Video Article

A Method for Investigating Age-related Differences in the Functional Connectivity of Cognitive Control Networks Associated with Dimensional Change Card Sort Performance

Bianca DeBenedictis¹, J. Bruce Morton¹

¹Cognitive Development and Neuroimaging Laboratory, Department of Psychology, Brain and Mind Institute, University of Western Ontario

Correspondence to: J. Bruce Morton at jbrucemorton@gmail.com

URL: <http://www.jove.com/video/51003>

DOI: [doi:10.3791/51003](https://doi.org/10.3791/51003)

Keywords: Behavior, Issue 87, Neurosciences, fMRI, Cognitive Control, Development, Functional Connectivity

Date Published: 5/7/2014

Citation: DeBenedictis, B., Morton, J.B. A Method for Investigating Age-related Differences in the Functional Connectivity of Cognitive Control Networks Associated with Dimensional Change Card Sort Performance. *J. Vis. Exp.* (87), e51003, doi:10.3791/51003 (2014).

Abstract

The ability to adjust behavior to sudden changes in the environment develops gradually in childhood and adolescence. For example, in the Dimensional Change Card Sort task, participants switch from sorting cards one way, such as shape, to sorting them a different way, such as color. Adjusting behavior in this way exacts a small performance cost, or switch cost, such that responses are typically slower and more error-prone on switch trials in which the sorting rule changes as compared to repeat trials in which the sorting rule remains the same. The ability to flexibly adjust behavior is often said to develop gradually, in part because behavioral costs such as switch costs typically decrease with increasing age. Why aspects of higher-order cognition, such as behavioral flexibility, develop so gradually remains an open question. One hypothesis is that these changes occur in association with functional changes in broad-scale cognitive control networks. On this view, complex mental operations, such as switching, involve rapid interactions between several distributed brain regions, including those that update and maintain task rules, re-orient attention, and select behaviors. With development, functional connections between these regions strengthen, leading to faster and more efficient switching operations. The current video describes a method of testing this hypothesis through the collection and multivariate analysis of fMRI data from participants of different ages.

Video Link

The video component of this article can be found at <http://www.jove.com/video/51003/>

Introduction

The ability to regulate behavior develops gradually in childhood and adolescence (for review, see Diamond¹). In the Dimensional Change Card Sort task, for example, participants switch from sorting cards one way, such as shape, to sorting them a different way, such as color² (see **Figure 2**). Switching exacts a small performance cost, or switch cost, such that responses are typically slower and more error-prone on switch trials in which the sorting rule changes as compared to repeat trials in which the sorting rule remains the same³. The magnitude of these costs typically gets smaller as children grow older⁴, illustrating the fact that the capacity for behavioral regulation undergoes continued development early in life.

Because complex mental operations, such as switching, involve rapid interactions between multiple brain regions⁵, there is growing interest in relating the development of higher-order cognition to changes in the functional organization of broad-scale cortical networks⁶.

One approach to investigating developmental change in broad-scale networks is through the use of seed-based functional connectivity analysis^{6,7}. The first step in this technique is to consult with available research literature and define *a priori* regions of interest, or ROIs, that seem to be relevant to the behavior in question. These ROIs, or nodes, define the basic skeleton of the network. Next, low-frequency fluctuations in activity (or T2*-weighted signal intensity) in these ROIs are measured for 5 to 10 min while participants are at rest in an MRI scanner. Functional connectivity between any two nodes of the network is then quantified as the correlation of their respective time courses. Nodes that are strongly connected functionally should have similar, and thus highly correlated, signal time courses. On the other hand, nodes that are weakly connected functionally should have dissimilar and thus weakly correlated, signal time courses. To complete a model of the network, edges (or links) are drawn between nodes whose time courses correlate above a chosen threshold. Tests for age-related differences in functional connectivity within a network can be conducted on any single node-to-node connection, or on the topology of the entire set of nodes and edges. These differences in functional connectivity can then be related to measures of cognitive performance collected offline.

