MOTION-CORRECTED INDEPENDENT COMPONENT ANALYSIS FOR ROBUST FUNCTIONAL MAGNETIC RESONANCE IMAGING

Rui Liao[1], Martin J. McKeown[2], Jeffrey L. Krolik[1],

[1]Department of Electrical and Computer Engineering, Duke University, USA
[2]Pacific Parkinson's Research Center, University of British Columbia, Canada

ABSTRACT

Head movement during fMRI data collection can result in confusing artifacts when estimating task-related brain activations. In this paper, we propose an improved version of Motion-Corrected Independent Component Analysis (MCICA), which mitigates motion effects of fMRI time-series by maximizing the entropy difference between the observed fMRI data and a nonlinear function of the derived ICA components. Specifically, the improved MCICA algorithm operates on all timepoints, removing the requirement on the existence of enough motionless timepoints in the time-series and the need to detect motion-corrupted timepoints. Simulations demonstrate that MCICA was robust to activation level and the results were more accurate than cubic interpolation even when the displacement was known. In a real data from a motor fMRI experiment, preprocessing the data with MCICA resulted in the emergence of activation in the primary motor and supplementary motor cortices, and the Mutual Information between all subsequent volumes and the first one was increased.

1. INTRODUCTION

Registration of fMRI time-series is typically done by aligning each timepoint in the series with respect to a "reference image". Motion parameters are estimated by optimizing the cost function quantifying the (mis)match between images, and the registered image is generated by resampling the motion-corrupted image using the estimated transformation. However, the cost functions in conventional approaches, such as image difference [1], image ratio uniformity [2] and mutual information [3], often fail to explicitly account for the activation present in fMRI data, and thus may be 'fooled' into inferring motion when changes in voxels are not due to motion, but coming from brain activations [4]. In addition, even with perfect motion estimation, the resampling procedure itself introduces significant artifacts in the registered image due to the large intensity gradient at the brain edge [5].

In this paper, we propose an improved version of the MCICA algorithm [8], which no longer reconstructs a motion-corrupted volume from a linear combination of assumed "motionless" volumes, but estimates the whole image using a linear combination of complete basis images, relaxing the assumption that there exist enough volumes in the fMRI time-series that are not corrupted with motion. Motion correction is performed on all timepoints, hence head motion in the forms of both "slow drifts" and "jerks" can, in principle, be corrected.

MCICA extends ICA for fMRI data analysis wherein motion correction is performed with the goal of minimizing the mutual information between the decomposed signal components, consistent with the statistical model used by ICA for source separation [6]. By not forcing registration to a single volume, this method allows the decoupling of variance in fMRI time-series due to movement from that coming from task-related activation. In addition, fine-scale alignment is achieved by taking data-adaptive linear combinations of basis images, without explicit motion modeling and non-adaptive resampling, minimizing interpolation error.

2. A STATISTICAL MODEL OF MOTION CORRUPTED FMRI SIGNAL

When Independent Component Analysis (ICA) applied to fMRI data [6], the data are modeled as: $\mathbf{X} = \mathbf{AS}$, where X_{ij} is the observed fMRI signal at the i^{th} timepoint for the j^{th} voxel, A_{ij} is the time-varying contribution of the j^{th} spatially independent component to the measured fMRI signal at the i^{th} timepoint, and S_{ij} is the map value of the i^{th} component for the j^{th} voxel. Each column of $\mathbf{X}$ and $\mathbf{S}$ can be viewed as independent realizations of the random vectors $\mathbf{x} = \left[x_1, \cdots, x_n\right]^T$ and $\mathbf{s} = \left[s_1, \cdots, s_n\right]^T$ respectively. The objective of ICA is to determine the unmixing matrix $\mathbf{W}$ to achieve the independent component map estimation $\tilde{\mathbf{s}} = \mathbf{Wx}$. Note that $\mathbf{W}$ may be interpreted as a temporal linear time-variant filter operating on the time-course of each voxel. With the Infomax algorithm [7], $\mathbf{W}$ is estimated by maximizing $H[\mathbf{y}]$, where $H[\cdot]$ denotes the Shannon entropy, $\mathbf{y} = g(\tilde{\mathbf{s}}) = g(\mathbf{Wx})$ and $y_j = g_j(\tilde{s}_j) = \frac{1}{1+e^{-\tilde{s}_j}}$ (*j*=1…n) for super-Gaussian fMRI signals. It can be shown that:

$$H[\mathbf{y}] = H[\mathbf{x}] + E\{\log|J|\} \quad (1)$$

where $E\{\cdot\}$ denotes statistical expectation and $|J|$ is the absolute value of the determinant of the Jacobian matrix of transformation from $\mathbf{x}$ to $\mathbf{y}$.

