Improved motion correction for functional MRI using an omnibus regression model

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Head motion is a significant source of noise in fMRI. It can:
- Account for over 30-90% of the fMRI signal
- Cause distance-dependent artifacts in functional connectivity
- Act as a major confounder. Systematically affect data from:
  - Children
  - Elderly
  - Diseases that cause increased head movement

Power et al. (2015)
Ciric et al. (2018)
Removing motion artifact is highly nontrivial
- More pipelines than papers!
- Motion correction involve a sequence of regression steps
- Artifact removed by a linear regression of data on nuisance covariates

Ciric et al. (2018)
Background: The problem with previous approaches

\[ y = X\beta + e \]

- A sequence of linear filtering operations can reintroduce artifacts
  - Regression = Projection onto subspace
  - Sequential projections = Orthogonality lost

\[
\begin{pmatrix}
Y_1 \\
Y_2 \\
Y_N
\end{pmatrix} =
\begin{pmatrix}
X'_{(t_1)} & X^2_{(t_1)} & \ldots & X^L_{(t_1)} \\
X'_{(t_2)} & X^2_{(t_2)} & \ldots & X^L_{(t_2)} \\
X'_{(tN)} & X^2_{(tN)} & \ldots & X^L_{(tN)}
\end{pmatrix}
\begin{pmatrix}
\beta_1 \\
\beta_2 \\
\beta_L
\end{pmatrix} +
\begin{pmatrix}
\varepsilon_{(t_1)} \\
\varepsilon_{(t_2)} \\
\varepsilon_{(tN)}
\end{pmatrix}
\]

\[ e_1 = y_1 - X_1\beta_1 \]
\[ e_2 = e_1 - X_2\beta_2 \]
Goal of this work

- Create an omnibus regression model that
  - combines state-of-the-art artifact suppression algorithms
  - avoids reintroduction of artifacts from sequential regression

- Quantitatively evaluate this model against other commonly used pipelines on a large clinically relevant dataset ($n = 151$)
### Data: Subjects

- **151 subjects** from the Parkinson’s Progression Markers Initiative (PPMI) database
  - 3T Siemens scanner
  - GE-EPI pulse sequence
  - TE=25 ms
  - TR=2400 ms,
  - resolution 68 x 66 x 40 voxels
  - voxel size 3.294 x 3.294 x 3.3 mm
  - scan duration 504 s

- Diseased and non-diseased subjects considered to capture diversity of motion artifact
Methods: Preprocessing

- **Standard steps for fMRI analysis**

  - **Affine realignment**
    - FMRIB’s Linear Image Registration Tool (MCFLIRT)
  - **Skull stripping**
    - FSL Brain Extraction Tool (BET)
    - Analysis of Functional Neuroimages (AFNI) 3dAutomask
  - **Spatial normalization**
    - Coregistration with EPI template in MNI space
    - Symmetric Normalization in Advanced Normalization Tools (ANTS)
  - **Smoothing**
    - 6 mm FWHM Gaussian kernel
  - **<Motion Correction model>**
  - **Functional Connectivity**
    - Gordon 333 ROI atlas
Methods: Nuisance regressors

- Three sets of nuisance regressors:
  - Head motion parameters (HMP)
  - ICA motion components (AROMA)
  - Physiological regressors (PHYSIO)

Ciric et al. (2018)
Patriat et al. (2017)
Pruim et al. (2015)
Methods: Motion correction pipelines

- 4 Pipelines compared
  - Baseline
    - No motion correction

- HMP > AROMA > Physio
  - \( e = ((y - X_{HMP}\beta_1) - X_{AROMA}\beta_2) - X_{Physio}\beta_3 \)

- AROMA > HMP > Physio
  - \( e = ((y - X_{AROMA}\beta_4) - X_{HMP}\beta_5) - X_{Physio}\beta_6 \)

- [AROMA, HMP, Physio]
  - \( e = y - [X_{HMP}X_{AROMA}X_{Physio}]\beta_7 \)
Methods: Quality assessment

- **Framewise Displacement (FD)**
  - To quantify subject’s head motion

  \[
  FD(t) = |d_x(t) - d_x(t-1)| + |d_y(t) - d_y(t-1)| \\
  + |d_z(t) - d_z(t-1)| + |\theta_x(t) - \theta_x(t-1)| \\
  + |\theta_y(t) - \theta_y(t-1)| + |\theta_z(t) - \theta_z(t-1)|
  \]

- **QC-FC correlation (FC-edge wise)**
  - Pearson’s correlation between mean FD and FC edges

Subject 1  Subject 2  Subject n

Pearson’s r

Subject 1 FD  Subject 2 FD  Subject n FD
Methods: Quality assessment

- **QC-FC distance dependence** *(QC-FC-edge wise)*
  - Spearman’s rank correlation between QC-FC correlation of each edge and the Euclidean length of the edge in the brain

- **QC-FC and QC-FC distance dependence metrics** extensively used previously

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*Parkes et al. (2018)*
*Power et al. (2015)*
Results: QC-FC

- All methods performed similarly at reducing motion noise from functional connectivity

![Graph showing motion noise reduction across different pipelines](image)
Results: QC-FC distance dependence

- Omnibus model alone eliminates all significant distance-dependent noise
Discussion: Omnibus regression model empirically robust

- **Motion correction is essential**
  - Without it, baseline images and derived functional connectivity measures are heavily contaminated

- **Omnibus model removed distance-dependent artifact**
  - The only model in the comparison to do so successfully
  - Sequential regression pipelines were significantly contaminated

- **No pipeline could completely remove motion artifact**
  - Sequential and omnibus pipelines had similar median QC-FC
  - There is no ground truth
Limitations

- **Single dataset:**
  - Fairly large (151 subjects) and diverse
  - Replication on independent dataset would further confirm findings

- **No ground truth:**
  - Simulation experiments could address this
Conclusions

- Benefits of omnibus regression model:
  - Significantly reduces distance-dependent artifact compared to standard sequential pipelines
  - Can be used to reduce confounds in fMRI analyses