In this paper, a different approach is described that is based on group independent component analysis of task-based fMRI data⁸. Independent component analysis (or ICA) is a statistical procedure for blindly revealing hidden sources underlying a set of observations such that the revealed sources are maximally independent. Applied to the analysis of fMRI data, the procedure assumes that each volume is a mixture of a finite number of spatially-independent sources. Using one of a variety of different algorithms, such as the infomax algorithm, ICA then estimates an unmixing matrix, which when applied to the original data yields a set of maximally independent sources, or components. Each component can be thought of as a network, insofar as it comprises of a set of voxels that share a common time course. Group ICA is a particular type of ICA in which a common set of group components is first estimated from an entire data set, and then participant-specific sets of the group

components are computed in a back-reconstruction step. Once an entire data set is decomposed into a set of components, the next step is to discard artifactual components that represent noise sources, and identify theoretically meaningful components that correspond with networks of interest. This can be achieved either by modeling component time courses in the context of a GLM to identify networks that activate in a predicted manner, spatially correlating components with a template of a network of interest, or both. The resulting set of components can then be submitted to a group comparison to test for possible age-related differences in functional connectivity within theoretically interesting networks^{7,9,10}.

Studying age-related changes in functional connectivity through the application of group ICA to task-based fMRI data has several advantages over the application of seed-based techniques to resting-state fMRI data. First, unlike seed-based techniques that focus on a small set of *a priori* defined ROIs, the current group ICA approach utilizes all voxels comprising a volumetric time series. This diminishes opportunities for bias that necessarily arise when a small group of seeds are selected *a priori* as regions of interest. Second, applying functional connectivity analysis (ICA-based or otherwise) to task- rather than resting-state fMRI data has the advantage of allowing network organization and network function to be more directly associated. If, for example, examining the cognitive or behavioral implications of functional connectivity (such as variation in DCCS performance) is a priority, it is important to show that the network of interest is associated with task performance. With resting-state protocols, this is very difficult because the researcher has no record of any cognitive, behavioral, or affective states experienced by the participant during data acquisition. It is therefore impossible to provide direct evidence that any network of interest is relevant for task performance. By contrast, when functional connectivity analysis, such as ICA, is applied to task-data, it is possible to confirm that the network of interest is at least associated with the performance of a task. Finally, ICA is less subject to the adverse influence of noise. Noise sources, such as those associated with subject motion and the cardiac rhythm, have unique spatio-temporal profiles. Therefore, in the context of a group ICA, these sources are isolated and assigned to separate components, leaving remaining components relatively free of these unwelcome sources of variance. Because seed-based analyses use raw time courses in the estimation of functional connectivity, and time courses are, by definition, mixtures of neurophysiological signal and artifactual noise, group differences in functional connectivity estimates can reflect true group differences in underlying neurophysiology, group differences in the structure of noise, or both¹¹.

Protocol

1. Obtain Approval for Working with Human Subjects

2. fMRI Data Acquisition

1. Acquire fMRI data following procedures suitable for young children (see Raschle, *et al.*¹²). Make every effort to limit possible age-related differences in task performance and motion, as these differences introduce unwanted confounds that limit one's capacity to draw inferences about developmentally-relevant differences in brain activation and functional connectivity.

Note: In the current protocol, a repeated-trials version of the DCCS was administered in the form of a block design¹³. Each run includes two 8-trial switch blocks and two 8-trial repeat blocks, where switch blocks consist of 4 switch trials and 4 repeat trials, and repeat blocks consist of 8 repeat trials. The protocol is perfectly suitable for use with event-related fMRI data. However, block designs are nice to work with when first getting acquainted with ICA, as it is easy to see task modulations in the component time courses.

2. Preprocess fMRI data following standard fMRI preprocessing procedures.
 1. Realign all functional images to the same orientation and position. Typically, the first functional volume is used as a reference image for all other volumes to be aligned to.
 2. Coregister the T1-weighted (anatomical) image with the T2*-weighted (functional) scans, so that activation is superimposed onto the correct anatomical location.
 3. Normalize all of the images to a standardized size, space, and position with the selection of a template brain (e.g. Talairach space). This helps to ensure that homologous regions from different subjects are being compared.

Note: Images are warped to Talairach space in the current protocol, although other templates may also be used (for example, MNI {Montreal Neurological Institute} space).

4. Smooth all functional volumes in the data set with a 6 to 10 mm smoothing kernel.
3. Sequester preprocessed volumes into a separate set of directories. Use "Functional scans" as the top directory. Within "Functional scans" include a separate directory for each participant, and within each participant directory, a separate directory for each run. The data is now ready for ICA analysis.

