A tutorial for resting state fMRI analysis using ANTsR

Introduction

Overview

fMRI issues

- Nuisance signal from CSF and WM [1]
- $\bullet \ \ {\rm Bandpass} \ {\rm filtering}$
- Motion correction [2, 3]
- Global signal[4]

ANTsR implementation

The main fMRI-specific functions are:

- fMRINormalization
- preprocessRestingBOLD (supplants preprocessfMRI?)
- antsBold
- antsMotionCalculation (supplants antsMotionCorr and antsMotionCorrStats?)
- antsSpatialICAfMRI
- filterfMRIforNetworkAnalysis
- frequencyFilterfMRI
- getfMRInuisanceVariables

Helper functions include:

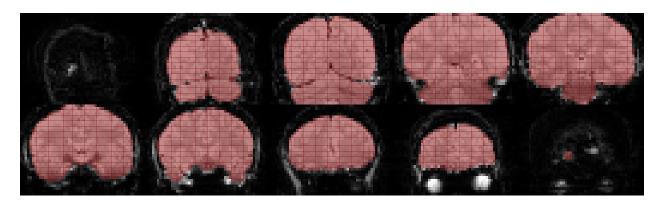
- timeseries2matrix
- matrixToImages
- icaWhiten

Tutorial

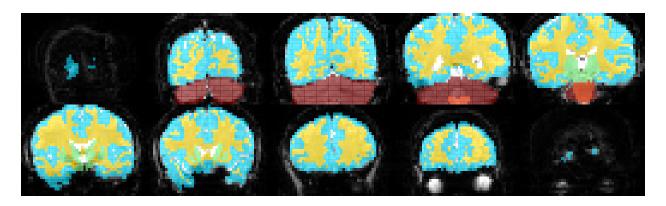
Initialization

Read in input data

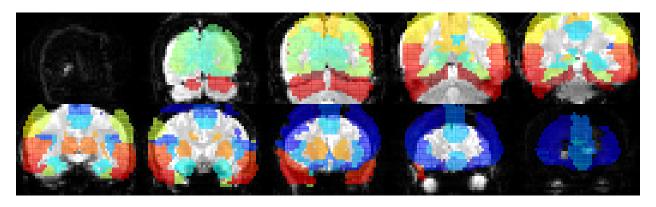
```
# Load the AAL (Automated Anatomical Labeling) data table and the AAL label image.
# Also load the individual subject resting state BOLD images: 4-D bold, 3-D bold
# mask image, and 3-D segmentation (csf, gm, wm, etc.) image.
data( aal, package = 'ANTsR' )
aalLabelTable <- aal
aalFileName <- paste0( dataDirectory, "aal.nii.gz" )</pre>
aalImage <- antsImageRead( filename = aalFileName, dimension = 3 )</pre>
restingStateBoldFile <- pasteO( dataDirectory, "rsbold.nii.gz" )</pre>
restingStateBoldImage <- antsImageRead( restingStateBoldFile, dimension = 4 )</pre>
restingStateBoldMaskFile <- paste0( dataDirectory, "rsboldmask.nii.gz" )</pre>
restingStateBoldMaskImage <- antsImageRead( restingStateBoldMaskFile, dimension = 3 )</pre>
restingStateBoldSegFile <- pasteO( dataDirectory, "rsboldseg.nii.gz" )</pre>
restingStateBoldSegImage <- antsImageRead( restingStateBoldSegFile, dimension = 3 )</pre>
# Let's look at the images to make sure things make sense, e.g. masks are aligned.
# Average of 4-D bold with mask superimposed
restingStateBoldAverage <- getAverageOfTimeSeries( restingStateBoldImage )</pre>
invisible(plot.antsImage(restingStateBoldAverage, restingStateBoldMaskImage,
   alpha = 0.75, ncolumns = 5)
```

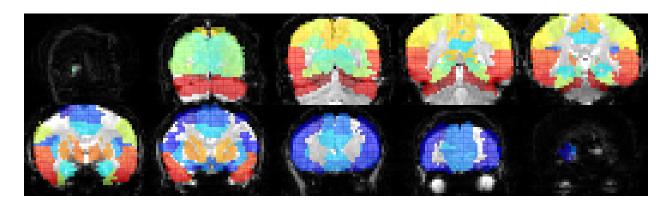


Average of 4-D bold with segmentation mask superimposed
invisible(plot.antsImage(restingStateBoldAverage, restingStateBoldSegImage,
 alpha = 0.9, ncolumns = 5))



