CO COMPONENT ESTIMATION BASED ON THE INDEPENDENT COMPONENT ANALYSIS

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Abstract

Fast Independent Component Analysis (FastICA) is a component separation algorithm based on the levels of non-Gaussianity. Here we apply FastICA to the component separation problem of the microwave background, including carbon monoxide (CO) line emissions that are found to contaminate the PLANCK High Frequency Instrument (HFI) data. Specifically, we prepare 100 GHz, 143 GHz, and 217 GHz mock microwave sky maps, which include galactic thermal dust, NANTEN CO line, and the cosmic microwave background (CMB) emissions, and then estimate the independent components based on the kurtosis. We find that FastICA can successfully estimate the CO component as the first independent component in our deflection algorithm because its distribution has the largest degree of non-Gaussianity among the components. Thus, FastICA can be a promising technique to extract CO-like components without prior assumptions about their distributions and frequency dependences.

Key words: cosmic background radiation – cosmology: observations – ISM: molecules – methods: data analysis

Online-only material: color figures

1. INTRODUCTION

Precise measurements of cosmic microwave background (CMB) anisotropies have been a powerful probe into the early universe and cosmology. Experiments such as COBE (Bennett et al. 1996), BOOMERanG (MacTavish et al. 2006), and the Wilkinson Microwave Anisotropy Probe (WMAP; Komatsu et al. 2011) have already placed strong constraints on the parameters of the cosmological model, examples include the age of the universe, baryon and cold dark matter densities, and so on. The third-generation CMB satellite, PLANCK (Tauber et al. 2010), is expected to release its cosmological results soon, which will include constraints on the amplitude of primordial gravitational waves, the spectral index and its running of the primordial curvature perturbations, the amount of primordial non-Gaussianity, and so on, and thereby will provide constraints on the physics of the early universe, such as inflation.

Such cosmological information can be obtained only when sources of uncertainty are removed successfully. With recent high-resolution and sensitive instruments, the main source of uncertainty is the contamination by foreground emissions from the Galaxy rather than the instrumental noise itself. Therefore, component separation methods have progressively developed so far based on the analyses of data at different frequencies and different frequency dependences of astrophysical emission laws (for a recent review, see Dunkley et al. 2009). The methods include template fitting (Efstathiou et al. 2009; Katayama & Komatsu 2011), internal linear combination (Eriksen et al. 2004), correlated component analysis (Bonaldi et al. 2006), maximum entropy method (Hobson et al. 1998), and others; the differences lie in both how they model the data and the assumptions made on the foreground components.

Along with the synchrotron and thermal dust emissions that constitute a substantial portion of the foreground component of the Galaxy at microwave frequencies, it now becomes clear that the rotational transitions of carbon monoxide (CO) significantly contaminate the PLANCK observing bands (Planck HFI Core Team et al. 2011). In particular, the frequencies of the lowest two rotational transitions of CO, namely \( J = 1 \rightarrow 0 \) and \( J = 2 \rightarrow 1 \), are at the first and third transmission bands of PLANCK’s High Frequency Instrument (HFI), the 100 and 217 GHz bands. Therefore, we must develop a method to remove this contribution for cosmological analysis.

A simple way to remove such a contribution may be to use a template with help from the other CO line surveys, such as a Columbia survey (e.g., Dame et al. 2001) and the NANTEN Galactic Plane Survey (NGPS) by NANTEN telescope (Onishi et al. 2001; Mizuno & Fukui 2004). However, these surveys are dedicated mainly to the Galactic plane where most molecular clouds have been found, and there has been no full sky CO map to be compared with the PLANCK full sky data. Thus it would be helpful to find a method to obtain (even rough) information about the distribution of the CO molecular clouds, especially at high galactic latitudes, from the PLANCK data alone.