3. Group Independent Component Analysis (ICA)

1. Download and install group ICA software. There are a number of toolboxes available for implementing ICA on different types of neurophysiological data, including fMRI. While any toolbox that performs group ICA would potentially be suitable, the one utilized in the current protocol is called GIFT. GIFT was developed by Vince Calhoun and colleagues at the University of New Mexico. The GIFT toolbox is a set of MATLAB scripts that works together with SPM, a well-known fMRI analysis package. Both can be downloaded for free from the internet (GIFT: mialab.mrn.org/software/gift/index.html#; SPM: www.fil.ion.ucl.ac.uk/spm/). Once downloaded, add the GIFT toolbox and all sub-directories to the MATLAB search path and save path file.
2. Computing a group ICA on fMRI data using GIFT makes substantial demands on RAM memory. The precise demands on memory will vary depending on the number of participants, the amount of data collected from each participant, and the resolution of the data. To avoid memory issues, it is best to run the ICA analysis on a server. If running the analysis on a local computer, the RAM requirements can be estimated through the use of a script "icatb_mem_ica.m" that is part of GIFT.

3. Set-up or parameterize the analysis. Do this by modifying a pre-existing batch script called "Input_data_subjects_1.m" that is stored in GIFT under "icatb_batch_files".

Note: This can also be done by using GIFT's Graphical User Interface. However, it is much easier, with a bit of practice, to set up the analysis by modifying this pre-existing script.

1. Specify data modality as fMRI
 2. Specify Type of Analysis as ICA with ICASSO. This will ensure the ICA is run with the ICASSO procedure. ICASSO estimates the reliability of the decomposition by running the ICA several times starting with different random seeds. It then tests the similarity of each result by means of clustering. Use of ICASSO is recommended as mean of checking the quality of the ICA decomposition, but will considerably extend the time it takes GIFT to complete the analysis.
 1. To run the ICA with the ICASSO procedure, select '2' under "Type of analysis" and then parameterize the ICASSO procedure in the succeeding lines of the setup file.
 3. Maximize the performance of the group PCA by choosing '1' under Group PCA performance settings. Consider setting this parameter to '2' should problems of insufficient RAM memory occur.
 4. To enable later sorting of resulting components using predictors from a standard SPM design matrix, specify whether or not there are different matrices for different subjects.
 5. Specify where the preprocessed functional data are stored and whether an SPM.mat file containing the design matrix is stored together with the preprocessed functional data.
 1. The most straightforward way of getting GIFT to read the data is if every participant has the same number of runs, and the data directory is structured as described in Step 2.3 under fMRI data acquisition. If so, then under DataSelectionMethod, chose '1' for Method 1, and complete the parameter "sourceDir_filePattern_flagLocation" by including the filepath where the data are stored, the file format of the data, and a statement indicating that individual sessions are stored as subdirectories within each subject folder.
 6. Indicate the directory where the output of the analysis should be written. Do not write the results to the same directory where the data are stored.
 7. Provide a prefix that will be added to all output files.
 8. Provide a filepath to a mask. All volumes submitted to ICA are masked. GIFT provides a default mask. For this work, an in-house script to generate a mask from the data that will be submitted to ICA. At a minimum, the mask should eliminate skull, extra-cerebral space, and especially the eyeballs. Signal from eyeball voxels will show very large fluctuations during a run and will therefore have a sizable influence on the structure of the final components. **Figure 3** illustrates what a good mask should look like.
 9. Specify the type of group PCA to be used. Use 'subject specific.'
 10. Specify the back-reconstruction method. In this stage, individual subject IC's and their associated time courses are computed from the results of the group analysis. GICA is recommended for obtaining the best time courses, although there is considerable discussion in the literature on this point.
 11. Specify data pre-processing type. Use intensity normalization to avoid non-numerical values (*i.e.* infinities, and NaN's) in the output. In this example, we chose the default of '1'.
 12. Specify the type of PCA (we use standard) and accept default values under PCA Options. GIFT performs a PCA on each run of each participant and retains a number of components equal to the number of sources to be unmixed in the ICA. The PCA serves two important purposes. First, it helps to eliminate sources of noise that are unique to each participant and each run. Second, it makes the computational demands of the analysis more tractable.
 13. Specify how many PCAs to run on the data before the ICA (2 is recommended). As well, specify how many components to retain after each PCA (if running 2, it is recommended that the number of components retained after the first PCA is twice the number retained after the second).
 14. Specify how the data should be scaled. For this work, z-score scaling was used.
 15. Choose a blind source separation algorithm for the ICA. For this work, Infomax was used. GIFT offers a choice of at least 10 different algorithms.
 16. Remaining parameters can be left as is.
4. Once the ICA is completed, select from among available components those that are of potential theoretical interest. Through the GIFT GUI, choose component selection: spatial sorting sorts the spatial components by means of spatial correlation with a pre-existing template; temporal sorting sorts the component time courses by means of linear predictors from the SPM design matrix that you can store with the data (see 3.3.5).

