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Separation of Correlated Astrophysical Sources Using Multiple-Lag Data Covariance Matrices

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This paper proposes a new strategy to separate astrophysical sources that are mutually correlated. This strategy is based on second-order statistics and exploits prior information about the possible structure of the mixing matrix. Unlike ICA blind separation approaches, where the sources are assumed mutually independent and no prior knowledge is assumed about the mixing matrix, our strategy allows the independence assumption to be relaxed and performs the separation of even significantly correlated sources. Besides the mixing matrix, our strategy is also capable to evaluate the source covariance functions at several lags. Moreover, once the mixing parameters have been identified, a simple deconvolution can be used to estimate the probability density functions of the source processes. To benchmark our algorithm, we used a database that simulates the one expected from the instruments that will operate onboard ESA's *Planck* Surveyor Satellite to measure the CMB anisotropies all over the celestial sphere.

Keywords and phrases: statistical, image processing, cosmic microwave background.

1. INTRODUCTION

Separating the individual radiations from the measured signals is a common problem in astrophysical data analysis [1]. As an example, in cosmic microwave background anisotropy surveys, the cosmological signal is normally combined with foreground radiations from both extragalactic and galactic sources, such as the Sunyaev-Zeldovich effects from clusters of galaxies, the effect of the individual galaxies, the emission from galactic dust, the galactic synchrotron and free-free emissions. If one is only interested in estimating the CMB anisotropies, the interfering signals can just be treated as noise, and reduced by suitable cancellation procedures. However, the foregrounds have an interest of their own, and it could be useful to extract all of them from multichannel data, by exploiting their different emission spectra.

Some authors [2, 3] have tried to extract a number of individual radiation data from measurements on different frequency channels, assuming that the physical mixture model is perfectly known. Unfortunately, such an assumption is rather unrealistic and could overconstrain the problem, thus leading to unphysical solutions. Attempts have been made to avoid this shortcoming by introducing criteria to evaluate *a posteriori* the closeness to reality of the mixture model and allowing individual sources to be split into separate templates to take spatial parameter variability into account [4, 5].

A class of techniques capable of estimating the source signals as well as identifying the mixture model has recently been proposed in astrophysics [6, 7, 8, 9]. In digital signal processing, these techniques are referred to as blind source separation (BSS) and rely on statistical assumptions on the source signals. In particular, mutual independence and non-Gaussianity of the source processes are often required [10]. This totally blind approach, denoted as independent component analysis (ICA), has already given promising results, proving to be a valid alternative to assuming a known data model. On the other hand, most ICA algorithms do not permit to introduce prior information. Since all available information should always be used, semiblind techniques are being studied to make astrophysical source separation more flexible with respect to the specific knowledge often available in this type of problem [11]. Moreover, the independence assumption is not always justified; if there is evidence of correlation between pairs of sources, it should be made possible to take this information into account, thus abandoning the strict ICA approach.

The first blind technique proposed to solve the separation problem in astrophysics [6] was based on ICA, and allowed simultaneous model identification and signal estimation to be performed. The independence requirement was fulfilled by taking the statistics of all orders into account, as in all ICA methods presented in the literature (see, e.g., [10, 12, 13]).

The problem of estimating all the model parameters and source signals cannot be solved by just using second-order statistics, since these are only able to enforce uncorrelation. However, this has been done in special cases, where additional hypotheses on the spatial correlations or, equivalently, on the spectra of the individual signals are assumed [9, 14, 15]. As will be clear in the following, within the framework of any noisy linear mixture model, the data covariance matrix at a particular lag is related to the source covariance matrix at the same lag, the mixing matrix, and the noise covariance matrix. If there is a sufficient number of lags for which the source covariance matrices are not null, then it is possible to identify the model parameters by estimating the data covariance matrices from the observed data. Indeed, if we know the noise covariance matrix, we are able to write a number of relationships from which the unknown parameters can be estimated. This is what is done by the second-order blind identification (SOBI) algorithm presented in [15]. SOBI, however, relies on joint diagonalization of covariance matrices at different lags, which is only applicable in the case of uncorrelated source signals. In our approach, we assumed that the mixing matrix can be parametrised. This allows us to relax the independence assumption, and to pursue identification by optimisation of a suitable function. A further advantage of this strategy is that the relevant correlation coefficients between pairs of sources can also be estimated. In our particular case, moreover, being able to parametrise the mixing matrix allows us to substantially reduce the number of unknowns. This permits to improve the performance of our technique. We will show that a very fast model learning algorithm can be devised by matching the theoretical and the observed covariance matrices, even if all the cross-covariances are nonnegligible.

The paper is organised as follows. In Section 2, we formalise the problem and introduce the relevant notation. In Section 3, we describe how the mixing matrix can be parametrised in our case. In Sections 4 and 5, we describe the methods we used to learn the mixing model and to estimate the original sources, respectively. In Section 6, we present some experimental results, with both stationary and nonstationary noises. In the final section, we give some remarks and future directions.

2. PROBLEM STATEMENT

As usual [2, 6], we assume that each radiation process $\tilde{s}_c(\xi, \eta, \nu)$ from the microwave sky has a spatial pattern $s_c(\xi, \eta)$ that is independent of its frequency spectrum $F_c(\nu)$:

$$\tilde{s}_c(\xi, \eta, \nu) = s_c(\xi, \eta)F_c(\nu). \tag{1}$$

Here, ξ and η are angular coordinates on the celestial sphere, and ν is frequency. The total radiation observed in a certain direction at a certain frequency is given by the sum of a number N of signals (processes, or components) of the type (1), where subscript c has the meaning of a process index. Assuming that the effects of the telescope beam on the angular resolution at different measurement channels have been equalised (see [16]), the observed signal at M different frequencies can be modelled as

$$\mathbf{x}(\xi, \eta) = \mathbf{A}\mathbf{s}(\xi, \eta) + \mathbf{n}(\xi, \eta), \tag{2}$$

where $\mathbf{x} = \{x_d,\ d = 1, \dots, M\}$ is the M-vector of the observations, d being a channel index, $\mathbf{A}$ is an $M \times N$ *mixing* matrix, $\mathbf{s} = \{s_c,\ c = 1, \dots, N\}$ is the N-vector of the individual source processes, and $\mathbf{n} = \{n_d,\ d = 1, \dots, M\}$ is the M-vector of instrumental noise. The elements of $\mathbf{A}$ are related to the source spectra and to the frequency responses through the following formula:

$$a_{dc} = \int F_c(\nu) b_d(\nu) d\nu, \tag{3}$$

where $b_d(\nu)$ is the instrumental frequency response in the dth measurement channel, which is normally known very well. If we assume that the source spectra are constant within the passbands of the different channels, (3) can be rewritten as

$$a_{dc} = F_c(\nu_d) \int b_d(\nu) d\nu. \tag{4}$$

The element a_{dc} is thus proportional to the spectrum of the cth source at the center frequency ν_d of the dth channel. The separation problem consists in estimating the source vector $\mathbf{s}$ from the observed vector $\mathbf{x}$. Several estimation algorithms have been derived assuming a perfect knowledge of the mixing matrix. As already said, however, this matrix is related to both the instrumental frequency responses, which are known, and the emission spectra $F_c(\nu)$, which are normally unknown. For this reason, relying on an assumed mutual independence of the source processes $s_c(\xi, \eta)$, some *blind* separation algorithms have been proposed [6, 7, 17], which are able to estimate both the mixing matrix and the source vector. Assuming that the source signals are mutually independent, the MN mixing coefficients can be estimated by finding a linear mixture that, when applied to the data vector, nullifies the cross-cumulants of all orders. If, however, some prior information allows us to reduce the number of unknowns, the identification problem can be solved by only using second-order statistics. This is the case with our approach, which is based on a parametrisation of matrix $\mathbf{A}$. This approach, described in Section 4, does not need a strict mutual independence assumption. Logically, any blind separation algorithm is divided into two phases: using the notation introduced here, the estimation of $\mathbf{A}$ will be referred to as *system identification* (or *model learning*), and the estimation of $\mathbf{s}$ will be referred to as *source separation*. In this paper, we first address aspects related to learning, and then give some details on source separation strategies derived from standard reconstruction procedures. Before describing our algorithm in detail, we recall here some applicability issues.

Source and noise processes

To estimate the covariance matrices from the available data, the source and the noise processes must necessarily be assumed stationary. While CMB satisfies this assumption, the foregrounds are not stationary all over the celestial sphere. This assumption can be made for small sky patches. However, depending on the particular sky scanning strategy, noise is normally nonstationary, even within small patches, and can also be autocorrelated. The noise covariance function should be known for any shift and for any angular coordinate in the celestial sphere. Provided that the noise nonstationarity and cross-correlation between sources can be neglected, various methods are available, both in space and frequency domains, to estimate samples of the noise covariance function or, equivalently, of noise spectrum [9]. Tackling the space-variant nature of the noise process is difficult, and no simple method has been proposed so far to this purpose. In [11] the noise variance at each pixel is assumed to be known and a method is proposed to estimate the mixing matrix and the probability density function of each component. In the present approach, we found experimentally that, if a noise covariance map is known, even nonstationary noise can be treated.

Frequency-dependent telescope beams

The model assumed in (2) is valid if the telescope radiation patterns are the same in all the frequency channels. As the beams are frequency-dependent, a way to tackle the problem is to preprocess the observed data in order to equalise the resolution on all the measurement channels, as in [16]. This also changes the autocorrelation function of each noise process, but in a way that can be exactly evaluated. A different way to tackle the problem has been to approach it in the frequency domain [2, 9]. Also in these cases, the validity of the solution relies on a number of simplifiying assumptions, such as the perfect circular symmetry of the telescope beams. Moreover, the actual capability of extrapolating the spectrum at spatial frequencies where reduced information is available has still to be assessed, especially in the cases where the signal-to-noise ratio is particularly low.

Structure of the source covariance matrices

In the *Planck* experiment, the sources of interest are the CMB signal and the foregrounds. While no correlation is expected between the CMB signal and foregrounds, some statistical dependence between pairs of foregrounds has to be taken into account. The off-diagonal entries of the source covariance matrices related to pairs of correlated sources will thus be nonzero, whereas all the remaining off-diagonal elements will be zero. When it is known that some of the cross-covariances are close to zero, these can be kept fixed at zero, thus further reducing the total number of unknowns. For instance, in a 3×3 case, if we assume the following structure for the source covariance matrix at zero shift:

$$\mathbf{C}_s(0,0) = \begin{pmatrix} \sigma_{11} & 0 & 0 \\ 0 & \sigma_{22} & \sigma_{23} \\ 0 & \sigma_{32} & \sigma_{33} \end{pmatrix}, \tag{5}$$

this means that we assume zero or negligible correlations between sources 1 and 2 and sources 1 and 3, and the remaining cross-covariance $\sigma_{23} = \sigma_{32}$ between sources 2 and 3 is an unknown of the problem, along with the autocovariances σ_{ii}. Note that, for the typical scaling ambiguity of the blind identification problem, the absolute values of both the diagonal and off-diagonal elements of matrices $\mathbf{C}_s(\tau, \psi)$ have no physical significance, while, by calculating ratios of the type

$$\frac{(\sigma_{ij})^2}{\sigma_{ii}\sigma_{jj}}, \tag{6}$$

we can actually estimate the correlation coefficients between different sources, whatever the values of the individual covariances.

3. PARAMETRISATION OF THE MIXING MATRIX

While in a general source separation problem the elements a_{dc} are totally unknown, in our case we have some knowledge about them. In fact, the integral in (4) is related to known instrumental features and to the emission spectra of the single source processes, on which we do have some knowledge. As an example, if the observations are made in the microwave and millimeter-wave range, the dominant radiations are the cosmic microwave background, the galactic dust, the free-free emission and the synchrotron (see [18]). Another significant signal comes from the extragalactic point sources. It is not possible to treat the point sources as a single signal to be separated from the others on the basis of its emission spectrum, since each source has its own spectrum. Since the brightest point sources are the ones that affect more strongly the study of the CMB [19], the usual approach is to remove them from the data before separating the other foregrounds. Bright resolved point sources can be removed by using some of the specific techniques proposed in the literature [19, 20, 21]. Faint unresolved point sources are usually considered as an additional noise term in (2) (referred to as "confusion noise" in the radio astronomy literature). For simplicity, we will not consider extragalactic point sources in our test examples. Moreover, although other sources (such as SZ and free-free) could be taken into account, in our experiments we only considered the synchrotron and dust foregrounds, which are the most significant in the *Planck* frequency range.

