Australian Journal of Basic and Applied Sciences, 8(18) December 2014, Pages: 79-83

AENSI Journals

Australian Journal of Basic and Applied Sciences

ISSN:1991-8178

Journal home page: www.ajbasweb.com

Detection and Delineation of Attention Deficit Hyperactivity Disorder Using a Mathematical Model

Dr. Nachamai, M.

Christ University, Department of Computer Science, Science, Box. 560029. Bangalore. India.

ARTICLE INFO

Article history:
Received 19 August 2014
Received in revised form
19 September 2014
Accepted 29 September 2014
Available online 12 November 2014

Keywords:
Attention deficit hyperactivity disorder, Naive Bayes Classifier, MRI images, MatLab

ABSTRACT

Attention Deficit Hyperactivity Disorder is a neuropsychiatric disorder is not a quantifiable disorder or in simple terms cannot be measured or defined perfectly with the percentage of neither deficiency, identification nor the treatment. The nature of this disorder makes it an arduous task to identify and measure this disorder. There are no automatic or straight forward methods available for identification. The available methods are qualitative and do not support treating this disorder. The research work is aimed in identifying this disorder and would give a precise quantitative definition for the same. A ten feature, feature-set based on the MRI images of the affected subjects was adopted to identify this deficiency in this work. A probability based classifier was deployed to classify the inputs as affected with the deficiency or not. The work has successfully yielded 87.5% true positive rate in identifying this deficiency.

To Cite This Article: Dr. Nachamai, M., Detection and Delineation of Attention Deficit Hyperactivity Disorder Using a Mathematical Model. ***Aust. J. Basic & Appl. Sci.,*** *8(18): 79-83, 2014*

INTRODUCTION

There are numerous neuropsychiatric disorders. One such disorder is ‘Attention Deficit Hyperactivity Disorder’ (ADHD). This can be identified in children above 10 years and it continues into the teenage and adulthood. There are no formal tasks or tests existent for identifying or diagnosing this disorder. Children with this disorder find it difficult to concentrate on any task or activity for evenatime duration of 2 seconds. The attention surpasses and they tend to move to another task. So there is lack of attention in any task thatactually leads to hyperactive behaviour. Identification of this disorder happens to be a great challengebecause neither the root cause nor the symptoms are identifiable, until the effect is shown as a disorder. This disorder is surely connected to the brain activity, but to what extent? Where exactly the problem lies? What activity in brain exhibits this disorder? Is connectivity in brain not complete? Since tasks are not completed,these entireset of questions still happen to be open for doctors and researchers to answer. Across the globe invariably there exist ADHD people. This happens to be a universal disorder so can’t be claimed under geographic conditions or genetic disorders.

There are a few qualitative techniques adopted to identify this disorder. One general technique is conducting an interview. The interview consistsof a set of questions for the parents, teachers and the children. The responses are collected at regular intervals. This data can’t be trustworthy as it involves too many human personnel and each one’s belief, perception and measure on one object would not be the same. No proven results are announced with the existing methods for the identification of ADHD. ADHD is not age specific, it is irrespective of age, a psychiatric disorder. The quantitative method or formal technique to find ADHD is still not framed. One major reason for this could be the various categories under this disorder and its sensitivity. ADHD can be catalogued as a behavioural disorder. A statistic says that 4% of adults and 5% of children are identified to have ADHD in United States. ADHD can be described as a disorganized behaviour which characterizes inattention, impulsivity and over activity.

Literature Review:

Magellan health had released a clinical practice guideline for patients with ADHD, which states an evidence based framework for practioners clinical decision making with child, adolescent and adult patients. This article included medications revised for the children who get a sudden heart arrest, that shows how serious are this ADHD dysfunction of brain (Carlton, T.G., 2014). The American psychiatric publishing has clearly stated that the DSM-5 had made special effort to address adults affected by ADHD. It is an alarming information that the

Corresponding Author: Dr. Nachamai, M., Christ University, Dept. Of Computer Science, Science, Box. 560029. Bangalore. India.