Note: Both approaches to component selection have utility. However, when working with task data, temporal selection criteria are particularly useful, as they provide a means of verifying that the selected component was activated by the task. In the case of the DCCS, use of temporal sorting can be used to confirm that the selected component was more active during switch blocks than during repeat blocks.

5. Test whether child and adult versions of these selected components differ. Aggregate child and adult components of interest into two separate groups and test by means of a two-sample t-test regions where the components vary. This is relatively easy to do through the GIFT GUI.

Representative Results

Group ICA, even on a relatively small fMRI data set, will return a set of components comparable to those observed in other studies. **Figure 4** is a superimposition of 5 such components and their associated time courses unmixed from a sample of 12 children and 13 adults, with approximately 800 volumes per participant. As shown in **Figure 4**, default mode, fronto-parietal, cingulo-insular, and visual networks can readily be seen from the results of this decomposition. As well, notice how easy it is to discern the block design in the time courses of the visual and default mode components.

A successful ICA decomposition should be reliable. The reliability of the decomposition can be evaluated by examining the output of the ICASSO procedure. **Figure 5** shows part of the ICASSO output for a reliable decomposition performed in GIFT.

When using spatial correlation as a basis for component selection, it is good to report the correlation coefficient and present the template and the selected component together for visual comparison. In a recent paper, spatial and temporal sorting were both used to identify a fronto-parietal component that was both spatially correlated with a template of an executive control network, and was more active for switch blocks than repeat blocks in the DCCS. **Figure 6** shows the template image and the selected component. Notice that there is good correspondence between the two images.

Group comparisons of component maps can be used to test for age-related differences in functional connectivity for the selected component. Voxels that appear on the resulting maps are those that "load" more strongly on the selected component for one group than another. In other words, these are voxels in which the time course of the voxels are more similar to the time course of the component (*i.e.* show strong functional connectivity to the network) for one group than for another. Following this procedure, we compared child and adult right fronto-parietal components - a component we confirmed was spatially correlated with a template of an executive control network and was activated by the DCCS - and found that voxels within lateral prefrontal, anterior cingulate, and parietal cortex loaded more strongly on this component in adults than in children¹⁴. This contrast image is shown in **Figure 7**.

Figure 1. Overall scheme of the experiment.

Accuracy

DCCS: Block design

Response Time

Accuracy

Figure 2. The block-design variant of the Dimensional Change Card Sort (DCCS) task. In the standard version of the task, children sort bivalent test cards into bins marked by bivalent targets that match each test card on a single dimension. Children sort a small number of cards one way (e.g. by color), and then are instructed to switch and sort the same cards a new way (e.g. by shape). The outcome measure is whether children correctly switch sorting criteria. (a) In the block-design variant, the task is computer-administered. Two bivalent targets appear on the screen throughout the task. Test cards are presented centrally for 1,750 msec and participants sort the cards by means of a button-press. Trials in which the sorting criterion is different than on the previous trial are switch trials; trials in which the sorting criterion is the same as on the previous trial are repeat trials. (b) Individual trials are presented in 8-trial blocks. Switch blocks contain 4 repeat and 4 switch trials; repeat blocks contain 8 repeat trials. (c, d) Outcome measures are the difference in response time and accuracy across switch and repeat blocks.