The core idea of the MCICA algorithm is based on the observation that motion effects within fMRI data will result in an increase in $H[\mathbf{x}]$ and a decrease in $H[\mathbf{y}]$ [8]. Specifically, misalignment of some timepoint in the fMRI data $\mathbf{X}$ tends to decrease the higher-order mutual information among the elements of the nominal random vector $\mathbf{x}$ and hence increases the joint entropy of the data, $H[\mathbf{x}]$, assuming that the marginal entropy calculated from the rows of $\mathbf{X}$ remains unchanged after motion. Simultaneously, $H[\mathbf{y}]$ tends to decrease for motion-corrupted data for two reasons: 1) motion-related ICA component(s) tend to be generated, and these have an accumulative distribution function that cannot be well approximated by the logistic function, decreasing the marginal entropy $H[y_j]$; and 2) the effect of motion at a given timepoint is equivalent to adding one more source to the observation $\mathbf{x}$ due to the fact that motion effects could not be easily described as a linear combination of the original sources of brain activations [9]. The task of source estimation becomes more difficult with increasing number of sources and the extracted ICA components for motion-corrupted data tend to become more dependent, potentially increasing the mutual information $M[\mathbf{y}]$ [4].

Since $H[\mathbf{x}]$ *increases* and $H[\mathbf{y}]$ *decreases* with motion, $E\{\log|J|\}$ in Eq. (1) represents a desirable cost function to be maximized for motion correction. The proposed objective function is defined on *an ensemble of volumes,* which allows for multiple representative images, instead of a single reference image, for registration purposes. Since using two reference images improves registration performance [10], extending this to an arbitrary number of reference images in a computationally tractable manner has the potential to particularly enhance performance. In addition, the proposed objective function allows for intensity variability among the fMRI time-series arising from stimuli to be explicitly modeled by some ICA components, whose time courses vary accordingly throughout the time-series. The explicit yet flexible modeling of non-motion related signal changes minimizes the potential interference of brain activation in fMRI data on motion estimation.

3. MOTION-CORRECTED INDEPENDENT COMPONENT ANALYSIS (MCICA)

In the improved version of MCICA, to register a motion-corrupted fMRI image, we approximate the correctly registered image by an optimal linear summation of a set of basis images, whereby resampling procedure is avoided which minimizes interpolation error. To align, say, the first timepoint, m_r basis images are constructed (explained in Section 4), each image denoted by a column vector $\mathbf{r}_i$, and collected into a matrix $\mathbf{R} = \left[\mathbf{r}_1, \cdots, \mathbf{r}_{m_r}\right]^T$. The objective of MCICA algorithm is to determine the unit-length $m_r \times 1$ motion-compensation vector $\mathbf{p}$ containing weights for each of the basis images, and the unmixing matrix $\mathbf{W}$, which maximize the cost function:

$$E\{\log|J|\} = \log|\det \mathbf{W}| + E\left\{\sum_{j=1}^{k} \log\ y_j^r(1-y_j^r)\right\} \quad (2)$$

where $\mathbf{y}^r = [y_1^r, ..., y_k^r] = g(\mathbf{s}^r) = g(\mathbf{Wx}^r)$ and $\mathbf{x}^r$ is the nominal random vector for the registered data matrix:

$$\mathbf{X}^r = \left[\mathbf{R}^T\mathbf{p} \quad \mathbf{x}_2 \quad \cdots \quad \mathbf{x}_k\right]^T \quad (3)$$

Here $\mathbf{x}_i$ ($i = 2, \cdots, k$) represents the subset of volumes that act as the "reference volumes" (defined in Section 4), and the first timepoint is now replaced by $\mathbf{R}^T\mathbf{p}$, a linear sum of the m_r basis images weighted by the motion-compensation vector $\mathbf{p}$. In essence, MCICA consists of designing an adaptive spatial resampling filter $\mathbf{p}$ that maintains maximum temporal independence among the recovered components.