The emission spectrum of the cosmic microwave background is perfectly known, being a blackbody radiation. In terms of antenna temperature, it is

$$F_{\mathrm{cmb}}(\nu) = \frac{\tilde{\nu}^2 \exp(\tilde{\nu})}{\left[\exp(\tilde{\nu}) - 1\right]^2}, \tag{7}$$

where $\tilde{\nu}$ is the frequency in GHz divided by 56.8. From (4) and (7), the column of $\mathbf{A}$ related to the CMB radiation is thus known up to an unessential scale factor. For the synchrotron radiation, we have

$$F_{\mathrm{syn}}(\nu) \propto \nu^{-n_s}. \tag{8}$$

Thus, the column of $\mathbf{A}$ related to synchrotron only depends on a scale factor and the spectral index n_s. For the thermal galactic dust, we have

$$F_{\mathrm{dust}}(\nu) \propto \frac{\bar{\nu}^{m+1}}{\exp(\bar{\nu}) - 1}, \tag{9}$$

where $\bar{\nu} = h\nu/kT_{\mathrm{dust}}$, h is the Planck constant, k is the Boltzmann constant, and T_{dust} is the physical dust temperature. If we assume a uniform temperature value, the frequency law (9), that is, the column of $\mathbf{A}$ related to dust emission, only depends on a scale factor and the parameter m.

The above properties enable us to describe the mixing matrix by means of just a few parameters. As an example, if we assume to have a perfectly known source spectrum (such as the one of CMB) and $N-1$ sources with one-parameter spectra, the number of unknowns in the identification problem is $N-1$ instead of NM.

4. A SECOND-ORDER IDENTIFICATION ALGORITHM

Let us consider the source and noise signals in (2) as realisations of two stationary vector random processes. The covariance matrices of these processes are, respectively,

$$\begin{aligned}\mathbf{C}_s(\tau,\psi) &= \left\langle \left[\mathbf{s}(\xi,\eta) - \mu_s\right]\left[\mathbf{s}(\xi+\tau,\eta+\psi) - \mu_s\right]^{\mathrm{T}} \right\rangle, \\ \mathbf{C}_n(\tau,\psi) &= \left\langle \left[\mathbf{n}(\xi,\eta) - \mu_n\right]\left[\mathbf{n}(\xi+\tau,\eta+\psi) - \mu_n\right]^{\mathrm{T}} \right\rangle,\end{aligned} \tag{10}$$

where $\langle\cdot\rangle$ denotes expectation under the appropriate joint probability, μ_s and μ_n are the mean vectors of processes $\mathbf{s}$ and $\mathbf{n}$, respectively, and the superscript T means transposition. As usual, the noise process is assumed signal-independent, white, and zero-mean, with known variances. Thus, for both τ and ψ equal to zero, $\mathbf{C}_n$ is a known diagonal matrix whose elements are the noise variances in all the measurement channels, whereas for any τ or ψ different from zero $\mathbf{C}_n$ is the null $M \times M$ matrix.

As already proved [15, 22], covariance matrices, that is, second-order statistics, permit blind separation to be achieved when the sources show a spatial structure, namely, when they are spatially correlated. Thus, the mutual independence requirement of ICA can be replaced by an equivalent requirement on the spatial structure of the signal, and the identifiability of the system is assured. In other words, finding matrices $\mathbf{A}$ and $\mathbf{C}_s$ is generally not possible from covariances at zero shift alone; to identify the mixing operator, either higher-order statistics or the covariance matrices at several nonzero shift pairs (τ,ψ) must be taken into account. Of course, this is also a requirement on the sources, since if the covariance matrices are null for any pair (τ,ψ), identification is not possible. This aspect will become clearer below.

Let us now see our approach to system identification. By exploiting (2), the covariance of the observed data can be written as

$$\begin{aligned}\mathbf{C}_x(\tau,\psi) &= \left\langle \left[\mathbf{x}(\xi,\eta) - \mu_x\right]\left[\mathbf{x}(\xi+\tau,\eta+\psi) - \mu_x\right]^{\mathrm{T}} \right\rangle \\ &= \mathbf{A}\mathbf{C}_s(\tau,\psi)\mathbf{A}^{\mathrm{T}} + \mathbf{C}_n(\tau,\psi),\end{aligned} \tag{11}$$

where $\mathbf{C}_x(\tau,\psi)$can be estimated from

$$\hat{\mathbf{C}}_{\mathbf{x}}(\tau,\psi) = \frac{1}{N_p}\sum_{\xi,\eta}\left[\mathbf{x}(\xi,\eta) - \mu_x\right]\left[\mathbf{x}(\xi+\tau,\eta+\psi) - \mu_x\right]^{\mathrm{T}}, \tag{12}$$

where N_p is the number of pixels. Equation (11) provides a number of independent nonlinear relationships that can be used to estimate both $\mathbf{A}$ and $\mathbf{C}_s$. Obviously, this possibility does not rely on mutual independence between the source signals, as required by the ICA approach: the only requirement is having a sufficient number of nonzero covariance matrices. In other words, spatial structure can be used in the place of mutual independence as a basis for model learning and signal separation. As assumed in the previous section, in this particular application the number of unknowns is reduced by parametrising the mixing matrix. This allows us to solve the identification problem from the relationships made available by (11) by only using the zero-shift covariance matrix, even if some of the sources are cross-correlated. We investigated this possibility in [23]. In a general case, matrices $\mathbf{A}$ and $\mathbf{C}_s(\tau,\psi)$ can be estimated from

$$(\Gamma, \Sigma(:,:)) = \arg\min \sum_{\tau,\psi} \Big\| \mathbf{A}(\Gamma)\mathbf{C}_s(\Sigma(\tau,\psi))\mathbf{A}^{\mathrm{T}}(\Gamma) - \hat{\mathbf{C}}_x(\tau,\psi) - \mathbf{C}_n(\tau,\psi) \Big\|. \tag{13}$$

The minimisation is performed over vectors Γ and $\Sigma(:,:)$, where Γ is the vector of all the parameters defining $\mathbf{A}$ (possibly consisting of all the matrix elements), and $\Sigma(:,:)$ is the vector containing all the unknown elements of matrices $\mathbf{C}_s$ for every shift pair. The matrix norm adopted is the Frobenius norm. Our present strategy to find the minimiser in (13) is to perform a stochastic minimisation in Γ, considering that $\mathbf{C}_s(\Sigma(\tau,\psi))$, for each (τ,ψ), can be calculated exactly once $\mathbf{A}(\Gamma)$ is fixed. A more accurate minimisation strategy is now being studied.