Figure 3. Group ICA results: representative components. (a) A composite image of 5 representative group components from an ICA of 11 adult and 12 child participants. The model order was 20. Runs were 78 volumes long. Components are color-coded (red = visual; blue = left fronto-parietal; green = default-mode; pink = right fronto-parietal; orange = cingulo-insular). **(b)** Component timecourses and block design overlay. From visual inspection, it is evident that task performance is associated with an increase in activity in visual and left fronto-parietal components and a decrease in activity in the default-mode network. These intuitive results illustrate how use of a basic block design makes it relatively easy to evaluate the quality of an ICA decomposition. [Please click here to view a larger version of this figure.](#)

Figure 4. Group ICA results: representative components. (a) A composite image of 5 representative group components from an ICA of 11 adult and 12 child participants. The model order was 20. Runs were 78 volumes long. Components are color-coded (red = visual; blue = left fronto-parietal; green = default-mode; pink = right fronto-parietal; orange = cingulo-insular). (b) Component time courses and block design overlay. From visual inspection, it is evident that task performance is associated with an increase in activity in visual and left fronto-parietal components and a decrease in activity in the default-mode network. These intuitive results illustrate how use of a basic block design makes it relatively easy to evaluate the quality of an ICA decomposition. [Please click here to view a larger version of this figure.](#)

Figure 5. Representative ICASSO output from a highly reliable decomposition. To test the reliability of any single decomposition, the ICA is run multiple times and the results across separate runs are plotted. This plot provides a concise summary of the results of all iterations of the ICA and allows one to visually assess the similarity or divergence in the solutions that emerge from different iterations of the ICA. Single points represent single run estimates of particular components. The light blue circles represent the centrotypes of clusters of single observations. Compact and isolated clusters that fall within the boundary of the centrotypes suggest good reliability. Scattered clusters that stray outside the boundary of the centrotypes suggest poor reliability. For most components in this figure, there was a high degree of similarity in the component across different iterations of the ICA. Components 58, 59, and 60 showed some minor variability across different iterations. [Click here to view larger image.](#)

Figure 6. The executive control template and the selected right fronto-parietal component, overlaid on identical slices from a high resolution anatomical scan, appear quite comparable. Spatial correlation can be used to quantify and statistically test for the similarity of these maps. [Please click here to view a larger version of this figure.](#)

Figure 7. Subtracting right fronto-parietal components of children from adults reveals regions whose functional connectivity to the selected executive network is stronger for adults than for children. These regions include medial prefrontal cortex and ventral tegmental area (see sagittal slice) and dorsolateral prefrontal and inferior parietal cortex (see axial slice). [Please click here to view a larger version of this figure.](#)

Discussion

Higher-order mental operations, such as the ability to switch sorting rules, develop rapidly throughout childhood and adolescence. Because these mental operations involve interactions between multiple distributed brain regions, there is growing interest in exploring the relationship between the development of higher-order cognition and age-related changes in the organization of broad-scale cortical networks. We present a method based on group independent component analysis applied to task-based fMRI data as a means of examining this relation directly.

As is true of any between-group comparison study, the success of the method is predicated on high-quality fMRI data from both adults and children. Group differences in motion-related artifact can have serious implications for the quality of the ICA decomposition and lead to spurious differences in the resulting components. Group differences in task performance can be potentially problematic as well, as they will undermine the viability of temporal sorting for all groups. If for example one group shows a large performance difference between experimental and control trials, but a second group does not, it will be hard to identify components that one could claim are linked to a task the same way for both groups. Therefore, be sure to take the time to collect your data properly. Follow pediatric neuroimaging protocols described well by Raschle *et al.*, 2009, and take time to develop cognitive-behavioral methods that mitigate between-group differences in performance/strategy-use.

Trouble-shooting/Caveats

Group ICA is an advanced multivariate technique, but one that is being adopted more and more frequently for a variety of fMRI analysis applications, including denoising, functional connectivity estimation, and imaging dynamic brain connectivity states (see below). For first time users, setting-up and interpreting the output of a group ICA will be a little disorienting. But, with a bit of practice/trial and error, things become much more straightforward. The following suggestions aided us tremendously in getting over our initial uncertainties.

