NeuroImage 129 (2016) 133–147

Contents lists available at ScienceDirect

NeuroImage

journal homepage: www.elsevier.com/locate/ynimg

Automatic EEG-assisted retrospective motion correction for fMRI (aE-REMCOR)

Chung-Ki Wong [a], Vadim Zotev [a], Masaya Misaki [a], Raquel Phillips [a], Qingfei Luo [a], Jerzy Bodurka [a,b,c,*]

[a] Laureate Institute for Brain Research, Tulsa, OK, USA
[b] College of Engineering, University of Oklahoma, Norman, OK, USA
[c] Center for Biomedical Engineering, University of Oklahoma, Norman, OK, USA

A R T I C L E I N F O

Article history:
Received 1 September 2015
Accepted 20 January 2016
Available online 27 January 2016

Keywords:
Motion correction
Motion artifacts
E-REMCOR
fMRI
EEG
EEG-fMRI
ICA

A B S T R A C T

Head motions during functional magnetic resonance imaging (fMRI) impair fMRI data quality and introduce systematic artifacts that can affect interpretation of fMRI results. Electroencephalography (EEG) recordings performed simultaneously with fMRI provide high-temporal-resolution information about ongoing brain activity as well as head movements. Recently, an EEG-assisted retrospective motion correction (E-REMCOR) method was introduced. E-REMCOR utilizes EEG motion artifacts to correct the effects of head movements in simultaneously acquired fMRI data on a slice-by-slice basis. While E-REMCOR is an efficient motion correction approach, it involves an independent component analysis (ICA) of the EEG data and identification of motion-related ICs. Here we report an automated implementation of E-REMCOR, referred to as aE-REMCOR, which we developed to facilitate the application of E-REMCOR in large-scale EEG-fMRI studies. The aE-REMCOR algorithm, implemented in MATLAB, enables an automated preprocessing of the EEG data, an ICA decomposition, and, importantly, an automatic identification of motion-related ICs. aE-REMCOR has been used to perform retrospective motion correction for 305 fMRI datasets from 16 subjects, who participated in EEG-fMRI experiments conducted on a 3 T MRI scanner. Performance of aE-REMCOR has been evaluated based on improvement in temporal signal-to-noise ratio (TSNR) of the fMRI data, as well as correction efficiency defined in terms of spike reduction in fMRI motion parameters. The results show that aE-REMCOR is capable of substantially reducing head motion artifacts in fMRI data. In particular, when there are significant rapid head movements during the scan, a large TSNR improvement and high correction efficiency can be achieved. Depending on a subject's motion, an average TSNR improvement over the brain upon the application of aE-REMCOR can be as high as 27%, with top ten percent of the TSNR improvement values exceeding 55%. The average correction efficiency over the 305 fMRI scans is 18% and the largest achieved efficiency is 71%. The utility of aE-REMCOR on the resting state fMRI connectivity of the default mode network is also examined. The motion-induced position-dependent error in the DMN connectivity analysis is shown to be reduced when aE-REMCOR is utilized. These results demonstrate that aE-REMCOR can be conveniently and efficiently used to improve fMRI motion correction in large clinical EEG-fMRI studies.

Introduction

Head motion has been recognized as a major source of artifacts in fMRI data since early days of fMRI (e.g. Cox and Hyde, 1997; Friston et al., 1995, 1996; Hajnal et al., 1994; Jiang et al., 1995). In task fMRI, motion-induced artifacts often correlate with experimental tasks (Hajnal et al., 1994), leading to inaccurate estimates of BOLD activity levels and reduced significance of fMRI findings. This issue is particularly important for frontal and prefrontal brain regions that usually exhibit the largest motions. In resting-state fMRI, head movements introduce systematic changes in estimated fMRI functional connectivity strength across the brain (Power et al., 2012; Van Dijk et al., 2012). Such spurious changes can lead to incorrect interpretations of the functional connectivity results on the group level if the data is ineffectively preprocessed (Power et al., 2012; Saad et al., 2013; Gotts et al., 2013; Jo et al., 2013). The traditional fMRI motion correction approach bases on spatial coregistration of 3D fMRI volumes (e.g. Friston et al., 1995; Cox and Jesmanowicz, 1999). Despiking at the beginning of the preprocessing pipeline further attenuates the fMRI motion effect (Jo et al., 2013; Satterthwaite et al., 2013). The traditional approach implicitly assumes that all motion occurs between the volume acquisitions (Cox and Hyde, 1997). Thus, it cannot adequately take into account effects of faster intra-volume movements (Beall and Lowe, 2014). It has been suggested that a slice-based fMRI motion correction can be superior to the

