A Robust Outlier Detection Approach for Scrubbing in fMRI

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StatMIND Statistical Methods for Individualized Neuro-Discovery

Motivation

The main goal is to develop a robust & nonparametric outlier detection method to identify artifact-contaminated fMRI scans.

- **fMRI** data contain **artifacts** from hardware and physiological sources, which **reduce** the signal-to-noise ratio (**SNR**) and violate common statistical assumptions.
- **"Scrubbing"** or removal of the artifactual volumes in fMRI scans is needed to improve the quality of the statistical results.
- We develop a **robust outlier detection approach** that considers the **high dimensional, auto-correlated, non-Gaussian** aspects of fMRI data.

Background

Distance-based outlier detection approaches:

- There exist approaches that use distances to detect outliers such as Mahalanobis distance (MD) and Robust Distance (RD)
- Since MD suffers from "masking" and "swamping" effects, RD has become a popular method to identify outliers.

MCD-based robust distance [1]:

- This RD approach uses the minimum covariance determinant (MCD) estimates of mean and covariance.
- The MCD estimates are calculated by dividing data into two subsets included set and excluded set.
- Included set contains observations located very close to the center of the data which are unlikely to contain outliers so that mean and covariance estimates are obtained from this subset robustly.
- MCD-based RDs of each observation are calculated analogously to MD but using the MCD estimates of the mean and covariance.

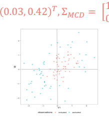
$$MD(x_i) = \sqrt{(x_i - \hat{\mu})^T \hat{\Sigma}^{-1} (x_i - \hat{\mu})}$$

$$RD(x_i) = \sqrt{(x_i - \hat{\mu}_{MCD})^T \hat{\Sigma}_{MCD}^{-1} (x_i - \hat{\mu}_{MCD})}$$

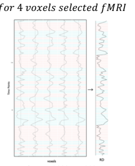
for $MVNormal(\mu, \Sigma)$

$N = 100$, $p = 2$ $\mu = (0,0)^T$ $\Sigma = \begin{bmatrix} 1 & 0.5 \\ 0.5 & 1 \end{bmatrix}$

$M_{MCD} = (0.03, 0.42)^T, \Sigma_{MCD} = \begin{bmatrix} 1.01 & 0.82 \\ 0.82 & 0.75 \end{bmatrix}$



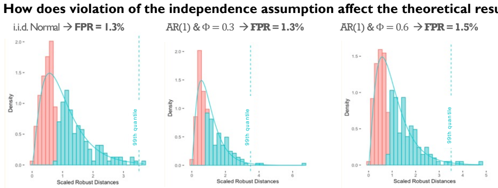
for 4 voxels selected fMRI



Distribution of MCD distances:

- [2] derived an F-distribution of a scaled MCD distance obtained from independently, identically, and Normally distributed data (theoretical distribution).
- Unfortunately, the empirical distribution of MCD distance has often been observed to deviate from the theoretical distribution. Previous work employing MCD distance attempted to improve the distributional fit of the theoretical distribution, for example using median matching [3].

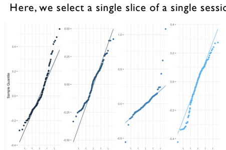
How does violation of the independence assumption affect the theoretical results in fMRI data?

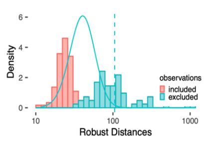


The independence violation of fMRI has a minor effect on the validity of the theoretical F distribution.

How does violation of the normality assumption affect the theoretical result in fMRI data?

- Autism spectrum disorder subjects and typically developing subjects (ABIDE [4])
- Includes 1112 subjects from 17 international sites (Repetition Time ranges 2-3 sec).
- Here, we select a single slice of a single session from a typically developing subject that is relatively free of artifacts for visualization.





The scaled F-distribution failed to fit the distribution of the RD's excluded observations which shows the effect of violation of the Normality assumption.

How can the identicality assumption hold?

Mean and variance detrending can be applied to meet the identicality assumption of the theoretical result.

fMRI data violate the independence and Normality assumptions of [1]'s result.

We develop a nonparametric robust outlier detection method appropriate for fMRI data.

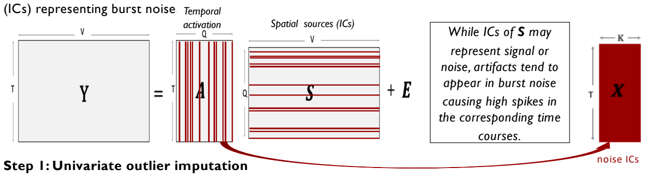
Methodology

The goal is to estimate the upper quantile of MCD distances in outlier-free data (threshold for outliers) using a non-parametric bootstrap approach.

Step 0: Dimension reduction & selection

Goal: *To identify a low dimensional subspace primarily related to artifactual signals.*

We adopt the "ICA projection scrubbing" method of [4] using *kurtosis* to identify independent components (ICs) representing burst noise

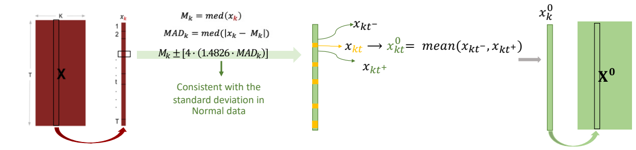


*While ICs of **S** may represent signal or noise, artifacts tend to appear in burst noise causing high spikes in the corresponding time courses.*

Step 1: Univariate outlier imputation

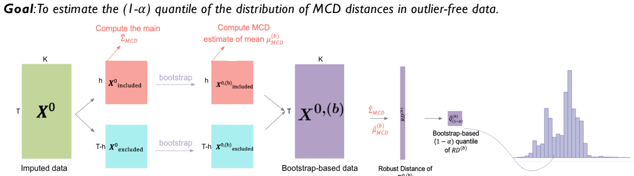
Goal: *To eliminate the effect of outliers on the upper quantile of the distribution of MCD distances.*

We use a robust empirical rule & impute based on neighboring time points.