First, start small and use data collected with a simple design. Block designs with 10 to 20 sec rest periods between blocks are ideal in this respect. To begin, try running an ICA run on 3 or 4 100-volume runs of block data from 4 or 5 participants. This will not yield publishable findings, but will run relatively quickly and produce sensible spatial components. As well, it should be relatively easy to see the block design represented in the time course of occipital components and default components, with these time courses positively and negatively associated with the task respectively (see **Figure 4**). This is a good way to quickly gain confidence with the procedure before scaling the analysis up to include an entire data set. Should things not be working out at this point, go back to your preprocessed images and check for data quality issues (e.g. severe motion artifacts, bad slices, etc.). If spatial components are extremely sparse (*i.e.* spatial ICs consist of many small scattered clusters of voxels), check to make sure volumes were smoothed - an 8-mm FWHM kernel is recommended.

Starting with a small data set is also a good way to get a feel for choosing the model order, or the number of components to include in a model. While there is no one right way to make this decision, there are a number of guidelines to consider. First, as GIFT implements a form of spatial ICA, the maximum number of components that can be unmixed from a volumetric time series is equal to the number of volumes in the timeseries. Second, GIFT computes an estimate of the dimensionality of the data using PCA, and these estimates are usually in the range of 18 to 22 components. Together, these considerations provide an upper and lower bound for your choice of model order. After that, it's up to you. Simply remember that components that were spatially aggregated at a lower model order will split apart into separate but statistically-related components as model order is increased. If you plan to select a component using a template from another research group, you might consider choosing a model order similar to what was used in the analysis that generated the template, as this will increase the likelihood that the component you are searching for remains spatially intact in your decomposition.

There are a few caveats that may be worth considering before moving forward with ICA. First, spatial components provide a basis for examining age-related differences in functional connectivity, but tell you nothing about how or even whether regions that comprise a component interact. Two regions can load on a component because of bidirectional, unidirectional, or indirect (*i.e.* via a third region) connectivity, or even by statistical accident. Therefore, be cautious in drawing conclusions. Second, if your interests are in testing a particular hypothesis about how regions interact and how these interactions change with development, you will need to consider additional analyses or methods. One possibility is to use the IC time courses and test for effective connectivity among components by means of lagged correlation analysis. Tools for these kinds of analyses are available as part of GIFT's Functional Network Connectivity (or FNC) toolbox. Alternatively, you may want to consider an entirely different approach such as Dynamic Causal Modeling (DCM), available in SPM8.

Advantages of existing methods

The principal strength of the current method is that it affords at least some basis for inferring the function of targeted brain networks. To the extent that networks are identified on the basis of covariance in signal time courses of different voxels, and these covariance estimates are a stable measure of functional connectivity, ICA and seed-based approaches lead to converging images of cortical networks whether they are applied to resting-state or task based fMRI data¹⁵. The important advantage of applying group ICA to task-data is that it is possible to form preliminary hypotheses about the function of selected networks. In the current method, we leverage this fact for the purpose of linking a particular cognitive operation - rule-switching - to a particular network. Were the same network imaged while participants were at rest, it would not be possible to associate a selected network with a particular behavior, at least not directly.

Additional applications and future directions

Group ICA has shown great potential for uncovering group differences in the organization and functioning of cortical networks, including those related to age, diagnostic status, personality, and so on¹⁶. Multivariate procedures such as ICA are also well-suited to the identification of associations across different data modalities, and ICA in particular has proven quite fruitful for identifying linkages between fMRI and structural MRI data, fMRI and EEG, and fMRI and genetics¹⁷.

One exciting new direction is the use of ICA in exploring dynamic changes in cortical connectivity¹⁸. To date, cortical networks have been conceptualized as architecturally static, at least over short timescales. Recent work however, has begun examining whether functional connectivity both within and between networks changes dynamically over relatively short timescales, possibly in association with changes in

cognition and behavior. Preliminary findings, based primarily on resting-state data, suggest that the brain cycles through a variety of microstates, each characterized by a distinct constellation of connections among different brain regions. One obvious extension of the current method would be to examine dynamic changes in network connectivity in association with changes in cognitive demands through the application of group ICA to task data. Applied to fMRI data collected from participants of different ages, the results could potentially reveal differences in how younger and older brains dynamically adapt to cognitive and behavioral challenges.

Disclosures

There are no competing financial interests.

