Guest Editorial: Special Issue on Blind Source Separation and De-convolution in Imaging and Image Processing

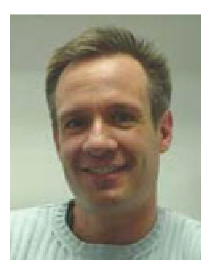
The relatively recent development of robust methods for blind-source separation (BSS) provides a new algorithmic toolset for addressing under-determined ill-posed problems in imaging, vision and image processing. In BSS a set of observations are assumed to be composed of a mixture (often assumed linear) of some so-called sources, in which neither the sources nor the mixing coefficients are known to the observer. The goal is to ''blindly'' recover the sources, either with or without recovering the mixing matrix, given the set of observations. Many approaches to BSS have been developed, employing probabilistic information, theoretic, geometric or variational-based techniques. BSS methodologies and algorithms have already shown great promise in imaging sciences, since the linear mixing model, or the approximations and variations of it are often encountered in many aspects of imaging, image processing, and analysis—e.g., unmixing of tissue signatures by means of MRI or optical imaging, spectral unmixing, linear data-adaptive feature extraction, blind separation of neural cliques and more.

A related problem of great importance is concerned with image restoration. Given a blurred and noisy image, the forward model assumes that an unknown image is convolved with a point-spread function (PSF) and then contaminated by additive noise. Even in the case of a known convolution kernel, the restoration of the unknown image is often a numerically ill-posed problem. Further, in many practical problems, neither the true image nor the convolution kernel is known to the cases. Thus, the most general blind de-convolution (BD) problem is concerned with the recovery, or estimation, of both the unknown image and the convolution kernel. The goal in such practical problems is to achieve both de-blurring and de-noising. As has been the case in BSS research, BD has also attracted a great deal of interest. Consequently, several promising approaches have been proposed, based on efficient optimization methods, statistical methods and inverse filtering.

In this special issue a select set of papers, from leading experts in the field, focus on both theoretical and applied aspects of these ill-posed problems, with special emphasis on the application of these approaches to imaging and image processing. Three papers address the importance of sparse representations in source separation and de-convolution. O'Grady et al. provide a thorough survey of sparse and non-sparse methods in BSS. They stress the important fact that by projecting the data onto a space of sparse representation, solutions to some problems intractable by non-sparse methods become possible. Bronstein et al. show how a geometric approach, based on sparse representation of the mixed images, can be applied in blind separation of transmitted images from those superimposed by semi-reflective medium. Finally, Balan et al. establish an equivalence with a principle for optimizing sparse representation, i.e. one with the minimal number of non-zero components and low-spread representations. This equivalence principle lends itself to the application of a simpler optimization algorithm in the context of the sparse representation problem.

The next set of papers is devoted to the problem of blind de-convolution. The contribution of He et al. is concerned with the general BD problem, i.e. recovering the true image and the convolution kernel by having any a priori knowledge about either one, by considering it as a joint minimization problem. They formulate a new time dependent model for BD, based on a constrained variational approach that uses the sum of the total variation (TV) norms of the signal and the convolution kernel as a regularizing functional. Chan et al. propose a TV-based approach to image restoration problems that require simultaneous BD and image inpainting. Their model is based on minimization of an energy function that is a natural generalization of the TV-BD and the TV inpainting energy functions. The paper of Kaftory et al. analyses multi-channel images by implementing a Beltrami-based restoration. The Polyakov action is used as a regularization operator for both the image and the blurring kernel. Since the Polyakov action measures the surface of the manifold, in which an image is a 2D surface embedded in a 5D space, minimizing it results in de-noising of the image.

The third set of papers considers particular applications and image types. Park and Lee present an unsupervised method for learning dependencies in natural images. Their method extends the linear ICA method and is based on a hierarchical representation. At the lowest level, the model makes use of the linear ICA representation, whereas a subsequent mixture of Laplacian distributions captures non-linear dependencies in natural images. Brown et al. present a Bayesian image decomposition (BID) method that factors a series of spatially registered MR images into spatial and acquisition-dependent components. Meinecke et al. implement ICA to separate images that might be corrupted by outliers or noise in the case of super-Gaussian source signals. Wei describes a novel method for unisotropic image de-noising.



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