In 2013 March, the first cosmological results from PLANCK came out (Planck Collaboration et al. 2013b). They show that the lines of \( J = 1 \rightarrow 0 \), \( J = 2 \rightarrow 1 \), and \( J = 3 \rightarrow 2 \) at 115, 230, and 345 GHz, respectively, give significant foreground contamination in the Planck intensity maps. They have derived CO component maps in several ways with different assumptions, since the total number of parameters for the foreground components exceed the number of observing frequency bands. Among them, the Type-1 maps are derived using the Modified Internal Linear Combination Algorithm (MILCA; Hurier et al. 2010), based on the differences in the spectral transmission of a CO line among the bolometers in a single-frequency channel. The Type-2 maps are derived using multi-frequency channels and the Ruler algorithm, which is based on a parametric model of the Galactic emissions. Because estimations of the CO component rely on different assumptions, it is desirable to apply several algorithms to the CO estimations and check the stability of the results.

To this end, we consider a fast component separation method to extract the CO distribution based on the Independent Component Analysis (FastICA; Hyvärinen & Oja 1997). The FastICA has several advantages in comparison with the methods mentioned above: the most important among them is that the FastICA method needs no prior assumptions about the distribution of the foreground components and their frequency dependences. (As such, it is called blind source separation in the statistics...
CMB. The ICA model is given by

\[ T^i(\hat{n}_i) = M^i_k S^k(\hat{n}_i), \quad (1) \]

where \( T^i(\hat{n}_i) \) are the observed temperatures at the \( i \)th band at the sky direction \( \hat{n}_i \), \( M^i_k \) is the mixing matrix, and \( S^k \) with \( k = 1, 2, 3 \) are the three independent sources considered in this paper that correspond to CO, thermal dust, and CMB emissions, respectively. In our simulation, we consider \( PLANCK \)'s \( j = 100, 143, \) and 217 GHz bands. The ICA algorithm estimates the sources and the mixing matrix simultaneously by maximizing the degree of non-Gaussianity of the variable \( Y^k \) with the matrix \( W^j \).

\[ Y^k(\hat{n}_i) = W^j_k T^j(\hat{n}_i). \quad (2) \]

In simple terms, this process is equivalent to maximizing “independency” between the variables \( Y^k \) because of the central limit theorem. When the non-Gaussianity of \( Y^k \) is at its maximum, \( W \) should be \( M^{-1} \), and \( Y^k \) approaches \( S^k \). In the present analysis, we consider a noisy ICA model given by

\[ T^i(\hat{n}_i) = M^i_k S^k(\hat{n}_i) + N^i(\hat{n}_i), \quad (3) \]

where instrumental (white) noise terms \( N^i \) are taken from the \( PLANCK \) specification (Planck Collaboration et al. 2011). Although the noise in \( PLANCK \) is highly anisotropic due to anisotropic hit counts across the sky, we treat it as if it were isotropic because we consider only a fraction of the sky. We have neglected the noise of the NANTEN telescope because it is not significant compared to that of \( PLANCK \) as shown in Figure 1.

In what follows, we use the vector notation and write \( T \) instead of \( T^i \), etc., for clarity. Following the standard ICA procedure, we first quasi-whiten the observed data. The whitening is done by the operations (Hyvärinen 1999):

\[ x(\hat{n}_i) = (T(\hat{n}_i) - \bar{T}), \quad (4) \]

\[ \tilde{x}(\hat{n}_i) = (C - \Sigma)^{-1/2} x(\hat{n}_i), \quad (5) \]

\[ \tilde{\Sigma} = (C - \Sigma)^{-1/2} \Sigma (C - \Sigma)^{-1/2}, \quad (6) \]

where \( \bar{T} = E[T] \) is the mean temperature in each observed band, \( C = E[xx^T] \) is the covariance matrix of the observed data, \( \Sigma = E[NN^T] \) is the known noise covariance matrix, and \( \tilde{\Sigma} \) is that after quasi-whitening. The ensemble average \( E[] \) is estimated from the sample average of the observed pixels \( \hat{n}_i \). Thus, the problem is recast to finding a matrix \( W \) that maximizes the levels of non-Gaussianity of the variables \( y = W\tilde{x} \).