From the above scheme, it is clear that for each independent element of the matrices $\mathbf{C}_x(\tau,\psi)$ we have an independent equation for the estimation of vector Γ and of all the vectors $\Sigma(\tau,\psi)$. Since for $(\tau,\psi) = (0,0)$ matrix $\mathbf{C}_x$ is symmetric, for zero shift we have $M(M+1)/2$ independent equations. For any other shift pair, $\mathbf{C}_x$ is a general matrix and thus, provided that it is not zero, we have M^2 additional independent equations. If N_s is the total number of nonzero shift pairs generating nonzero data covariance matrices, we thus have a total number of $M(M+1)/2+N_s \cdot M^2 = M[(2N_s+1)M+1]/2$ independent equations. The number of unknowns is at most $NM+N(N+1)/2+N_s \cdot N^2$, in the case where all the elements of $\mathbf{A}$ are unknown and all the source covariance matrices are full, that is, all the sources at any shift are correlated to each other. Note that, in this worst case situation, if it is $M = N$, we always have N^2 more unknowns than equations, independently of N_s. As soon as we have $M > N$, there are always a number of nonzero shift pairs for which we have more independent equations than unknowns to be estimated. This observation gives an idea of the amount of information we have available for our estimation problem. The number of independent equations affects the behaviour of the nonlinear optimization landscape in (13). Qualitatively, we can affirm that the more independent equations we have, the more well-posed the optimization problem will be. In particular, it is likely that, in absence of any prior information about the structure of $\mathbf{A}$ and $\mathbf{C}_s(\tau,\psi)$, having a number of observed channels equal to the number of sources always leads to insufficient information, independently of the number of shift pairs chosen. If, instead, the number of the available observations is larger than the number of sources, the possibility of estimating the unknowns relies on the number of shift pairs for which the data covariance matrices are nonzero. The availability of prior information, as in the application considered here, can of course alleviate these requirements. For example, if we have a 4×4 mixing matrix only depending on four parameters and only two sources significantly correlated, the unknowns to be determined are $4 + 5 + N_s \cdot 6$, by using a maximum of $M(M+1)/2 + N_s \cdot M^2$ equations. This means that in this case, as soon as $M = 4$, the number of independent equations is larger than the number of unknowns even for $N_s = 0$.

5. SIGNAL SEPARATION STRATEGY

Model learning is only the first step in solving the problem of source separation. Although, in principle, one could simply use multichannel inverse filtering to recover the source maps, this approach is not feasible in practice, for the presence of noise. In our treatment, the data are assumed to be an ergodic process, in order to be able to evaluate its statistics from the available sample. This entails a space invariant noise process. The estimation of the individual source maps should be made on the basis of all the products of the learning stage. In our case, we have estimates of the mixing matrix and of the source covariance matrices at several shift pairs. In the hypothesis of stationary noise, we could exploit this information to implement a multichannel Wiener filter for source reconstruction. If the noise is not stationary, a generalized Kalman filter should be used. Our point here is on model learning, and thus we do not address the separation issues in detail. We only observe that a possible Bayesian separation scheme would make use of the source probability densities, and these can be estimated from our mixing matrix. Indeed, let us assume that our learning procedure has given a good estimate of $\mathbf{A}$. Let $\mathbf{B}$ be its Moore-Penrose generalised inverse. In our case, we have $M \geq N$, thus, as is known,

$$\mathbf{B} = \left(\mathbf{A}^{\mathrm{T}}\mathbf{A}\right)^{-1}\mathbf{A}^{\mathrm{T}}. \tag{14}$$

From (2), we have

$$\mathbf{Bx} = \mathbf{s} + \mathbf{Bn}. \tag{15}$$

Let us denote each of the N rows of $\mathbf{B}$ as an M-vector $\mathbf{b}_i$, $i = 1,\ldots,N$, and consider the generic element y_i of the N-vector $\mathbf{Bx}$,

$$y_i := \mathbf{b}_i^{\mathrm{T}} \cdot \mathbf{x} = s_i + \mathbf{b}_i^{\mathrm{T}} \cdot \mathbf{n} := s_i + n_{t_i}. \tag{16}$$

The probability density function of y_i, $p(y_i)$, can be estimated from $\mathbf{b}_i$ and the data record $\mathbf{x}(\xi,\eta)$, while the probability density function of n_{t_i}, $p(n_{t_i})$, is a Gaussian, whose parameters can be easily derived from $\mathbf{C}_n$ and $\mathbf{b}_i$. The pdf of y_i is the convolution between $p(s_i)$ and $p(n_{t_i})$:

$$p(y_i) = p(s_i) * p(n_{t_i}). \tag{17}$$

From this relationship, $p(s_i)$ can be estimated by deconvolution. As is well known, deconvolution is normally an ill-posed problem and, as such, it lacks a stable solution. In our case, we can regularise it by enforcing smoothness, positivity, and the normalisation condition for pdfs.

Any Bayesian estimation approach should exploit the knowledge of the source densities to regularise the solution, but these are normally unknown. In the case examined here, the source distributions can be efficiently estimated as summarised above, and the computational cost of otherwise expensive Bayesian algorithms can be reduced. As an example, in [11], the source densities are modelled as mixtures of Gaussians, and the related parameters are estimated by an independent factor analysis approach (see [24, 25]). The method we propose here could well be used to fix the source densities, thus reducing the overall cost of the identification-separation task.

From (15), it can be seen that the generalised inverse solution is already an estimate of the sources, since it is composed of the original source vectors corrupted by amplified noise. Thus, a simple source estimation strategy could be first to apply (15) and then to reduce the influence of noise by filtering the result. In next section, we show some experimental results obtained by pseudoinversion of the estimated mixing matrix, followed by Wiener filtering of each individual source. This strategy would be strictly valid with stationary noise and high signal-to-noise ratio, however, interesting results have been found even with strong nonstationary noise. Multichannel Wiener filtering for stationary noise and an extended Kalman filter for the nonstationary case are now being developed.

6. EXPERIMENTAL RESULTS

In this section, we present some results from our extensive experimentation with the method described above. Our data were drawn from a data set that simulates the one expected from *Planck* (see the *Planck* homepage).[1] The source maps we considered were the CMB anisotropy, the galactic synchrotron, and thermal dust emissions over the four measurement channels centred at 30 GHz, 44 GHz, 70 GHz, and 100 GHz. The test data maps have been generated by extracting several sky patches at different galactic coordinates from the simulated database, scaling them exactly according to formulas (7), (8), and (9), generating the mixtures for the channels chosen, and adding realisations of Gaussian, signal-independent, white noise. Several noise levels have been used, from a ten percent to more than one hundred percent of the CMB standard deviation. The range chosen contains noise levels within the *Planck* specifications. Although our method would be only suited for uniform noise, we also tried to apply it to data corrupted by nonuniform noise, and obtained promising results.