ratio is increasing in adults (Campbell, S., 2000). Soumyabrata Dey *et al* (2014)., the ADHD subjects were modelled as graphs, they cannot be directly classified so a mapping of the features into the graph had been attempted. The classification on the projected space was done by using a support vector machine. Sina *et al*., has implemented a clinical tool that would diagnose psychiatric illness using functional MRI images. The results obtained would be of assistance to the physicians treating the ADHD subjects. Emma *et al* (2014), had attempted to study the language problems in children with ADHD, this gives a clear indication that there would also exist a speech problem in connection to the ADHD disorder. The regional results have proved a higher prevalence of language problems after adjustment with socio demographic features and comorbidities. In 2009 the Australian guidelines on ADHD report, gives an extensive history of all dimensions of ADHD. It voices all aspects of ADHD from clinical practice to MRI diagnosis of the subjects (Australian Guidelines on Attention Deficit Hyperactivity Disorder). The university of Michigan health system in the release of guidelines for clinical care of ADHD, has stated 'recognize and treat ADHD early and take primary care', as its primary objective. As stated recognition is not an easy task (Guidelines for clinical care" Faculty Group Practice, University of Michigan Health System). According to the evidence update of The National Institute for care and excellence July 2013, a complete and update diagnosis and management of ADHD in children, teen agreed and adults is stated. The new evidences taken and the uncertainties prevailing is also released in this report (Evidence update 45). Naomi *et al* (2014)., has evaluated the efficacy of second and fourth grade children with neuro feedback, in cognitive training and some under controlled conditions. Children who received neuro feedback had shown a better improvement was the conclusion. This gives enough hope that the generated output can be used for treating the children. The white paper by S.Toung *et al* (2014)., gives a clear overview of the current and long term outcomes of ADHD and the state of art methodologies used for improving the recognition till date. Xiang-zhen had attempted to learn the head motion patterns in children with ADHD through their resting state brain imaging. The results have proved that taking head motions into account during scanning are helpful for ADHD diagnosis and treatment with neuro-imaging (Kong, Xiang-zhen, 2014). The work by Laura *et al*., (2012) gave an automatic method for external and internal segmentation of nucleus in MRI. The results have proved the manual annotation and system output have correlated well when tested on the ADHD dataset. Ariana Anderson *et al*., (2013) has done a matrix factorization of multimodal MRI, FMRI, and phenotypic data from ADHD subjects can be interpreted by latent dimensions. They are not treated as independent data, a subset of features from each modality map is taken into the generative model. Fabio *et al*., (2011) has diagnosed ADHD by testing ADHD children on a supermarket game. Children categorised according to the DSM-IV symptoms were asked to play the game and a feature set was captured. Two algorithms Naive bayes and decision tree was deployed and had shown good results.

METHODS AND MATERIALS

The aim of the work is to identify whether the subjects are affected with ADHD or not. The flow of the system is depicted in the figure 1. A sample image file is taken and features are extracted, the features are input to a Naive Bayes Classifier(NBC), along with the class label in the training phase. In testing phase this class label is predicted for an unseen or new sample data. The figure 1a shows the training phase of the system where the class label is also given as an input and the figure 1b shows the testing phase where the predicted class label is the output.

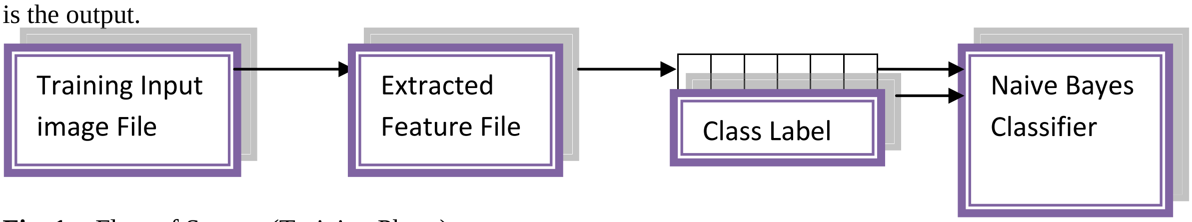


Fig. 1a: Flow of System (Training Phase).

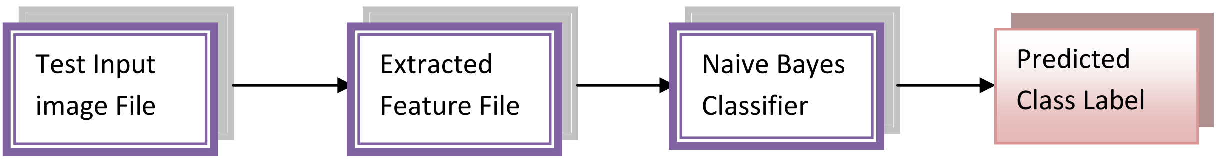


Fig. 1b: Flow of System (Testing Phase).