* Corresponding author at: Laureate Institute for Brain Research, Tulsa, OK, USA.
E-mail address: jbodurka@laureateinstitute.org (J. Bodurka).

http://dx.doi.org/10.1016/j.neuroimage.2016.01.042
1053-8119/

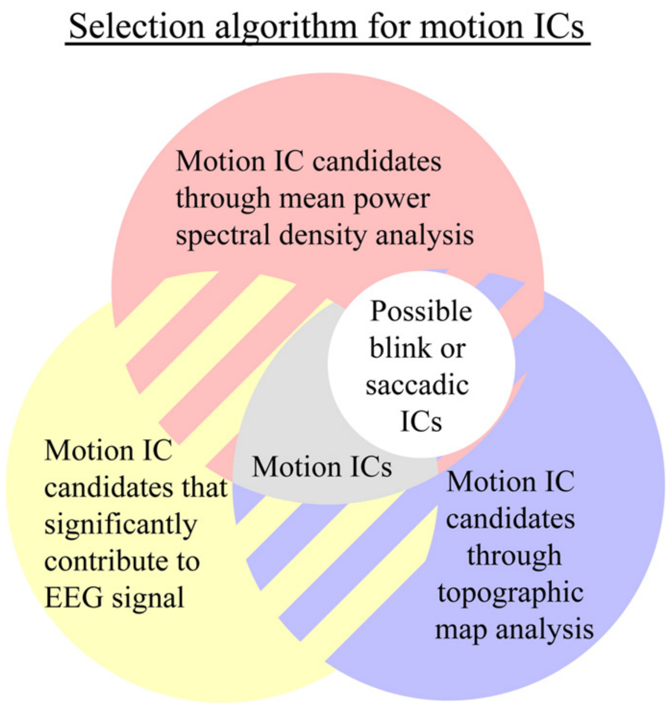

Fig. 1. The sketch of the automatic identification of ICs through the analyses of the mean power spectral density, topographic map, and contribution to the EEG signal. Possible blink and saccade ICs are removed from the motion ICs selection.

traditional volume registration approach (Beall and Lowe, 2014; Zotev et al., 2012).

Multimodal brain imaging, combining fMRI with simultaneous EEG recordings (e.g. Mulert and Lemieux, 2010), offers new exciting opportunities for fMRI motion correction. Simultaneous EEG-fMRI combines the advantages of the high temporal resolution of EEG and the high spatial resolution of fMRI. While the artifact on the fMRI data can be minimized with the use of MR-compatible EEG system, introduction of fMRI environment related artifacts to the EEG data is inevitable. In particular, cardioballistic and motion artifacts are exacerbated inside an MR scanner. These artifacts can be reduced with designated hardware setup (Bonmassar et al., 2002; Masterton et al., 2007), or corrected effectively by independent component analysis (Srivastava et al., 2005; Mantini et al., 2007).

Recently, we introduced a method for EEG-assisted retrospective motion correction of fMRI data (E-REMCOR) that employs the EEG array as a sensitive motion detector in addition to recording neuronal activity (Zotev et al., 2012). In this method, voltage artifacts induced in the EEG array leads due to head motion in a strong uniform magnetic field of an MRI scanner are used to define regressors describing rotational head movements with millisecond temporal resolution. E-REMCOR makes it possible to regress out the effects of rapid head movements from unprocessed fMRI data on a slice-by-slice basis prior to volume registration. Thus, E-REMCOR complements both the traditional fMRI volume registration approach, which performs better for slower head motions, and the RETROICOR method for slice-specific correction of fMRI cardiorespiratory artifacts (Glover et al., 2000). E-REMCOR does not require any specialized equipment (beyond the EEG-fMRI instrumentation) and can be applied retrospectively to any existing EEG-fMRI dataset.