Within this section, we will divide the results obtained in model learning from the results in separation, and the cases with stationary noise from those with nonstationary noise. In these latter cases, knowledge of a noise variance map is assumed, and the additional problem arises of choosing the appropriate noise covariance matrix.

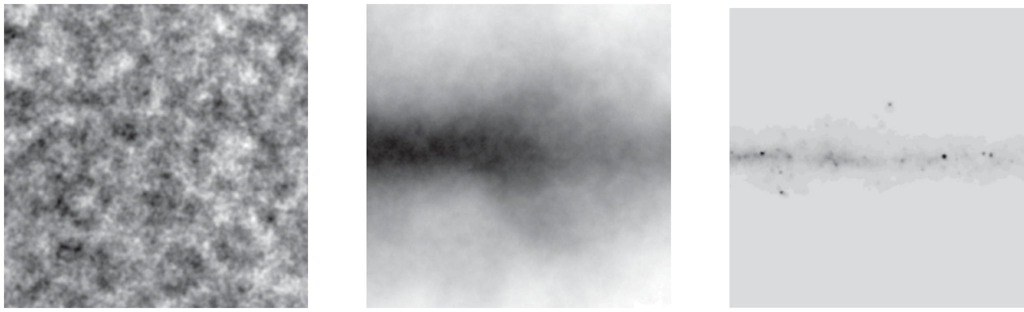
[1]http://astro.estec.esa.nl/SA-general/Projects/Planck/.

The results from learning are the mixing matrix and the source covariance matrices at the shift pairs chosen. From the estimate of the mixing matrix, it is also possible to derive the marginal source densities, by using relationships (16) and (17). As already mentioned, the estimates of the mixing matrix and of the source covariance matrices are very robust against noise. Conversely, the estimates of the source distributions by means of (16) and (17) are more sensitive to noise. To obtain satisfactory results, it is necessary to rely on regularization methods; the choice of regularization parameters, however, is known to be critical. In our case, we selected them empirically, by checking the smoothness of the solutions.

Our separation results are all derived from the application of the Moore-Penrose pseudoinverse of the estimated mixing matrix, followed by a classical Wiener filtering on each output image. From this processing, estimates of the source maps are obtained. Also, estimated source power spectra can be obtained from either the maps or the source autocorrelation matrices. In particular, the results we show here are derived from the unfiltered pseudoinverse solutions, showing that, although the reconstructed images are heavily affected by noise, the derived power spectra can be corrected for the theoretical noise spectrum and thus estimated quite accurately.

The results presented here will all be related to a single data record, derived from a simulated $15^\circ \times 15^\circ$ sky patch centered at 40° galactic longitude and 0° galactic latitude. It is to be noted that in such a patch, located on the galactic plane, the measured data will be affected by strong foreground interference, thus making the problem very difficult to solve. Indeed, many separation approaches experimented so far simply fail in proximity of the galactic plane, and they are normally applied after masking the all-sky data in the high-interference regions. Here, the dust emission is stronger than CMB, and separation is strictly necessary if CMB is to be distinguished from the foregrounds. Our method performed very well with these data, and all the relevant parameters were satisfactorily estimated even with the strongest noise components. The noise standard deviation we adopted in the case shown here is 30% the standard deviation of CMB at 100 GHz. The noise level in the other channels has been simply obtained by scaling the level at 100 GHz in accordance with the expected *Planck* sensitivity at those frequencies. For each patch considered, we tried different noise levels, up to more than 100% of the CMB level at 100 GHz, and for each noise level, we performed a Monte Carlo simulation with hundreds of different noise realizations. This analysis is not reported in detail here, but we can say that no significant bias has been found in the results.

It is to remark that, at high galactic latitudes, the CMB radiation is dominant at our frequencies, and the foregrounds are well below the noise level assumed in our experiments. Thus, the CMB is almost the only measured radiation, and is estimated very well with all the assigned signal-to-noise ratios. Conversely, as expected with these noise levels, the foregrounds cannot be estimated correctly. Assuming much



(a) (b) (c)

Figure 1: Source maps from a $15^\circ \times 15^\circ$ patch centered at 0° galactic latitude and 40° galactic longitude, at 100 GHz: (a) CMB; (b) synchrotron; (c) thermal dust.

lower noise levels, our method, as other techniques such as ICA (see [6]), allows the foregrounds to be estimated satisfactorily.

In Figure 1, we show the three source maps we used in the situation described above. In this figure and in all the others shown here, the grayscale is linear with black corresponding to the maximum image value. We assigned the sources s_1 to CMB, s_2 to synchrotron, and s_3 to dust, and the signals x_1, x_2, x_3, and x_4 to the measurement channels at 100, 70, 44, and 30 GHz, respectively. Therefore, the first, second, and third columns of the mixing matrix will be related to CMB, synchrotron, and dust, respectively, and the first, second, third, and fourth rows of the mixing matrix will be related to the 100 GHz, 70 GHz, 44 GHz, and 30 GHz channels, respectively. The mixing matrix, $\mathbf{A}_o$, has been derived from (7), (8), and (9) with spectral indices $n_s = 2.9$ and $m = 1.8$ (see, e.g., [26, 27]):

$$\mathbf{A}_o = \begin{pmatrix} 1 & 1 & 1 \\ 1.1353 & 2.8133 & 0.5485 \\ 1.2241 & 10.8140 & 0.2464 \\ 1.2570 & 32.8359 & 0.1260 \end{pmatrix}. \tag{18}$$

In Figure 2, we show the data maps for stationary noise. Also, note that the case examined does not fit the ICA assumptions. For example, the normalized source covariance matrix at zero shift is

$$\mathbf{C}_s(0,0) = \begin{pmatrix} 1.0000 & 0.1961 & 0.0985 \\ 0.1961 & 1.0000 & 0.6495 \\ 0.0985 & 0.6495 & 1.0000 \end{pmatrix}, \tag{19}$$

where a significant correlation, of the order of 65%, can be observed between the dust and synchrotron maps.