Acknowledgements

This research was made possible with the support of grants from the National Science and Engineering Research Council (NSERC) to J. Bruce Morton.

References

1. Diamond, A. Normal Development of Prefrontal Cortex from Birth to Young Adulthood: Cognitive Functions, Anatomy, and Biochemistry. *Principles of Frontal Lobe Function*. Stuss, D.T., & Knight, R. T. eds. 1-38 (2002).
2. Zelazo, P. D. The Dimensional Change Card Sort (DCCS): a method of assessing executive function in children. *Nat Protoc.* **1**, 297-301, doi:10.1038/nprot.2006.46 (2006).
3. Monsell, S. Task switching. *Trends Cogn Sci (Regul Ed)*. **7**, 134-140 (2003).
4. Crone, E. A., Bunge, S. A., van der Molen, M. W., & Ridderinkhof, K. R. Switching between tasks and responses: a developmental study. *Developmental Science*. **9**, 278-287, doi:10.1111/j.1467-7687.2006.00490.x (2006).
5. Cole, M. W., & Schneider, W. The cognitive control network: Integrated cortical regions with dissociable functions. *Neuroimage*. **37**, 343-360, doi:10.1016/j.neuroimage.2007.03.071 (2007).
6. Fair, D. A., et al. Development of distinct control networks through segregation and integration. *Proc Natl Acad Sci USA*. **104**, 13507-13512, doi:10.1073/pnas.0705843104 (2007).
7. Uddin, L. Q., Supekar, K., & Menon, V. Typical and atypical development of functional human brain networks: insights from resting-state fMRI. *Frontiers in systems neuroscience*. **4**, 21, doi:10.3389/fnsys.2010.00021 (2010).
8. Calhoun, V. D., Adali, T., Pearlson, G. D., & Pekar, J. J. A method for making group inferences from functional MRI data using independent component analysis. *Human brain mapping*. **14**, 140-151 (2001).
9. Fransson, P., et al. Resting-state networks in the infant brain. *Proceedings of the National Academy of Sciences of the United States of America*. **104**, 15531-15536, doi:10.1073/pnas.0704380104 (2007).
10. Supekar, K., & Menon, V. Developmental maturation of dynamic causal control signals in higher-order cognition: a neurocognitive network model. *PLoS computational biology*. **8**, e1002374, doi:10.1371/journal.pcbi.1002374 (2012).
11. Power, J. D., Barnes, K. A., Snyder, A. Z., Schlaggar, B. L., & Petersen, S. E. Spurious but systematic correlations in functional connectivity MRI networks arise from subject motion. *Neuroimage*. **59**, 2142-2154, doi:10.1016/j.neuroimage.2011.10.018 (2012).
12. Raschle, N. M., et al. Making MR Imaging Child's Play - Pediatric Neuroimaging Protocol, Guidelines and Procedure. *J. Vis. Exp.* (29) (2009).
13. Morton, J. B., Bosma, R., & Ansari, D. Age-related changes in brain activation associated with dimensional shifts of attention: an fMRI study. *Neuroimage*. **46**, 249-256, doi:10.1016/j.neuroimage.2009.01.037 (2009).
14. Ezekiel, F., Bosma, R., & Morton, J. B. Dimensional Change Card Sort performance associated with age-related differences in functional connectivity of lateral prefrontal cortex. *Developmental Cognitive Neuroscience*. (2013).
15. Calhoun, V. D., Kiehl, K. A., & Pearlson, G. D. Modulation of temporally coherent brain networks estimated using ICA at rest and during cognitive tasks. *Human brain mapping*. **29**, 828-838, doi:10.1002/hbm.20581 (2008).
16. Allen, E. A., et al. A baseline for the multivariate comparison of resting-state networks. *Front Syst Neurosci*. **5**, 2, doi:10.3389/fnsys.2011.00002 (2011).
17. Calhoun, V. D., Liu, J., & Adali, T. A review of group ICA for fMRI data and ICA for joint inference of imaging, genetic, and ERP data. *Neuroimage*. **45**, S163-172, doi:10.1016/j.neuroimage.2008.10.057 (2009).
18. Allen, E. A., et al. Tracking whole-brain connectivity dynamics in the resting state *Cerebral Cortex*. (2012).