capture the interdependency between two image modalities. The proposed model yields a challenging optimization problem, which is addressed elegantly with a conjugate gradient algorithm on manifolds. The paper shows very promising results for depth-map super-resolution and image registration.
- The paper "Image Deblurring with Coupled Dictionary Learning" (doi:10.1007/s11263-014-0755-z) by Xiang et al. proposes variants of the coupled dictionary learning (or task-driven dictionary learning) model for image deblurring, and achieves outstanding results, both in the blind, and non-blind settings.

Sparse representations for signal and image classification. Our last cluster of papers uses sparse representation for classification tasks.

- The paper "Sparse Illumination Learning and Transfer for Single-Sample Face Recognition with Image Corruption and Misalignment" (doi:10.1007/s11263-014-0749-x) by Zhuang et al. extends the classical face recognition technique developed by Wright, Yang, Ganesh and Ma, to deal with difficult conditions—that is, image misalignment, pixel corruption, and under the assumption that only one sample per class is available. This work results in a pipeline that may operate in realistic conditions with state-of-the-art performance.
- The paper "Generalized Dictionaries for Multiple Instance Learning" (doi:10.1007/s11263-015-0831-z) by Shrivastava et al. proposes a new discriminative dictionary learning model for multiple instance learning problems.
- The paper "Dictionary learning for fast classification based on soft-thresholding" (doi:10.1007/s11263-014-0784-7) by Fawzi et al. makes a strong link between dictionary learning and neural networks where, non-linearities are based on the soft-thresholding function. The proposed approach achieves competitive classification performance with greater speed than dictionary learning alternatives.
- The paper "Collaborative Linear Coding for Robust Image Classification" (doi:10.1007/s11263-014-0739-z) by Wang et al. uses some ideas that have been successful in the past for image restoration, in the context of local descriptor encoding. Local image features are encoded in a collaborative way—that is, similar local descriptors are encouraged to share similar sparse codes. This increases the robustness of the descriptor encoding part, which improves the overall classification performance.