For the data described above, we ran our learning algorithm for 500 different noise realisations; for each run, 10 000 iterations of the minimisation procedure described in the previous section were performed. The unknown parameters were the spectral indices n_s and m, and all the elements of matrices $\mathbf{C}_s(\tau, \psi)$. The cost defined in (13), as a function of the iteration number in a particular run, is shown in Figure 3. The typical elapsed times per run were a few minutes on a 2 GHz CPU computer, with a Matlab interpreted code. In the case described here, we estimated $n_s = 2.8985$ and $m = 1.7957$, corresponding to the mixing matrix

$$\mathbf{A} = \begin{pmatrix} 1 & 1 & 1 \\ 1.1353 & 2.8118 & 0.5494 \\ 1.2241 & 10.8009 & 0.2473 \\ 1.2570 & 32.7775 & 0.1267 \end{pmatrix}. \tag{20}$$

As a quality index for our estimation, we adopted the matrix $\mathbf{Q} = (\mathbf{A}^{\mathrm{T}}\mathbf{C}_n^{-1}\mathbf{A})^{-1}(\mathbf{A}^{\mathrm{T}}\mathbf{C}_n^{-1}\mathbf{A}_o)$, which, in the ideal case, should be the $N \times N$ identity matrix $\mathbf{I}$. In the present case, we have

$$\mathbf{Q} = \begin{pmatrix} 1.0000 & -0.0074 & -0.0013 \\ 0.0000 & 1.0020 & 0.0000 \\ 0.0000 & 0.0054 & 1.0013 \end{pmatrix}. \tag{21}$$

The Frobenius norm of matrix $\mathbf{Q} - \mathbf{I}$ should be zero in the case of perfect model learning. In this case, it is 0.0096.

These results have been found by considering 25 uniformly distributed shift pairs, with $0 \leq \tau \leq 20$ and $0 \leq \psi \leq 20$. As a synthetic index for the quality of the reconstructed source covariance matrices, we adopted a matrix $\mathbf{E}$, where each element is the relative error in the same covariance element, averaged over all the pairs (τ, ψ):

$$\mathbf{E}_{i,j} = \frac{1}{N_s + 1} \sum_{\tau,\psi} \frac{\left| \widehat{\mathbf{C}}_{\mathbf{s}i,j}(\tau,\psi) - \mathbf{C}_{\mathbf{s}i,j}(\tau,\psi) \right|}{\left| \mathbf{C}_{\mathbf{s}i,j}(\tau,\psi) \right|}, \tag{22}$$

where $\widehat{\mathbf{C}}_{\mathbf{s}}$ are the estimated source covariance matrices. Of course, matrix (22) is only defined when all the denominators are nonzero. A more accurate analysis of the results can be made from the element-by-element comparison of the estimated and the original matrices, but we do not report these results here. For the case shown above, we have

$$\mathbf{E} = \begin{pmatrix} 0.0274 & 0.0392 & 0.0496 \\ 0.0472 & 0.0170 & 0.0120 \\ 0.0917 & 0.0125 & 0.0050 \end{pmatrix}. \tag{23}$$

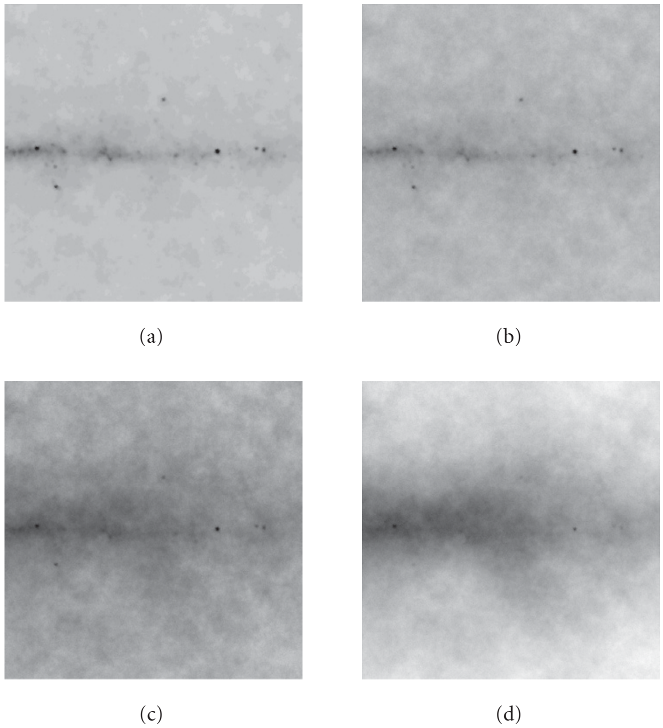


Figure 2: Noisy data maps at (a) 100 GHz; (b) 70 GHz; (c) 44 GHz; (d) 30 GHz.

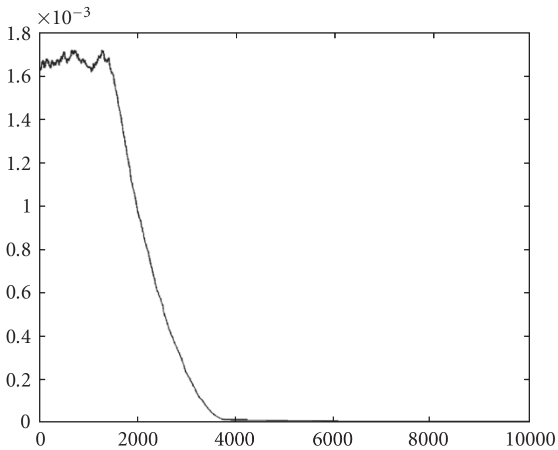


Figure 3: Norm of the residual in (13) as a function of the iteration number.

The reconstructed probability density functions of the source processes, estimated from (16) and (17), are shown in Figure 4.

We separated the sources by multiplying the data matrix by the Moore-Penrose generalised inverse, as in (15), and then by applying a Wiener filter to the results thus obtained. As already said, this is not the best choice reconstruction algorithm at all, especially when the data are particularly noisy and the noise is not stationary. However, the results we obtained are visually very good, as shown in Figure 5. To evaluate more quantitatively the results of the whole learning-separation procedure, we compared the power spectrum of the CMB map with the one of the reconstructed map. This comparison is shown in Figure 6, where we also show the possibility of correcting the reconstructed spectrum for the known theoretical spectrum of the noise component n_{t_1}, obtained as in (16). As can be seen, the reconstructed spectrum is very similar to the original within a multipole $l = 2000$.