In the analysis, we adopt the deflation algorithm, i.e., we estimate the independent components one-by-one by maximizing the non-Gaussianity of the variable \( y^{(k)}(\hat{n}_i) = w^{(k)T}\tilde{x}(\hat{n}_i) \), under a constraint \( |w|^2 = 1 \), where the superscript \( (k) \) indicates the \( k \)th independent component. In this case, the vector \( w^{(k)T} \) is the \( k \)th row of the matrix \( W \). To find \( w^{(k)T} \), which maximizes the non-Gaussianity of the variable \( y^{(k)} \), we need an evaluation function of the level of non-Gaussianity. Here we use the kurtosis as the evaluation function \( g(y) \):

\[ g(y) = \text{kurt}(y) = E[y^4] - 3(E[y^2])^2. \quad (7) \]

The function \( g(y) \) takes the minimum \( g(y) = 0 \) when the variable \( y \) is Gaussian distributed. The gradient of the kurtosis is given by

\[ \frac{\partial g}{\partial w} = 4E[(w^T\tilde{x})^3\tilde{x}] - 12w^T(I + \tilde{\Sigma})w(I + \tilde{\Sigma})w, \quad (8) \]

where we have used the fact that \( E[\tilde{x}\tilde{x}^T] = I + \tilde{\Sigma} \). In the standard gradient method, the parameter \( w \) should be updated by

\[ \Delta w \propto \frac{\partial g}{\partial w} \propto E[(w^T\tilde{x})^3]\tilde{x} - 3w^T(I + \tilde{\Sigma})w(I + \tilde{\Sigma})w. \quad (9) \]

Because we have restricted the parameter space by the constraint \( |w|^2 = 1 \), the vector \( w \) should satisfy the condition \( w \propto \Delta w \) at the stable point. Therefore, one obtains the fixed point algorithm for the \( k \)th independent component (Hyvärinen & Oja 1997),

\[ w^{(k)\text{new}} = E[(w^{(k)T}\tilde{x})^3\tilde{x}] - 3w^{(k)T}(I + \tilde{\Sigma})w^{(k)}(I + \tilde{\Sigma})w^{(k)}, \quad (10) \]
which is followed by a normalization $w_{\text{new}}^{(k)} \leftarrow w_{\text{new}}^{(k)}/|w_{\text{new}}^{(k)}|$. The above procedure maximizes the non-Gaussianity of the variable $y^{(k)} = w^{(k)T}x$ in terms of the kurtosis.

When we need to estimate more than one independent component, we can repeat the above procedure. In this case, an orthogonalization step must be utilized at every iteration before the normalization step to prevent the new vector $w^{(k+1)}$ from converging to the previously estimated vectors $w^{(p)}$ ($p = 1, 2, \ldots, k$). The orthogonalization can be done, for example, by a Gram–Schmidt-like decorrelation method:

$$w^{(k+1)} = w^{(k+1)} - \sum_{p=1}^{k} (w^{(k+1)} \cdot w^{(p)}) w^{(p)}. \quad (11)$$

3. SKY MODEL

In Figure 2, we show simulated sky maps at the 100, 143, and 217 GHz PLANCK bands, including the CMB, foreground components, and the PLANCK instrumental noises ($T^\text{in}$ in Equation (1)). For the CMB component, we generate random Gaussian skies with an angular power spectrum consistent with the PLANCK 2013 results (Planck Collaboration et al. 2013d). The skies are convolved with a spherical beam of the greatest beam width among the three bands, namely, FWHM = 9:59 at the 100 GHz band (Planck Collaboration et al. 2011, 2013b).

For the instrumental noises, we assume white noises with the amplitudes (Planck Collaboration 2013c)

$$\Delta T[\mu K \text{pix}^{-1}] = \Delta T[\mu K \text{ beam}^{-1}] \frac{\theta_{\text{beam}}}{\theta_{\text{pix}}} = \begin{cases} 5.12 & (100 \text{ GHz}) \\ 2.16 & (143 \text{ GHz}) \\ 2.95 & (217 \text{ GHz}) \end{cases}, \quad (12)$$

where $\theta_{\text{pix}} = 6:87$ (Gaussian) with the HEALPIX parameter $N_{\text{side}} = 512$ (Górski et al. 2005). The noise terms $N^i$ in Equation (3) are realized randomly from normal distributions with variances given by Equation (12).