The Lagrange multiplier method is used to convert the constrained maximization into an unconstrained one and gradient-ascent techniques are used to update $\mathbf{W}$, $\mathbf{p}$ and the Lagrange multiplier λ for the constraint $\|\mathbf{p}\| = 1$:

$$\mathbf{W}^+ = \mathbf{W} + \alpha\left(E\left\{\mathbf{I} + (\mathbf{1} - 2\mathbf{y}^r)(\mathbf{s}^r)^T\right\}\mathbf{W}\right) \quad (4)$$

$$\mathbf{p}^+ = \mathbf{p} + \alpha\left(E\left\{\mathbf{r}(\mathbf{1} - 2\mathbf{y}^r)^T\mathbf{w}_1\right\} + \lambda\mathbf{p}\right) \quad (5)$$

$$\lambda^+ = \lambda + \alpha(1 - \mathbf{p}^T\mathbf{p}) \quad (6)$$

where $\mathbf{w}_1 = [w_{11}, \ldots, w_{k1}]^T$ is the first column of the unmixing matrix $\mathbf{W}$, $\mathbf{r}$ is the nominal random vector for the matrix $\mathbf{R}$, $\mathbf{I}$ is the identity matrix, $\mathbf{1}$ is a vector of ones, and α is the learning rate. The convergence results of the iterative optimization were demonstrated in [11].

4. SIMULATIONS AND REAL DATA

The performance of MCICA was quantitatively evaluated on both surrogate data and real fMRI time-series. To generate the basis images in **R** for registration of a motion-corrupted image, we first estimated any large motion by aligning the centroid and principal axes of activation of that image to that of the mean image of the reference volumes. The preprocessed image was then rotated about its centroid using all combinations of the rotation (Euler) angles of [-2, -1, 0, 1, 2] degrees in three dimensions to generate $5^3 = 125$ rotated images. Two translated versions were then generated for each of the rotated images by random three-dimensional translations within [-0.25 0.25] voxels. 100 eigenimages obtained from Principal Component Analysis (PCA) on these shifted/rotated images were used as the basis images.

The first experiment evaluates the robustness of MCICA in the presence of simulated activations. A simulated data set **X** was formed by left-multiplying a component map matrix **S** mimicking *n=9* brain activations with a time course matrix **A** consisting of sinusoids corrupted with noise. An artificial time-series was generated by duplicating the simulated brain image 40 times and then superimposing each timepoint in the series with a selected component in **S** multiplied by an activation weight varying throughout the time-series according to the time course given in Figure 1. Each timepoint in the time-series was then moved by the same motion parameter (translations of [0.1, 0.08, 0.05] voxels and rotations of [0.2, 0.1, 0.4] degrees which are typical for real fMRI data) and was registered by MCICA one by one to be into alignment with the data set **X**. Nine images (rows) in **X** were used as the reference volumes.

Figure 1 demonstrates the activation level and mean absolute error (mean of the absolute differences in voxel intensity between the original motionless image and the registered image (MAE)) versus timepoint. The correlation between the course of MAE and the activation course (CAME) is shown to be 0.231, suggesting that the performance of MCICA was relatively invariant to the simulated activation level.

The second experiment evaluates the registration accuracy of MCICA for real fMRI data corrupted with simulated motion. Real fMRI time-series were obtained from 1.5T GE Sigma MRI system during a simple motor task consisting of six 15-s blocks of left hand movement alternating with rest. Each time-series consisted of 32 axially-acquired 64-by-64 slices at each timepoint, and totaled 65 timepoints. Ten timepoints that had the least discrepancy between their centroids and principal axes of activation were selected to form the reference ensemble. One timepoint in the reference ensemble was then moved by the same rigid-body motion as that in the previous experiment and then registered by MCICA using the other nine images in the reference ensemble. The original presumed 'motionless' image thus could be used as the gold standard to evaluate registration accuracy.