The dataset for the work was taken from NITRC, NeuroBurea, ADHD200 processed data. The input dataset was a ten-columned data available as a .csv file. The data was captured for different subjects in the form of MRI scan images. The image data is in processed form and represented as ten different attributes namely column1: Max Motion(mm),column2:Max Motion Time Point,column3:Max Rotation(Degree),column4: Max Rotation

Time Point, column5:Max X(mm), column6:Max Y(mm), column7: Max Z(mm), column8: Max Roll(Degree), column9: Max Pitch(Degree), column10: Max Yaw(degree). The ten-columned input training data distribution is uniform or even, throughout the dataset taken. It is depicted through the uniformity input data plot in figure 2, where the diagonal of the figure plots, the histograms of the input vectors. The entries other than the principal diagonal show the scatter plots of the features that exist in the dataset.

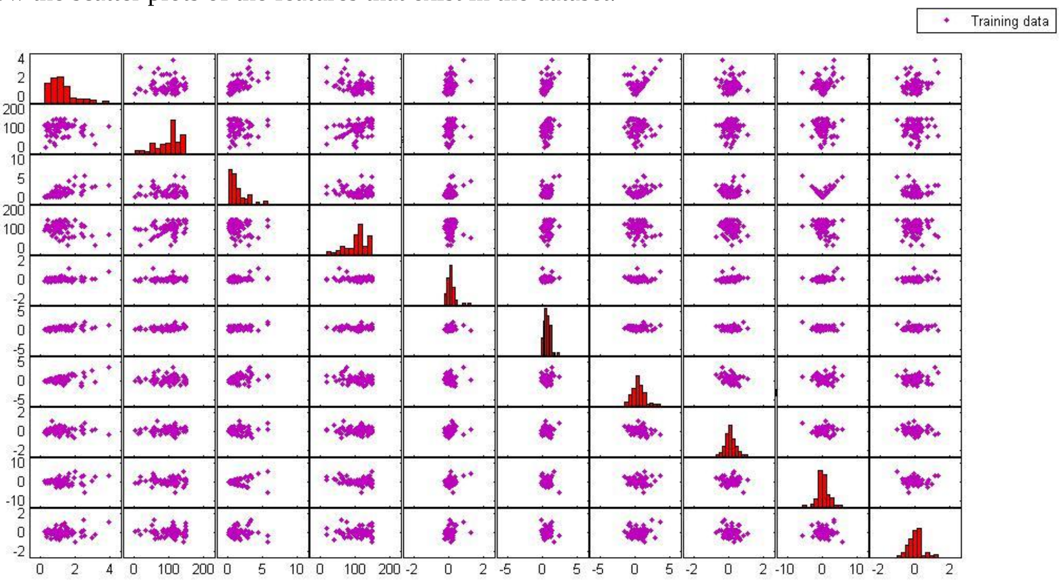


Fig. 2: Uniformity Input Data Plot.

A NBC was used for classifying the data into the categories as affected with ADHD or not affected with ADHD. It is a probabilistic classifier which is capable of identifying or predicting for a given sample input from a set of classes, rather than predicting a class for the sample. The classifier follows Bayes theorem, which is a conditional model and can be written as

$$Posterior\ probability = \frac{PriorProbability \times Likelihood}{evidence}$$

NBC assume that attributes have independent distributions, it is a fast and space efficient classifier. One major advantage for the choice of NBC for ADHD classification is, it is not sensitive to irrelevant features. It can handle both real and discrete data. NBC can be trained very efficiently in a supervised learning environment. If the conditional independence holds good NBC will converge quicker than other models, so with less training data it would perform better. Its main advantage is it can’t learn relationships between features which do not affect the current problem as in real time there is no single discretion on which factor or attributes contribute significantly for ADHD. Since the classifier assumes that the value of a particular feature is unrelated to the presence or absence of any other parameter or feature, given the class variable it can assure performance. Since the identification of ADHD in the sample of subjects does not depend on any particular feature. Therefore it becomes a mandate to provide and make a conclusive classification using all the features in the dataset. The classifier following normal distribution was applied and the implementation was done in MatLab. The idea is to calculate the posterior probability to identify which is greater. For classification as Class-I affected with ADHD the posterior is given by