Spatially normalize AAL image





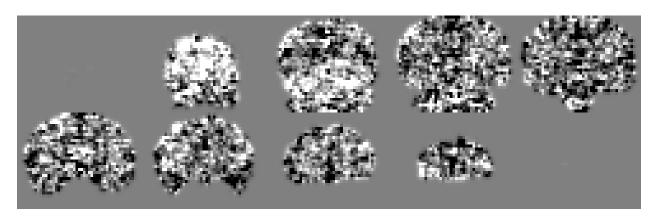
Preprocessing the resting state fMRI data

```
# The evolution of fMRI functionality in ANTsR is still ongoing. It began with # various utility functions to perform different aspects of fMRI preprocessing # (e.g., motion correction, band-pass filtering). The function ``preprocessfMRI`` # was created to join all these components into a single function with slight # enhancements made to create the function ``preprocessRestingBOLD``. We should # probably deprecate the former. Although this basic functionality should suffice # for most users, Brian has recently created the function ``fmriNormalization`` to # take advantage of fMRI with simultaneous structural T1-weighted acquisitions that # have been processed through the ``antsCorticalThickness.sh`` script.
```

Table 1: Returned values from the function preprocessResting-BOLD.

	Length	Class	Mode
cleanBoldImage	1	antsImage	S4
${f maskImage}$	1	antsImage	S4
DVARS	225	-none-	numeric
DVARSpostCleaning	225	-none-	numeric
\mathbf{FD}	225	-none-	numeric
${f global Signal}$	225	-none-	numeric
${ m nuisance Variables}$	1350	-none-	numeric

```
invisible( plot.antsImage(
   getAverageOfTimeSeries( preprocessedRestingState$cleanBoldImage ), ncolumns = 5 ) )
```



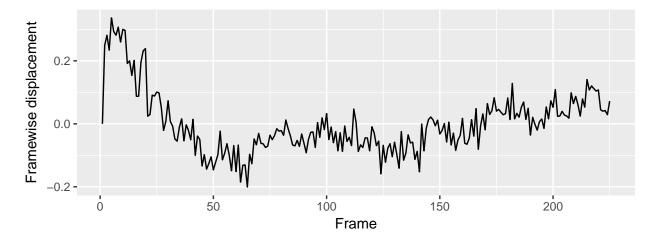
```
# We continue to check the preprocessing by plotting:
# 1. the framewise displacement (FD)
# 2. the global signal before and after regression (globalSignal)
# 3. comparing the DVARS of the original data (DVARS) and the processed
# data (DVARSpostCleaning)
```

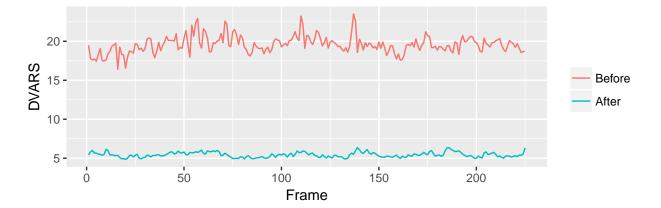
```
# 4. Plot the CompCor nuisance variables
numberOfTimeFrames <- dim( restingStateBoldImage )[4]

# Plot the framewise displacement.

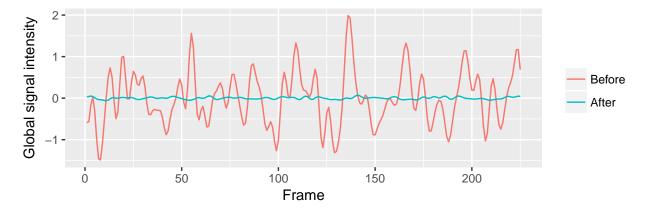
fdDataFrame <- data.frame( Frame = 1:numberOfTimeFrames,
   FD = preprocessedRestingState$FD - mean( preprocessedRestingState$FD ) )

ggplot( fdDataFrame ) +
   geom_line( aes( x = Frame, y = FD ), size = 0.5 ) +
        xlab( "Frame" ) + ylab( "Framewise displacement" ) +
        theme( legend.title = element_blank() ) + theme( aspect.ratio=1/3 )</pre>
```





```
# Plot the global signal. Do we regress out the global signal? Still an open issue.
# Let's just explore the approach to regressing it out afterwards. A better way would
# be to include it as an ``initialNuisanceVariable`` in ``preprocessRestingBOLD()``.
boldMatrix <- timeseries2matrix(</pre>
  preprocessedRestingState$cleanBoldImage, restingStateBoldMaskImage )
boldMatrixGlobalSignalRegressedOut <-
  residuals( lm( boldMatrix ~ scale( preprocessedRestingState$globalSignal ) ) )
globalSignalDataFrame <- data.frame( Frame = rep( 1:numberOfTimeFrames, 2 ),</pre>
       GlobalSignal = c( preprocessedRestingState$globalSignal,
          apply( boldMatrixGlobalSignalRegressedOut, mean, MARGIN = 1 ) ),
       Type = factor( c( rep( "Before", numberOfTimeFrames ),
               rep( "After", numberOfTimeFrames ) ), levels = c( "Before", "After" ) ) )
ggplot( globalSignalDataFrame ) +
   geom_line( aes( x = Frame, y = GlobalSignal, colour = Type ), size = 0.5 ) +
     xlab( "Frame" ) + ylab( "Global signal intensity" ) +
     theme( legend.title = element_blank() ) + theme( aspect.ratio = 1/3 )
```