For the foreground components, we assume galactic thermal dust and CO line emissions. In particular, thermal dust emissions and CO line contaminations are prominent at 217 GHz and the 100 and 217 GHz bands, respectively. For the thermal dust emissions, we follow “model 8” of Finkbeiner et al. (1999), which gives predictions of dust maps at microwave frequencies through extrapolations from Schlegel et al. (1998). The same model maps are implemented in a recent paper (Sehgal et al. 2010), and slightly different maps (“model 7”) are used in the PLANCK Sky Model (Delabrouille et al. 2013). For the CO line contamination at the 100 GHz band, we use real data at the MBM (the high-latitude molecular cloud detected by Magnani, Blitz, & Mundy 1985) and Pegasus region observed by NANTEN telescope (Yamamoto et al. 2003, 2006) and convert the NANTEN velocity-integrated intensity map to the CMB temperature map at 100 GHz band by multiplying the conversion factor $\alpha^{J=1-0} = T_{\text{CO}}^{100 \text{ GHz}}/J_{\text{CO}}^{1-0} = 14.2$ found by the Planck team (Planck HFI Core Team et al. 2011; Planck Collaboration et al. 2013a). The FWHM of the NANTEN beam is about 2:6, and we smooth the map to 9:59 by using the subroutine alteralm in the HEALPix facilities in order to match the FWHM of the PLANCK 100 GHz band. While the CO line contamination at the 143 GHz band is found not to be significant (Planck HFI Core Team et al. 2011), we must take into consideration the contamination at the 217 GHz band where the transition $J = (2-1)$ comes in. As NANTEN data are not available for this
transitions, we make a simple assumption that the intensity of the $J = (2–1)$ transition is proportional to that of $J = (1–0)$.

Specifically, we make a toy sky map for the CO line emission at 217 GHz by

$$T_{\text{CO}}^{217\text{GHz}}(\hat{n}_i) = R_{J = 2–1}^{J = 1–0}\alpha_{J = 2–1}^{J = 1–0}T_{\text{CO}}^{100\text{GHz}}(\hat{n}_i). \quad (13)$$

Here the conversion factor $\alpha_{J = 2–1}^{J = 1–0}$ = 45.0 is given by the Planck team (Planck Collaboration et al. 2013a), and the integrated line ratio, $R_{J = 2–1}^{J = 1–0} = 0.77 \pm 0.24$, is taken from Ingalls et al. (2000), in which they estimated the ratio between $J = (4–3)$, $(2–1)$, and $(1–0)$ at high galactic molecular clouds based on observations using the Antarctic Submillimeter Telescope, Remote Observatory, and the Five College Radio Astronomy Observatory.\(^3\) Because the CO line emission data is limited to the MBM and Pegasus region ($f_{\text{sky}} \approx 0.8\%$) shown in Figure 3, we concentrate our analysis only on this region. We do not consider the contributions from Sunyaev–Zel’dovich clusters and point sources in our simulation, and in real applications we have to use masks for these contributions, as in the Planck analysis (Planck Collaboration et al. 2013a).

### 3.1. Foreground Components in the CMB Angular Power Spectrum

We depict the angular power spectra in Figure 4 showing the impact of the foreground components at the MBM and Pegasus region and instrumental noises on the power spectra. To estimate the power spectra, we mask all the pixels outside the MBM and Pegasus region and use the Polspice code (Szapudi et al. 2001; Chon et al. 2004). Errors are estimated by generating five hundred mock CMB and instrumental white noise maps, as described earlier. We bin the spectra with the bandwidth $\Delta\ell = 25$ because the mask covers most part of the sky ($f_{\text{sky}} \approx 0.8\%$ for the MBM and Pegasus region), and we thus have large cosmic variance errors with correlations between neighboring multipoles.

