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The aforementioned constraints lead us to the following optimization problem: Constraints We introduce the Resolved Components Analysis RCA , which is dimension reduction and super-resolution method based on the following priors: The vectors wi i weight the sparsity against the other constraints and allow some adaptivity of the penalty, with respect to the uncertainties propagated to each entry of S [10]. The Problem 6 being non-convex, we solve approximately using the following alternate scheme[12]: The optimization problem involved in step b is solved using an instance of the family of locations in the FOV. We compared our approach to the standard PCA and the methods presented in [5] and [8] the pixels domain. PSFs ellipticities and sizes [15, 16, 17] and the pixels mean As previously stated, the proximity constraint relies on the square error, with and without downsampling. An example is structure of the matrix A. Each line of A is calculated as a given in Fig. As a linear dimension reduction than the lower frequencies because of the PSFs field smooth- method, RCA computes the input data as linear combinations ness. This, in turn, enforces local similarity of the PSFs. The of few components which are estimated, as well as the linear dictionary V is built as follows: Example of reconstructions from undersampled images; from the left to the right: Sparse BSS with corrupted data in transformed domains C. Most techniques of Blind Source Separation BSS , well-suited to extract the meaningful information from the observations, are sensitive to gross errors. We propose a new method for handling outliers, assuming that their morphology is different from the one of the sources. The proposed method is two-step. Then the mixing matrix, the outliers and the sources are jointly estimated by employing a reweighting procedure. Preliminary numerical experiments show the effectiveness of the proposed method compared to the state-of-the-art algorithms. Besides, we assume that these measurements can be corrupted by a Gaussian noise accounting for small and dense noise and also by few large errors, designated as outliers. The model can be recast with the following matrix form: The outliers designate large corrupted entries in the measurements which can encompass errors done by defective sensors or large local mismodeling deviations for instance. According to the rarity of these errors, we will consider that O is sparse in the direct domain. Besides, we assume that the outliers are in general position: For this purpose, we will assume in the following that the outliers corrupt independently some columns of X. In hyperspectral imaging for instance, this corresponds to the presence of spectrally distinct anomalies in the observed scene. Although the percentage of corrupted data is generally low, the presence of outliers is common in real-world applications. Unfortunately, few BSS methods are able to handle them. This has particularly been popularized in hyperspectral imaging, where the low-rank assumption is valid [4], [5]. Last, the outliers, the sources and the mixing matrix can be jointly estimated using appropriate priors for each components such as the non-negativity of A and S in [6], [7], [8], and [9] or the parsimony of O and S in a same dictionary [10], [11]. In many domains such as astrophysics [12], the sought-after signals are not sparse in the direct domain whereas the outliers can still be considered as being sparse in the direct domain, or at least are sparse in another dictionary than the one used for the sources. To the best of our knowledge, the difference of morphology between sources and outliers has not been exploited to retrieve robustly the mixing matrix, the sources and the outliers simultaneously. We propose a two-steps method to perform the BSS problem in the presence of outliers taking advantage of the difference of morphology between outliers and the sources, as well as the clustering structure of the term AS. To estimate jointly A, S and O, we propose to minimize the following problem: The main difficulty in the minimization of the above problem is its non-convexity due to the product AS. In the presence of large outliers, it would be nearly impossible to recover the signals if the problem were not correctly initialized. That is why, we adopt a two-step method: To do so, the outliers are firstly separated from AS by using a modified MCA [13] and then the sources are unmixed from the outliers-free observations by using AMCA [14] as follows: Moreover, this also provides some robustness against local minima. The weights W are updated once the convergence given the current weights has been reached [18]. The amplitudes of the entries of O are generated from a centered Gaus- 1.