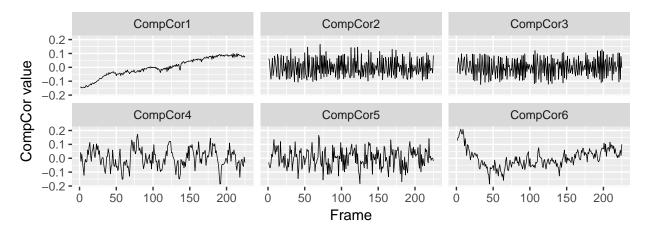
```
# Plot the CompCor nuisance signals. Defined in terms of the PCA decomposition of
# the high frequency components of the BOLD signal.

numberOfCompCorComponents <- ncol( preprocessedRestingState$nuisanceVariables )
whichComponentLevels <- pasteO( "CompCor", 1:numberOfCompCorComponents )
whichComponent <- factor( as.vector(
    matrix( rep( whichComponentLevels, numberOfTimeFrames ),</pre>
```

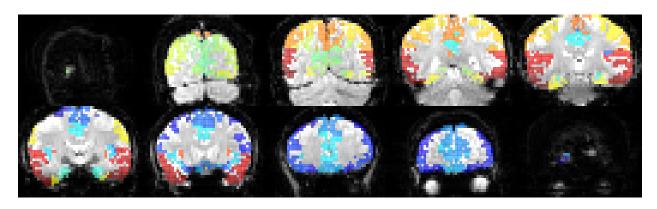
```
nrow = numberOfTimeFrames, byrow = TRUE ) ), levels = whichComponentLevels )

compCorDataFrame <- data.frame(
   Frame = rep( 1:numberOfTimeFrames, numberOfCompCorComponents ),
   WhichComponent = whichComponent,
   Values = as.vector( preprocessedRestingState$nuisanceVariables ) )

ggplot( compCorDataFrame ) +
   geom_line( aes( x = Frame, y = Values ), size = 0.25 ) +
   facet_wrap( ~ WhichComponent, ncol = 3 ) +
        xlab( "Frame" ) + ylab( "CompCor value" ) +
        theme( legend.title = element_blank() ) + theme( aspect.ratio = 1/3 )</pre>
```



Calculate functional connectivity measures



```
# Determine the unique AAL labels and construct the correlation matrix
aalRoiLabelVector <- as.vector( as.array( aalWarpedImage[aalWarpedImage > 0] ) )
aalUniqueLabels <- sort( unique( aalRoiLabelVector ) )</pre>
boldMatrix <- timeseries2matrix(</pre>
  preprocessedRestingState$cleanBoldImage, restingStateBoldMaskImage )
boldLabelMatrix <- matrix( NA, nrow = nrow( boldMatrix ), ncol = length( aalUniqueLabels ) )</pre>
for( j in 1:length( aalUniqueLabels ) )
  currentLabelIndices <- which( aalRoiLabelVector == aalUniqueLabels[j] )</pre>
  if( length( currentLabelIndices ) > 1 )
    {
    boldLabelMatrix[, j] <- rowMeans( boldMatrix[, currentLabelIndices] )</pre>
  else
    boldLabelMatrix[, j] <- mean( boldMatrix[, currentLabelIndices] )</pre>
  }
correlationMatrix <- cor( boldLabelMatrix, boldLabelMatrix )</pre>
correlationMatrix[which( is.na( correlationMatrix ) )] <- 0</pre>
rownames( correlationMatrix ) <- colnames( correlationMatrix ) <-</pre>
  aalLabelTable$label_name[aalUniqueLabels]
# We calculate the significance for each entry.
cor.mtest <- function( mat, ... )</pre>
  {
  mat <- as.matrix( mat )</pre>
  n <- ncol( mat )</pre>
  p.mat <- matrix( NA, n, n )</pre>
  diag( p.mat ) <- 0</pre>
  for( i in 1:( n - 1 ) )
    {
    for( j in ( i + 1 ):n )
      tmp <- cor.test( mat[, i], mat[, j], ... )</pre>
      p.mat[i, j] <- p.mat[j, i] <- tmp$p.value</pre>
  colnames( p.mat ) <- rownames( p.mat ) <- colnames( mat )</pre>
  p.mat
  }
p.mat <- cor.mtest( correlationMatrix )</pre>
uvaColors <- colorRampPalette( c( "#F59A2C", "#F1E5C7", "#E6E7E8", "#46A8C2", "#0D3268" ) )
correlationPlotFile <- pasteO( figuresDirectory, '/CorrelationMatrix.pdf' );</pre>
pdf( height=10, width=10, file = correlationPlotFile )
corrplot( correlationMatrix, method = "circle", diag = FALSE, type = "upper",
```

```
tl.col = "black", tl.cex = 0.48, tl.srt = 45, col = uvaColors( 200 ),
p.mat = p.mat, sig.level = 0.01, insig = "blank" )
invisible( dev.off() )
```