Application of E-REMCOR involves an independent component analysis (ICA) of EEG data and identification of independent components (ICs) corresponding to different head motions. This process requires a close examination of the EEG recordings and a careful evaluation of the IC properties. Therefore, an automation of E-REMCOR to enable a robust and efficient motion correction without human supervision is desirable. In this paper, we describe such an automation extension of E-REMCOR, which we refer to as aE-REMCOR. We explicitly detail the quantitative criteria that effectively distinguish the different motion ICs. We also evaluate its performance for a large number of EEG-fMRI datasets. An improved automatic fMRI motion correction afforded by aE-REMCOR would provide an additional incentive for recording EEG during fMRI, and thus encourage a broader use of simultaneous EEG-fMRI. It would also greatly benefit large clinical studies by improving fMRI data quality and reducing numbers of subjects excluded due to excessive motion.

Methods

E-REMCOR

The aE-REMCOR method is an automation extension of E-REMCOR. E-REMCOR is based on the observation that voltage artifacts (electromotive force, EMF) induced in EEG leads due to rigid-body movements of the head in the uniform magnetic field of an MRI scanner can be analytically related to time derivatives of real-time rotational head motion parameters (Zotev et al., 2012). Definition of the high-temporal-resolution E-REMCOR regressors is independent of the fMRI pulse sequence properties. The MR artifacts are removed from the EEG data by means of the average artifact subtraction (Allen et al., 2000) before the EEG data are used for E-REMCOR.

Application of E-REMCOR for fMRI motion correction includes three steps. First, an independent component analysis (ICA, e.g. Bell and Sejnowski, 1995; Makeig et al., 1997) is performed for the EEG data:

$$V_i(t) = \sum_{j=1}^{N} b_{ij} F_j(t) + \varepsilon_i(t), \quad i = 1 \ldots N. \tag{1}$$

Here, $\{V_i(t)\}$ are signals from N EEG channels, $\{F_j(t)\}$ are the corresponding independent components (ICs), $\{b_{ij}\}$ are elements of the ICA back-projection matrix, and $\varepsilon_i(t)$ is an error term also including the ith-channel's Gaussian noise The ICs $F_k(t)$, $k = 1 \ldots K$, approximating random-motion and/or cardioballistic (CB) artifacts $V_{\text{EMF}}^{(i)}(t)$ are

$$V_{\text{EMF}}^{(i)}(t) \approx \sum_{k=1}^{K} b_{ik} F_k(t), \quad i = 1 \ldots N, K \leq N. \tag{2}$$

The identification criteria for the random head motion are outlined in Zotev et al., 2012. The quantitative classification of the criteria for the random head motion, together with the cardioballistic motions caused by cardiac pulsations, will be detailed in the following sections.

Second, each motion-related IC $F_k(t)$ is band-pass filtered from 0.1 to 20 Hz and integrated over time (with constant $\Delta t = 0.4$ s) to yield two E-REMCOR regressors, $R_1^{(k)}(t)$ and $R_2^{(k)}(t)$, having the same temporal

Fig. 2. (a)–(f) The mean power spectral density of (a) a rapid head movement IC; (b) a cardioballistic motion IC; (c) a mixture of cardioballistic motion and rapid head movement IC; (d) another rapid head movement IC with reflection points in the RM range; (e) a blink IC; (f) a saccade IC. (g)–(h): The rises of peaks B and E in (c) from their neighboring left and right minima when the neighboring right minimum is below 8 Hz. (i)–(j): The rises of the NR peaks G and K in (c) and (e). (k): The rise of the reflection points in (d). In (a)–(f), S_0 is the difference between the maximum and minimum spectrum power below 4 Hz. Motion frequency range (MO) refers to the combined frequency range of RM and CB. RM, CB and MO peaks stand for the peaks found in the RM, CB and MO frequency ranges respectively. In (g)–(h), the peak rise is defined as the average of the left and right rises. In (i), the peak rise is the power difference between the peak G and the minimum between F and G. In (j), the peak rise is the power difference between the peak K and the minimum value between J and K. In (k), the rise of the reflection point H is the power difference between H and I, and the rise of the reflection point I is the power difference between I and $S(\nu = 4.5 \text{ Hz})$.