Strictly speaking, our algorithm could not be applied to nonstationary processes. However, let us assume that the original sources are stationary, and the noise is nonstationary but still spatially white and uncorrelated. This means that its pixel-dependent covariance matrices, $\mathbf{R_n}(\tau, \psi; \xi, \eta)$, are zero for any nonzero shift pair (τ, ψ). We tried our method on nonstationary data, by assuming to know $\mathbf{R_n}(0, 0; \xi, \eta)$, and using a constant covariance matrix given by

$$\mathbf{C_n}(0, 0) = \frac{1}{N_p} \sum_{\xi,\eta} \mathbf{R_n}(0, 0; \xi, \eta). \tag{24}$$

The nonstationary data were obtained from a spatial template of noise standard deviations expected for typical *Planck* observations, shown in Figure 7. The actual standard deviations were adjusted so as to obtain the average signal-to-noise ratios desired for the different channels. The separation results for a case where these SNRs were the same as in the above stationary case are shown in Figure 8, where the degradation in the reconstruction is apparent in the regions where the noise is stronger. The results, in terms of recontructed power spectra, are perfectly comparable to the ones

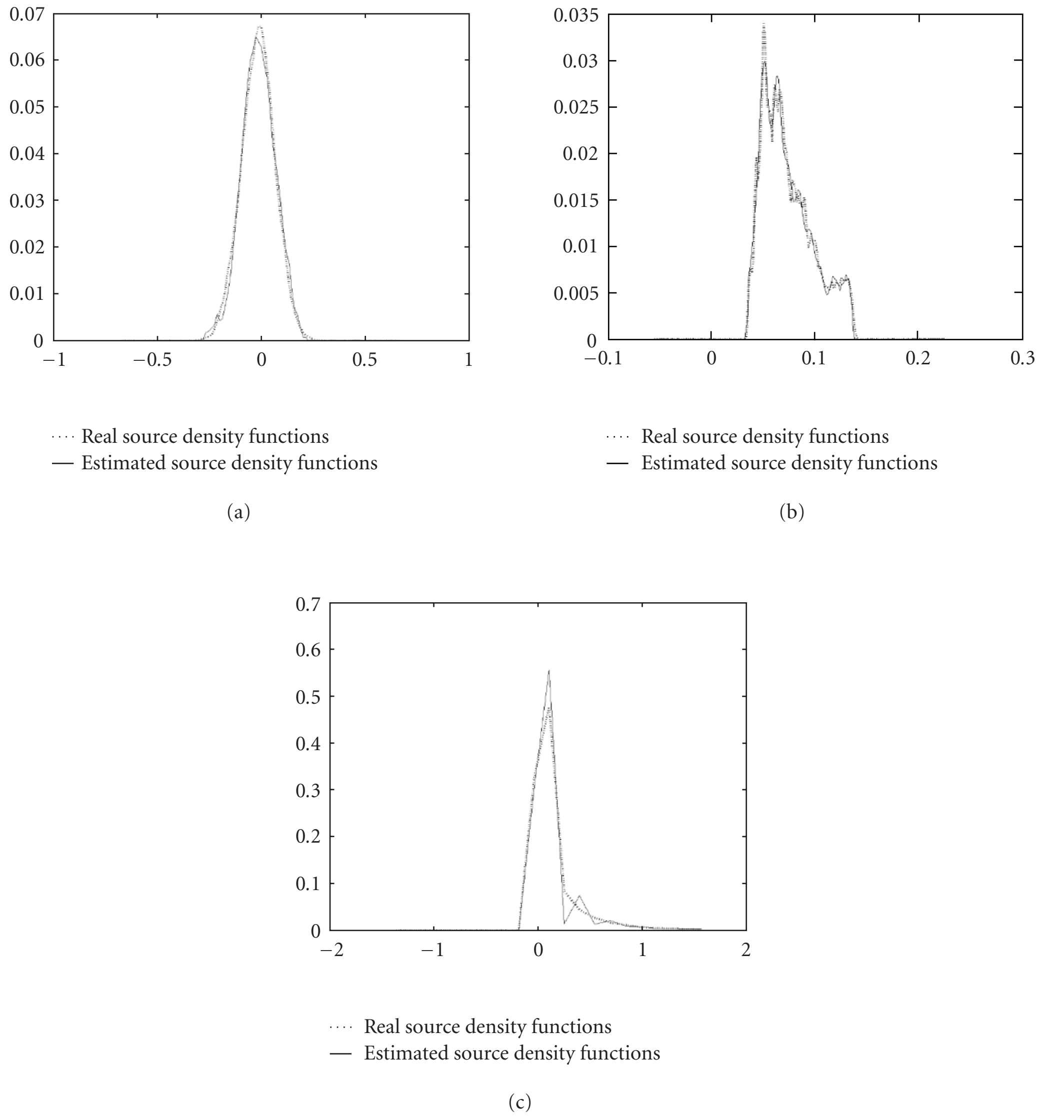
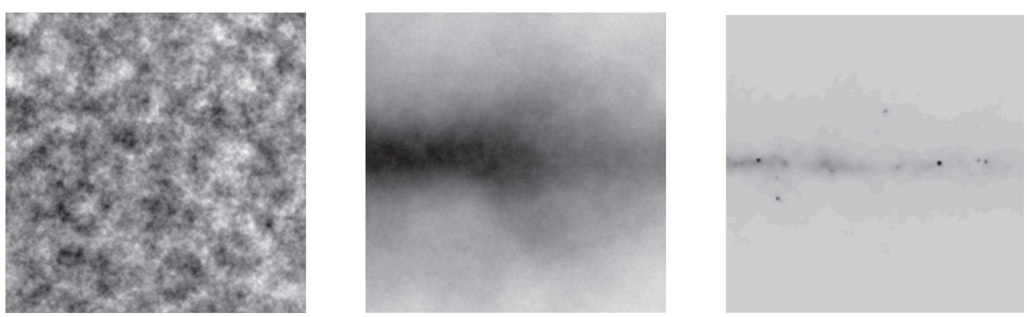
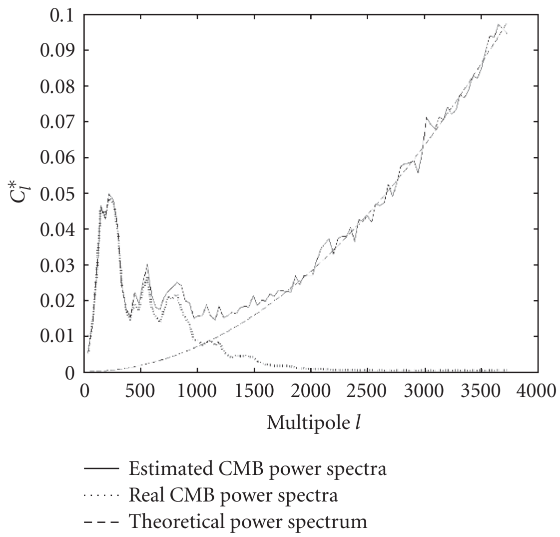


Figure 4: Real (dotted) and estimated (solid) source density functions for (a) CMB, (b) synchrotron, and (c) dust.