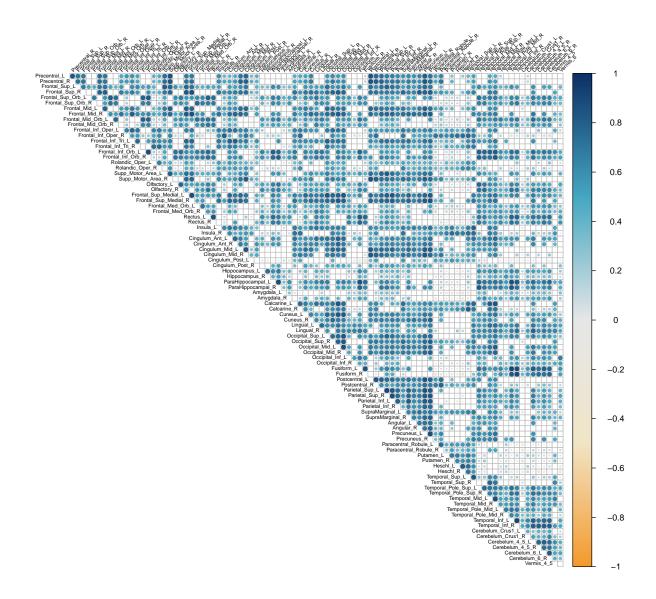


Figure 1: Correlation plot illustrating the functional connectivity relationships between AAL-defined regions.

```
# Now we calculate various graph-based measures from the connectivity relationships.

networkGraph <- makeGraph( correlationMatrix, graphdensity = 0.25, getEfficiency = TRUE )

pander( summary( networkGraph ), style = "rmarkdown",
    caption = "Graph-based connectivity measures." )</pre>
```

Table 2: Graph-based connectivity measures.

	Length	Class	Mode
mygraph	10	igraph	list
centrality	92	-none-	numeric
closeness	92	-none-	numeric
pagerank	92	-none-	$\operatorname{numeric}$
degree	92	-none-	$\operatorname{numeric}$
betweeness	92	-none-	numeric
localtransitivity	92	-none-	numeric
globalTransitivity	1	-none-	numeric
${f strength}$	92	-none-	numeric
$\operatorname{\mathbf{degcent}}$	92	-none-	numeric
${f hubScore}$	92	-none-	numeric
effinv	92	-none-	numeric
${\bf community}$	1	-none-	logical
walktrapcomm	7	communities	list
${\it adjacency} {\it Matrix}$	8464	-none-	numeric

References

- 1. Behzadi, Y., Restom, K., Liau, J., and Liu, T. T. "A Component Based Noise Correction Method (CompCor) for BOLD and Perfusion Based FMRI" Neuroimage 37, no. 1 (2007): 90–101. doi:10.1016/j.neuroimage.2007.04.042
- 2. Power, J. D., Barnes, K. A., Snyder, A. Z., Schlaggar, B. L., and Petersen, S. E. "Spurious but Systematic Correlations in Functional Connectivity MRI Networks Arise from Subject Motion" *Neuroimage* 59, no. 3 (2012): 2142–54. doi:10.1016/j.neuroimage.2011.10.018
- 3. Power, J. D., Mitra, A., Laumann, T. O., Snyder, A. Z., Schlaggar, B. L., and Petersen, S. E. "Methods to Detect, Characterize, and Remove Motion Artifact in Resting State FMRI" Neuroimage 84, (2014): 320–41. doi:10.1016/j.neuroimage.2013.08.048
- 4. Liu, T. T., Nalci, A., and Falahpour, M. "The Global Signal in FMRI: Nuisance or Information?" Neuroimage 150, (2017): 213–229. doi:10.1016/j.neuroimage.2017.02.036