It has been known that the thermal dust component has larger power at higher frequencies and affected the spectrum mainly at larger angular scales (Tegmark et al. 2000; Masi 2004). We find that this holds true for the MBM and Pegasus region considered here. On the other hand, we find that the CO component gives significant contaminations at smaller angular scales. The contamination can be larger than the instrumental and cosmic variance errors at $\ell \gtrsim 900$ and $\ell \gtrsim 400$ at the 100 and 217 GHz bands, respectively. Galactic synchrotron emissions are found to be always subdominant in those frequencies and the multipole range because the MBM and Pegasus region is far away from the galactic disk, and we have omitted them in the current analysis.

### 4. RESULTS

We apply the FastICA algorithm to the sky maps prepared in the previous section in order to estimate the CO contribution and subtract it from the maps. As described earlier, we use the sky maps at three frequency bands to separate out three independent components based on the kurtosis.

In Figure 5, the three sources obtained from the ICA algorithm are shown. We find that in our deflation algorithm, the algorithm always finds the CO-like component as the first independent component ($S^1$), irrespective of the initial condition for the vector $\mathbf{w}$. This is caused by the fact that the distribution of the CO line intensity has the largest non-Gaussianity in terms of the kurtosis among the three components (CO, dust, and CMB). It is also evident from the figure that the second independent component $S^2$ is most responsible for the thermal dust component given by the dust model of Finkbeiner et al. (1999).

In order to investigate the performance of the FastICA method as an estimator of the CO component, we make a scatter plot as shown in the top panel of Figure 6. In the figure, we show the intensity of the first independent component estimated by the

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\(^3\) PLANCK $J = (2–1)$ data are now available and the mean line ratio for CO(2→1)/CO(1→0) is found as $R_{J = 2–1}^{J = 1–0} \approx 0.595$ with significant variation among the molecular clouds (Planck Collaboration et al. 2013a).
Figure 5. Independent components ($S_1$, $S_2$, and $S_3$) obtained from the ICA algorithm. The source with the largest non-Gaussianity is shown in the top panel and the smallest in the bottom. It is clear that the ICA successfully estimates the CO distribution ($S_1$) in the top panel. The second source seems to be thermal dust emissions. The amplitudes are arbitrary because of the degeneracy between the sources and mixing matrix components.

Figure 6. Top: the fractional errors in the estimated CO intensity at each pixel at the 100 GHz band for three particular realizations. Here the CO is assumed to be the first independent component. Different colors and points correspond to the different realizations. Bottom: expected reconstruction errors in the estimated CO and dust components from 500 Monte Carlo simulations.

Figure 7. Two dimensional distributions of the estimated CO and dust temperatures obtained from our Monte Carlo simulations. No significant correlation can be seen.

FastICA at each pixel against the input CO intensity. We find that the accuracy depends on realizations, namely on particular CMB and noise realizations on which the CO emissions are superimposed. The FastICA method relies on the independence between the signals, and therefore chance correlations between the CMB and CO signals can affect the reconstruction.
The performance depends on realizations, so we again use the Monte Carlo simulations described earlier to rate the performance statistically. In the bottom panel of Figure 6, we estimate errors in the CO and dust temperature reconstructions from our 500 Monte Carlo simulations. In the case of CO, while the errors can be large at pixels in which the CO intensities are intrinsically as small as $T_{\text{CO}} \lesssim 50 \mu K$, the errors are less than $\pm 30\%$ in pixels with high temperatures. On the other hand, dust temperature can be reconstructed within $\pm 15\%$. We find that the error distributions of CO and dust reconstructions are well approximated by Gaussian distributions for pixels where foreground emissions are strong.

5. SUMMARY AND DISCUSSION

In this paper, we considered the CMB foreground subtraction problem, paying particular attention to the lowest two rotational transitions of CO molecules $J = (1–0)$ and $J = (2–1)$ that contaminate the PLANCK 100 GHz and 217 GHz bands, respectively. First, we estimated the angular power spectrum of the CO line emissions at the MBM and Pegasus region observed by the NANTEN telescope and found that the CO line emissions have significant contribution to the angular power spectrum, especially at small angular scales ($\ell \gtrsim 900$ and 400 for the 100 and 217 GHz bands, respectively.)