Figure 2 compares the registration errors produced by MCICA and cubic interpolation using the known transformation parameters that reversed the previously applied rigid-body motion. Note that across the whole image, the errors produced by MCICA were considerably smaller than that of cubic interpolation.

Finally, MCICA was run on two fMRI time-series: one time-series was acquired from a normal subject with minimal head motion; the other time-series was acquired from a stroke subject and was corrupted with significant motion. The correlation between the time course of each voxel and the task-rest behavioral paradigm was calculated for the two time-series before and after MCICA registration. The voxels with correlations higher than 0.5 were regarded as 'activated' and are highlighted in Figure 3. For the data from the normal subject, similar 'activated' voxels in the primary motor area and the supplementary motor area were detected both before and after registration. In contrast, for the stroke data, the 'activated' voxels in the expected area could not be detected, and emerged after MCICA registration. Also, preprocessing the latter data set with MCICA resulted in a consistently increased MI between the first timepoint and all subsequent timepoints (Figure 4).

5. DISCUSSIONS AND CONCLUSION

We have proposed a novel method for 3D motion correction of fMRI time series. The main advantage of MCICA over conventional registration methods is that it effectively allows several representative volumes to act as reference volumes, and allows the changes in fMRI signals due to activation to be explicitly separated from changes due to motion. A systematical evaluation of the registration performance of MCICA algorithm in comparison with conventional methods that do not explicitly account for task-related signal changes in fMRI data is given in [12]. Future work will focus on developing better ways to construct the basis volumes, especially for big motions where a dense generation of representative rotated/shifted images may be computationally impractical.

6. ACKNOWLEDGEMENT

This work was supported by the Center for Neural Engineering, Duke University and NINDS P01NS41328-01A1 (core C).

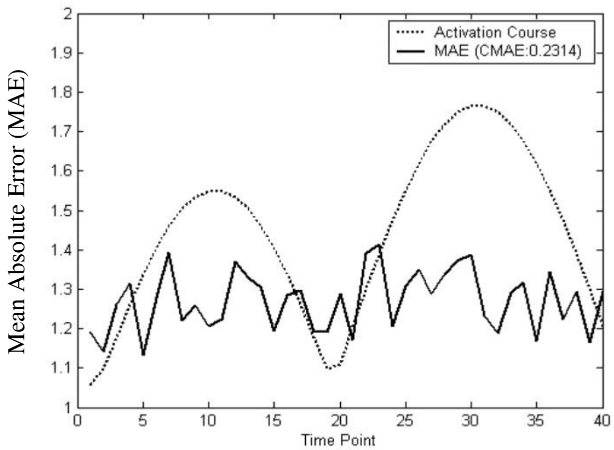

Figure 1. MCICA registration with different activation levels for simulated data corrupted with simulated motion.

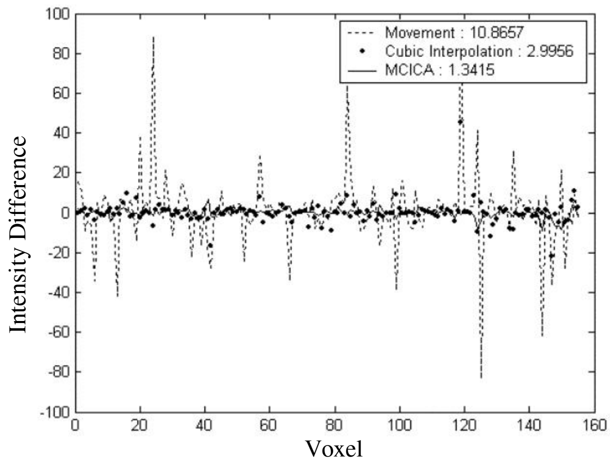

Figure 2. Difference in voxel intensity between the assumed motionless image and the image after movement, cubic interpolation with known motion parameter and