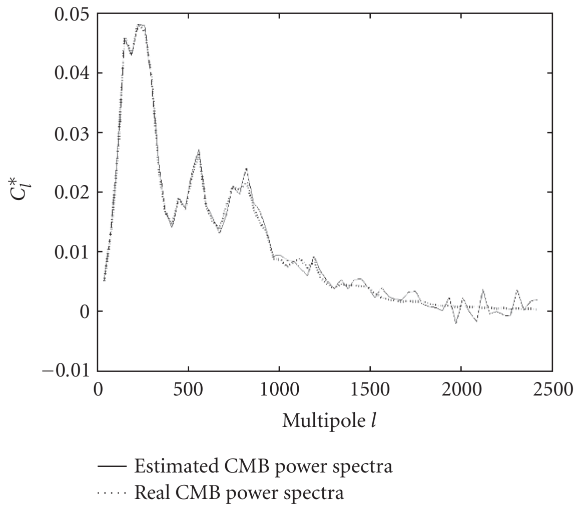


(a) (b) (c)

Figure 5: Wiener-filtered estimated maps: (a) CMB; (b) synchrotron; (c) dust.



(a)



(b)

Figure 6: (a) Real (dotted) and estimated (solid) CMB power spectra. The dashed line represents the theoretical power spectrum of the noise component n_{t_1} in (16), evaluated from the noise covariance and the Moore-Penrose pseudoinverse of the estimated mixing matrix. (b) Real (dotted) and estimated (solid) CMB power spectra, corrected for theoretical noise.

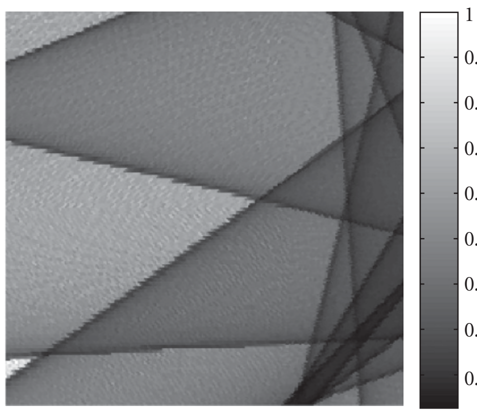


Figure 7: Map of noise standard deviations used to generate nonstationary data.

exemplified in Figure 6. The estimated spectral indices were $n_s = 2.8885$ and $m = 1.7881$, corresponding to the mixing matrix

$$\mathbf{A} = \begin{pmatrix} 1 & 1 & 1 \\ 1.1353 & 2.8018 & 0.5509 \\ 1.2241 & 10.7128 & 0.2488 \\ 1.2570 & 32.3861 & 0.1279 \end{pmatrix}. \tag{25}$$

The average error on covariance matrices is in this case

$$\mathbf{E} = \begin{pmatrix} 0.0158 & 0.1165 & 0.1930 \\ 0.1163 & 0.0331 & 0.0254 \\ 0.2440 & 0.0261 & 0.0144 \end{pmatrix}. \tag{26}$$

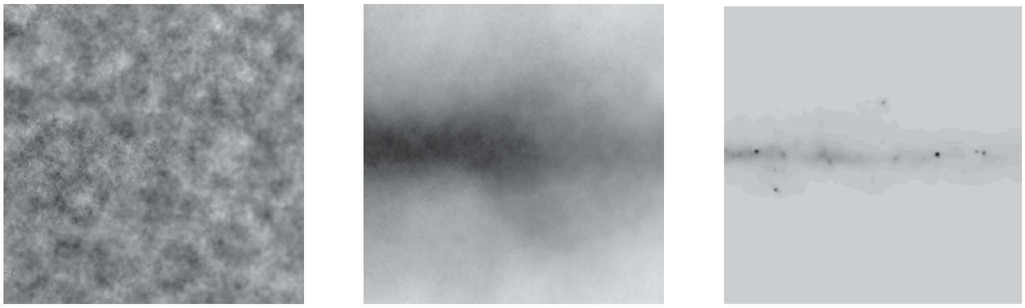
The Frobenius norm of matrix $\mathbf{Q} - \mathbf{I}$ is now 0.0736, that is, slightly worse than for the above stationary case.

7. CONCLUDING REMARKS

By exploiting the spatial structure of the sources, we developed an identification and separation algorithm that is able to exploit any available information on possible structure of the mixing matrix and the source covariance matrices. This can include the fully blind approach and the case exemplified here, where the mixing matrix is known to only depend on two parameters. The identification task is performed by a simple optimization strategy, while the proper separation can be faced by different approaches. We experimented the simplest one, but we are also developing more accurate techniques, especially suited to treat nonstationary noise on the data.

Our method is suitable to work directly with all-sky maps, but it could be necessary to apply it to small patches, as is shown in the above experimental section, to cope with the expected variability of the spectral indices and the noise variances in different sky regions.

It has been observed that it does not make sense to try source separation in those regions where the foreground emissions are much smaller than CMB and well below the noise level. In any case, the CMB angular power spectrum has always been estimated fairly well up to a multipole $l = 2000$, irrespective of the galactic latitude. The estimation of the source densities has also given good results. Source separation by our method has been particularly interesting with data from low galactic latitudes, where the foreground variance is often higher than the one of the CMB signal.



(a) (b) (c)

Figure 8: Wiener-filtered estimated maps from nonstationary data: (a) CMB; (b) synchrotron; (c) dust.

Note that many separation strategies, both blind and nonblind, have failed their goal in this region of the celestial sphere. As an example, WMAP data analysis (see [28]) was often performed by using pixel intensity masks that exclude the brightest sky portion from being considered. Another interesting feature of our method is that significant cross-correlations between pairs of foregrounds can be straighforwardly taken into account. Recently, some methods for a completely blind separation of correlated sources have been proposed in the literature (see, e.g., [29]). Their effectiveness in astrophysical map separation has not been proved yet. Moreover, they have a high computational complexity.

Recently [9], a frequency-domain implementation of the method in [15] has been proposed. This method allows to take antenna beam effects into account straightforwardly by including the effect of the antenna transfer functions in the model. It also permits to introduce prior information about the entries of the mixing matrix and the spatial power spectra of the components. An open problem is the extension of these methods to the case of correlated sources. A possible extended method might be implemented in the space or in the frequency domain according to convenience. Another problem that is still open with the expected *Planck* data is the different resolution of the data maps in some of the measurement channels. The identification part of our method can work with maps whose resolution has been degraded in order to be the same in all the channels. The result would be an estimate of the mixing matrix, which can be used in any nonblind separation approach with channel-dependent resolution, such as maximum entropy [2]. However, the possible asymmetry of the telescope beam patterns should be taken into account in verifying this possibility.

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