CO contamination, if it is not to be taken into account correctly, will cause a wrong estimation of cosmological parameters. In particular, the parameters related to the primordial fluctuation amplitude, such as the amplitude of the curvature perturbation and its spectral index, will be significantly affected. Indeed, we had found that even for a small MBM and Pegasus region, the bias about the estimations of these parameters are beyond the $1\sigma$ error bars, toward larger amplitude and larger spectral index. We should stress, however, that this result holds only for the MBM and Pegasus region of the sky. How large the CO contamination is in the estimation of the full sky CMB angular power spectrum will be a future issue.

Second, we applied the FastICA to the component separation problem, including the CO line emissions. The FastICA algorithm can separate the components based on the independency of the components or, equivalently, the level of non-Gaussianity, without any prior knowledge of distribution and frequency dependence of each foreground component. We find that a CO-like component is extracted as the first independent component in our deflection algorithm, as the CO distribution has the largest non-Gaussianity among the components considered here. This fact can be used to quickly estimate the CO component in the PLANCK data.

Based on the Monte Carlo simulations of the microwave sky including CMB, CO, and thermal dust emissions, we investigated how the CO component is recovered by the FastICA algorithm. Though the accuracy depends on the particular realization of the instrumental noises and the CMB, we find that the recovery is done very well in a statistical sense. The errors are about $\pm 30\%$ and $\pm 15\%$ for the CO and dust component reconstructions, respectively.

The accuracy of the FastICA for the CO reconstruction should be compared with that of the method adopted by the Planck team. In the recent PLANCK 2013 results paper, the PLANCK Type-I map was directly compared with the NANTEN2 survey in a $9^\circ \times 3^\circ$ section of the Galactic plane. They found that the level of the residual is about $\pm 10\%$, which is better than the error of $\pm 30\%$ in the FastICA method discussed above (Planck Collaboration et al. 2013a). Although the FastICA will be less accurate for the CO reconstruction compared with the Type-I map, we still consider the method as a helpful and complementary technique to extract the foreground components because it is based on a different criteria (the level of non-Gaussianity) from the usual frequency-based method.

In order to quantify the effect of the dust emissions on the CO component separation, we examine the correlation in the estimations between the two components in the pixel where the NANTEN CO emission is the strongest. We find that there is no significant correlation between these two estimations, as shown in Figure 7. Therefore, we conclude that the success of the FastICA is due to the approximate statistical independence between the foreground components and background CMB. This is consistent with the result in the earlier literature where the authors applied the FastICA method to the WMAP data and found that it can recover the CMB angular power spectrum consistent with the spectrum independently derived by the WMAP team (Maino et al. 2007).

Finally, we should comment on the impact of the FastICA method on the level of non-Gaussianity in the estimated CMB map. As the method relies on the non-Gaussianity to estimate the independent components, one would expect that it should affect the non-Gaussianity of the CMB, which probably has the smallest degree of non-Gaussianity among the components in the microwave sky. In Figure 8, we show the kurtoses in the estimated CMB (red) and CMB+Foreground (blue) maps against the value in the input CMB maps at the 217 GHz band in the MBM and Pegasus region. Clearly, it is seen that the bulk of the kurtosis that comes from the thermal dust and CO components is removed through use of the FastICA method. Interestingly, we find that some portion of the kurtosis in the CMB maps (which should be zero in the mean in our Gaussian simulation) is recovered with a scatter about 20% when the kurtosis has large value ($|\text{kurt}| \gtrsim 0.2$). However, the accuracy depends on the size of the kurtosis, and the method induces a false signal of the kurtosis in the estimated CMB map when the input kurtosis is too small. We leave this issue for future investigation.

In conclusion, in this paper we found that the FastICA can efficiently extract the CO line foregrounds that contaminate the PLANCK HFI bands. The method will be useful to estimate
the CO distribution in the real PLANCK data as well as any foreground component whose distribution is not known in advance in the future CMB experiments.

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