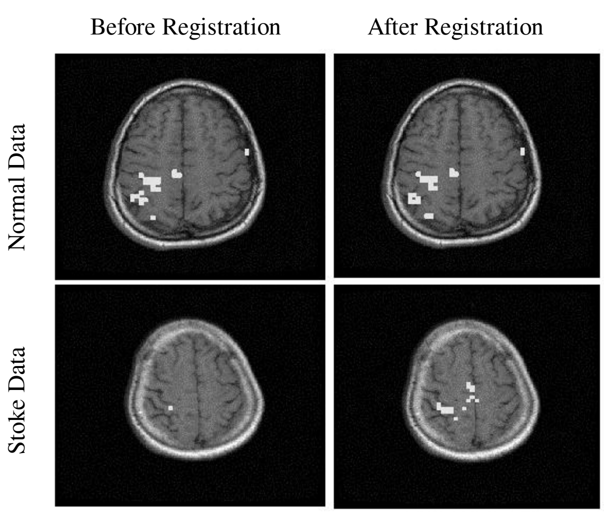

Figure 3. Comparison of activated areas detected by simple correlation method before and after MCICA registration for a normal data and a stroke data.

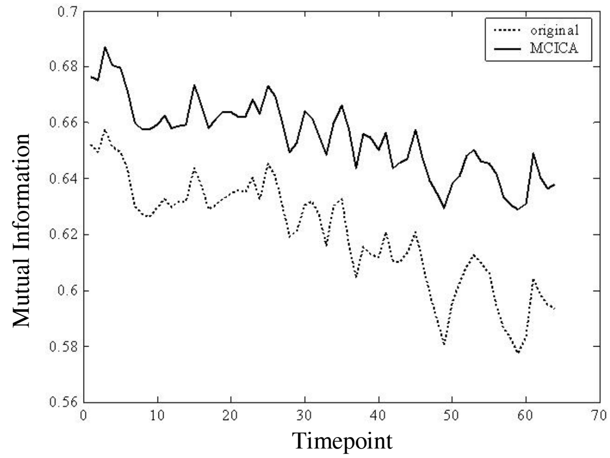

Figure 4. Comparison of mutual information between the first timepoint and subsequent timepoints in a real fMRI time-series before and after MCICA motion correction.

7. REFERENCES

[1] K.J.Friston et al., "Analysis of Functional MRI Time-Series", *Human Brain Mapping* 2, pp.69-78, 1994.

[2] R.P.Woods et al., "Automate Image Registration: I. General Methods and Intrasubject, Intramodality Validation", *Journal of Computer Assisted Tomography*, vol. 22, pp. 139-152, 1998.

[3] F.Maes et al., "Comparative Evaluation of Multiresolution Optimization Strategies for Multimodality Image Registration by Maximization of Mutual Information", *Medical Image Analysis*, pp. 373-386, 1999.

[4] L.Freire, and J.F.Mangin, "Motion Correction Algorithms May Create Spurious Brain Activations in the Absence of Subject Motion", *NeuroImage*, vol. 14, pp. 709-722, 2001.

[5] S.Grootoonk et al., "Characterization and Correction of Interpolation Effects in the Realignment of fMRI Time Series", *NeuroImage*, vol.11, pp. 49-57, 2000.

[6] M.J.McKeown et al., "Analysis of fMRI Data by Blind Separation into Independent Spatial Components", *Human Brain Mapping*, vol. 6, pp. 160-188, 1998.

[7] A.J.Bell, and T.J.Sejnowski, "An Information-maximization Approach to Blind Separation and Blind Deconvolution", *Neural Computation*, vol. 7, no. 6, pp. 1004-1034, 1995.

[8] R. Liao, J. Krolik, and M. McKeown, "Motion Correction of fMRI Time-series Using Intrinsic Statistical Properties of Images", *the first IEEE ISBI*, pp. 765-768, July 2002.

[9] R.Liao, J.Krolik, and M.McKeown, "An Information-Theoretic Criterion for Intra-Subject Alignment of fMRI Time-Series: Motion-Corrected Independent Component Analysis", submitted to *IEEE Trans. on Medical Imaging*, 2003.

[10] J.Boes et al., "Multi-variate Mutual Information for Registration", *Lecture Notes in Comp. Sci.*, pp. 606-612, 1999.

[11] K. J., Arrow et al., "Studies in Linear and Nonlinear Programming", Stanford University Press, 1958.

[12] R. Liao, M. McKeown, and J. Krolik, "Isolation and Minimization of Head Motion-Induced Signal Variations in fMRI data Using Independent Component Analysis", submitted to *IEEE Trans. on Medical Imaging*, 2003.