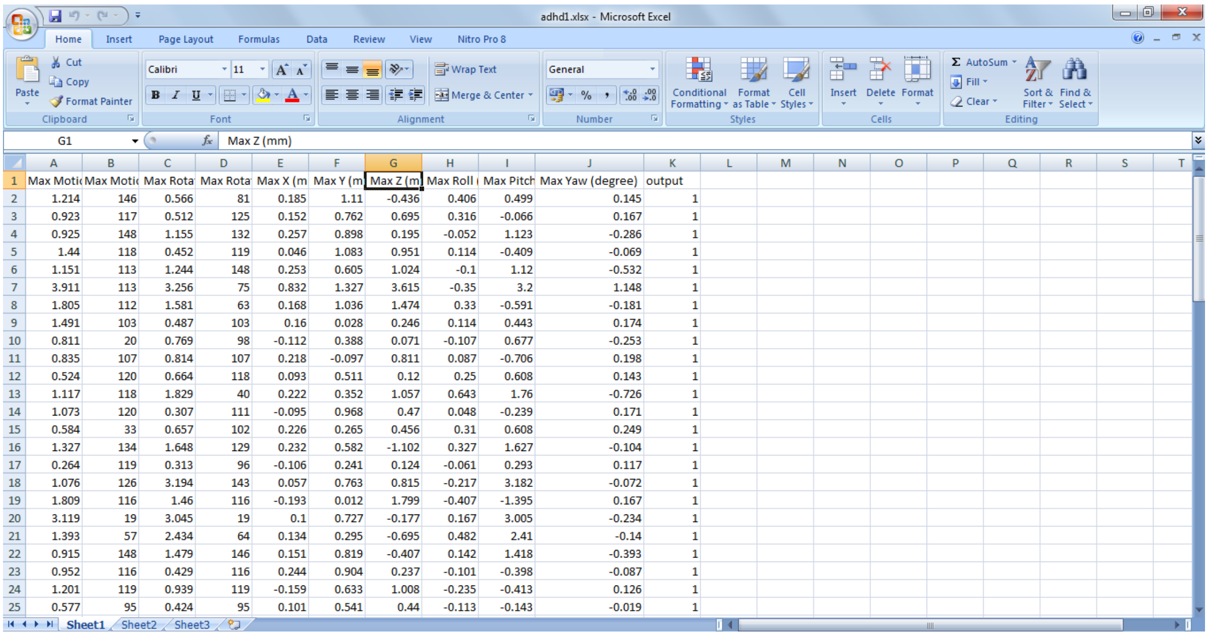
$$P(class - I) = \frac{P(Class - I)P(product\ of\ each\ feature|Class - I)}{evidence}$$

$$evidence = P(class - I)P(product\ of\ each\ feature|Class - I)P(class - II)P(product\ of\ each\ feature|Class - II)$$

$P(Class - I) and\ P(Class - II)$ are the prior probability distribution and in this work it is based on the frequencies in the training set.

RESULTS AND DISCUSSION

A cross validation partition was adopted in the dataset. The data partition defines a random partition on the set of data. This partition defines test and training sets for validating a statistical model using cross validation. A ‘holdout’ validation was done on the input. The partition divides the observations into a training set and a test set or holdout set. The test set is randomly selected from the input observations. The snapshot of the 10-column dataset is depicted in the figure3.