Step 2: Bootstrap Procedure

Goal: *To estimate the (1-α) quantile of the distribution of MCD distances in outlier-free data.*



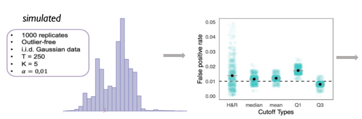
Step 3: Multivariate Outlier Identification

Goal: *To determine a threshold value for outlier detection from the bootstrap-based quantiles* $\hat{Q}^{(b)}_{1-\alpha}$, $b = 1, \dots, B$.

Possible objectives when summarizing across bootstrap samples

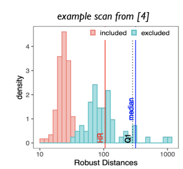
1. *Average false positive rate (FPR) of α → use mean or median*
2. *FPR of at most α with some statistical certainty → use upper quantile*
3. *FPR of at least α with some statistical certainty to maintain power for detecting outlier → use lower quantile*

simulated



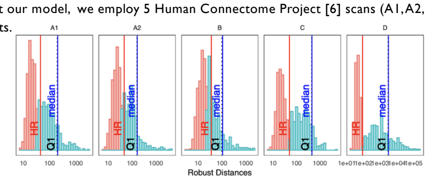
We proceed with median & Q1 to follow objectives 1. & 3.

example scan from [4]



Application on real datasets

To test our model, we employ 5 Human Connectome Project [6] scans (A1, A2, B, C, and D) with 4 unique subjects.



Since both Q1 and median produce threshold values that are very close to each other regardless of the dataset, we adopt the median as a threshold measure for further analysis.

References

A preprint version of this poster: https://github.com/parlakfatma/RobustDetection/blob/main/RobustDetection.pdf

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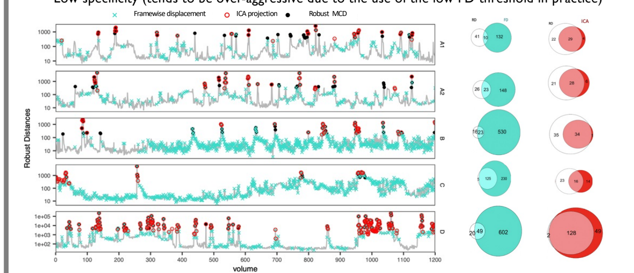
Results: Comparison with other scrubbing methods

We compare our method with the following alternative scrubbing approaches.

1. **A statistical approach (ICA projection scrubbing [5])**
   - Uses the same dimension reduction & selection approach but uses leverage as a non-robust distance measure.
   - masking and/ or swamping effects
2. **A hardware approach (Motion scrubbing based on framewise displacement (FD) [7])**
   - No principled or universally accepted threshold value
   - Low sensitivity (not data-driven, can only identify motion-based artifacts)
   - Low specificity (tends to be over-aggressive due to the use of the low FD threshold in practice)



Conclusions from the comparison with ICA projection

- ICA projection fails to detect some volumes with high RD in A1, A2, B, and C.
- Our robust MCD approach almost doubled the number of identified artifactual volumes that are identified by Leverage in A1, A2, B, and C.
- However, our MCD distance approach seems to be inefficient to detect artifacts in D which may be due to strong deviations from Normality in the univariate outlier imputation step (see Future Work, 2)

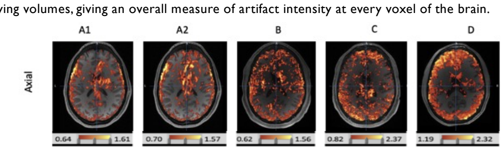
Conclusions from the comparison with Framewise Displacement (FD)

- Many volumes flagged artifacts with motion scrubbing which do not exhibit large MCD distances.
- Some volumes with low motion have large MCD distance which is possibly die to lagged effects of motion or other sources of artifacts.

Results: Spatial patterns of artifacts

Unlike existing scrubbing methods, ICA projection scrubbing allows us to localize the source of burst noise artifacts. We display the spatial patterns of artifactual volumes identified by our method.

- Recall that **X** is obtained by selecting a subset of the detrended columns of **A**. Let A^* and S^* contain only the selected rows and columns of **A** and **S**.
- For each outlying volume t, an image of artifact intensity can be obtained by multiplying t-th row of A^* by S^*.
- Since each of these volumes cannot be displayed due to space constrains, we only visualize the average across all outlying volumes, giving an overall measure of artifact intensity at every voxel of the brain.



- The images show a ring of intensity on the outer edge of the brain, which is often caused by head movements. It is possible that these head movements cause mis-localizing signals, which cause artifacts in the brain volume.
- We see similar spatial patterns for subject A across two different scans.

Future work

1. The method could be tested on non-Normal and outlier-contaminated simulated data.
2. Incorporating multiple imputations into bootstrap samples could provide better results.
3. Our method has been applied to resting-state fMRI data. However, the method could be applied and tested on task fMRI data by regressing the task-related signals.
4. Analyzing more subjects would also allow us to better quantify our method's performance.
5. A comparative analysis with [3] any quantile matching approach could be done upon testing the performance.