	A	B	C	D	E	F	G	H	I	J	K
1	Max Motic	Max Motic	Max Rota	Max Rota	Max X (m	Max Y (m	Max Z (m	Max Roll (	Max Pitch	Max Yaw (degree)	output
2	1.214	146	0.566	81	0.185	1.11	-0.436	0.406	0.499	0.145	1
3	0.923	117	0.512	125	0.152	0.762	0.695	0.316	-0.066	0.167	1
4	0.925	148	1.155	132	0.257	0.898	0.195	-0.052	1.123	-0.286	1
5	1.44	118	0.452	119	0.046	1.083	0.951	0.114	-0.409	-0.069	1
6	1.151	113	1.244	148	0.253	0.605	1.024	-0.1	1.12	-0.532	1
7	3.911	113	3.256	75	0.832	1.327	3.615	-0.35	3.2	1.148	1
8	1.805	112	1.581	63	0.168	1.036	1.474	0.33	-0.591	-0.181	1
9	1.491	103	0.487	103	0.16	0.028	0.246	0.114	0.443	0.174	1
10	0.811	20	0.769	98	-0.112	0.388	0.071	-0.107	0.677	-0.253	1
11	0.835	107	0.814	107	0.218	-0.097	0.811	0.087	-0.706	0.198	1
12	0.524	120	0.664	118	0.093	0.511	0.12	0.25	0.608	0.143	1
13	1.117	118	1.829	40	0.222	0.352	1.057	0.643	1.76	-0.726	1
14	1.073	120	0.307	111	-0.095	0.968	0.47	0.048	-0.239	0.171	1
15	0.584	33	0.657	102	0.226	0.265	0.456	0.31	0.608	0.249	1
16	1.327	134	1.648	129	0.232	0.582	-1.102	0.327	1.627	-0.104	1
17	0.264	119	0.313	96	-0.106	0.241	0.124	-0.061	0.293	0.117	1
18	1.076	126	3.194	143	0.057	0.763	0.815	-0.217	3.182	-0.072	1
19	1.809	116	1.46	116	-0.193	0.012	1.799	-0.407	-1.395	0.167	1
20	3.119	19	3.045	19	0.1	0.727	-0.177	0.167	3.005	-0.234	1
21	1.393	57	2.434	64	0.134	0.295	-0.695	0.482	2.41	-0.14	1
22	0.915	148	1.479	146	0.151	0.819	-0.407	0.142	1.418	-0.393	1
23	0.952	116	0.429	116	0.244	0.904	0.237	-0.101	-0.398	-0.087	1
24	1.201	119	0.939	119	-0.159	0.633	1.008	-0.235	-0.413	0.126	1
25	0.577	95	0.424	95	0.101	0.541	0.44	-0.113	-0.143	-0.019	1

Fig. 3: NITRC Dataset snapshot.

The total number of subjects/observations in the dataset was 83 samples. A hold-out cross validation partition resulted in 67 samples for training set and 16 samples for hold set or testing set. The 16 samples vary for each run that is made. The random partition of holdout in MatLab always picks a different set of samples. The normal distribution was applied on the training set. The normal PDF was calculated as

$$y = f(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} e^{\frac{-(x-\mu)^2}{2\sigma^2}}$$

Where μ is the mean and σ is the standard deviation. The number of classes is two, labelled as affected or not-affected. The class probability is computed for each training sample. The normal cumulative distribution function is used to compute the confidence bounds for the test set with the corresponding mean and standard deviation. The normal CDF is

$$p = F(x|\mu,\sigma) = \frac{1}{\sigma\sqrt{2\pi}} \int_{-\infty}^{x} e^{\frac{-(x-\mu)^2}{2\sigma^2}} dt$$

P is the probability that a single observation from a normal distribution with parameters μ *and* σ will fall in the interval $(-\infty, x]$.

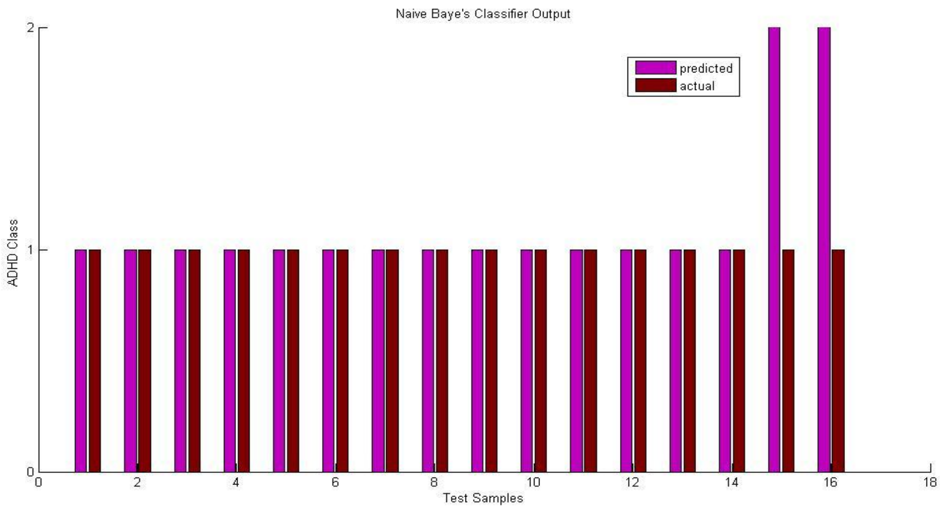


Fig. 4: Prediction accuracy plot.

The 11th column in the training dataset was fed with the class data as class-1 or class-2. Class-1 states affected by ADHD and Class-2 label states not affected by ADHD. The probability computed for each test

Australian Journal of Basic and Applied Sciences, 8(18) December 2014, Pages: 79-83

sample i.e. The probability is converted to class 1 or class-2 based on the highest value among the two classes. Then this predicted output is compared to the original output given in the dataset. The confusion matrix shows the classification statistics

$$\begin{bmatrix} 14 & 0 \\ 2 & 0 \end{bmatrix}$$

14 samples out of the 16 samples were classified accurately. The accuracy percentage yielded was 87.5%. The prediction accuracy is plotted as a bar graph in Matlab, as shown in figure4 where it clearly depicts the last two misclassifications or wrongly predicted class label.

Conclusion:

The attempt to classify ADHD subjects was successful. As expected, the ten-columned input when fed to the NBC has shown satisfactory performance. Since hold out cross validation is done, across the dataset testing samples were picked. In future, the work can be tried out with a different classifier. The dataset used is a .csv file that is pre-processed data from the NITRC. The image file of the MRI scan of the subjects, which is an .nii file can be read and an extensive feature set can be framed which may support better classification of ADHD subjects.

REFERENCES

"Evidence update 45", NICE-National Institute for Health and Care Excellence, July 2013.

"Guidelines for clinical care" Faculty Group Practice, University of Michigan Health System", April 2013.

“Australian Guidelines on Attention Deficit Hyperactivity Disorder (ADHD).

Anderson, A., P.K. Douglas, W.T. Kerr, V.S. Haynes, A.L. Yuille, J. Xie, Y.N. Wu, J. Brown and M.S. Cohen, 2013. “Non-negative matrix factorization of multimodal MRI, fMRI and phenotypic data reveals differential changes in default mode subnetworks in ADHD.,” Neuroimage.

Campbell, S., 2000. “Attention-deficit/hyperactivity disorder,” Handb. Dev. Psychopathol.

Carlton, T.G., N.D. Donachie, G. Henschen, P.E. Kumar, C.A. Smith, F. Waxenberg and D. Ph, 2014. “Clinical Practice Guideline for Patients with Attention Deficit / Hyperactivity Disorder Magellan Health Clinical Practice Guideline Task Force,”.

Dey, S., R. Rao and M. Shah, 2014. “Attributed graph distance measure for automatic detection of attention deficit hyperactive disordered subjects.,” Front. Neural Circuits, 8: 64.

Ghiassian, S., R. Greiner, P. Jin and M.R.G. Brown, “Learning to Classify Psychiatric Disorders based on fMR Images : Autism vs Healthy and ADHD vs Healthy,” pp: 1-7.

Igual, L., I. Speaker, J.C. Soliva, A. Hern and S. Escalera, 2012. “Supervised Brain Segmentation and Classification in Diagnostic of Attention-Deficit / Hyperactivity Disorder,” 2: 182-187.

Kong, Xiang-zhen, 2014. "Head motion in children with ADHD during resting-state brain imaging." PeerJ PrePrints, 2.

Santos, F.E.G., A.P.Z. Bastos, L.C.V. Andrade, K. Revoredo and P. Mattos, 2011. “Assessment of ADHD through a Computer Game: An Experiment with a Sample of Students,” 2011 Third Int. Conf. Games Virtual Worlds Serious Appl., pp: 104-111.

Sciberras, E., K.L. Mueller, D. Efron, M. Bisset, V. Anderson, E.J. Schilpzand, B. Jongeling and J.M. Nicholson, 2014. “Language Problems in Children With ADHD: A Community-Based Study.,” Pediatrics.

Steiner, N.J., E.C. Frenette, K.M. Rene, R.T. Brennan and E.C. Perrin, 2014. “Neurofeedback and cognitive attention training for children with attention-deficit hyperactivity disorder in schools.,” J. Dev. Behav. Pediatr., 35(1): 18-27.

Young, S. and M. Fitzgerald, 2014. “ADHD : making the invisible visible” , white paper.