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Data Classification and Applied Bioinformatics for Monitoring of Autism Using Neural Network

Ammar Ibrahim Shihab
Department of Computer Science, College of Science, University of Baghdad, Baghdad, Iraq

Abstract: Autism is a developmental disorder characterized among other early by alterations of socialization associated with a deficit of visual perception and/or aural and emotional expressions. To better understand the processes involved in autism, neurophysiologists analyzed responses to stimuli of autistic audio and video. The tools are commonly used fMRI, EEG and more recently "eye tracking". This device is simple to implement and use has begun to yield interesting results on the processes possibly involved in the perception of lack of photographs or films involving human presence. The study involving tools from Euclidean geometry and non-Euclidean, the trajectory of eye patients also showed interesting results. In this research, we want to confirm the results of the preliminary study but also going forward in understanding the processes involved in these experiments. Two tracks are followed, the first will concern the development of classifiers based on statistical data already provided by the system "eye tracking" and the second will be more focused on finding new descriptors from the eye trajectories. Regarding the classification several types of classification will be studied and implemented. The first classification study (the easiest) is to classify into two groups (people with autism and people without autism) results from the experiments. However, the test population is composed of more or less rehabilitated with autism, several groups will be proposed. The classifiers of the type "k-means", "neural networks", "SVM" will be tested in priority while knowing that other classifiers can be studied. The extraction parameters are most informative when studied in order to connect them with the processes involved in autism spectrum disorders. Concerning the second aspect of this research, it will be directed towards the search for new parameters from the analysis of the trajectory eye. Given the complex dynamics underlying the time series or trajectories, it is natural to turn to tools from the information theory or chaos theory. This assumption is realistic if we consider that the trajectory corresponds to the output of a nonlinear dynamic system excited by an input: the visual stimulus.

Key words: Neural networks, autism, visual stimulus, corresponds, assumption, classification

INTRODUCTION

Autism is an early developmental disorder characterised by alterations in socialisation associated with a deficit in the perception of faces and emotional expressions. This deficit in the perception of faces and emotional expressions seems to be linked to peculiarities of the gaze in autistic pathology (Dalton *et al*., 2005). The study of this behavioural disorder is carried out through the measurement of different ocular parameters (fixation time, distance and speed of exploration, ocular path) during the perception of neutral faces (featuring a direct or averted gaze) or emotions (the expression of joy or sadness) (Dalton *et al*., 2007).

Classifying autism automatically according to time is interesting in more ways than one. First, it allows the researcher to follow the evolution of the pathology according to the medication or non-drug therapy practised. One can for example, judge the relevant re-education based on whether or not the subject is positioned close to a group of people without autism. The second point concerns the informative parameters that allowed this classification. The temporal follow-up and the connection of these parameters with neurophysiological information can certainly help in understanding the mechanisms put into action for people with autism (Cattaneo *et al*., 2007). For now, we will focus exclusively on the search for automated and non-automated classification methods (Latash, 2008; Gallese, 2006).

In this research, we focus on the classification of the data provided in the follow-up material according to two groups, the autistic group and the control group. The idea is to implement the following three methods: Principal Component Analysis (PCA) which will allow us to reduce the size of the representation space and to retain only the parameters that provide discriminating information (Tadevosyan-Leyfer *et al*., 2003), neural networks (Orru *et al*., 2012).

Eye tracking is a system of gaze monitoring implemented by grouping together a set of techniques

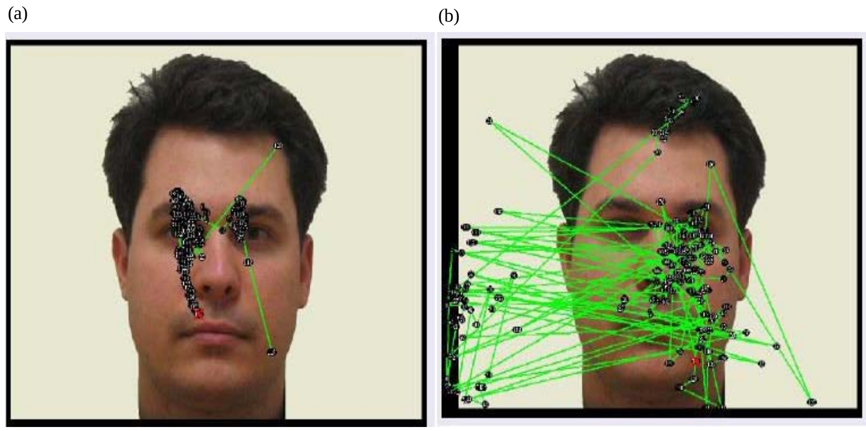

Fig. 1: Eye-tracking trajectories of the participating patients: a) Trajectory of healthy person and b) Trajectory of person with autism

that make it possible to record ocular movements and to measure several parameters such as the time of fixation of the image, the number of fixations for an area of the image and so on.

In the first part, we will describe the material of the eye tracking in the first place. In the second part, we will establish the mathematical foundations of PCA which is a method of reducing the size of the data. Then, we will present the two supervised classification methods, namely, networks of neurons.

The paradigm utilized in this test is to show a human face (or a movie involving social interaction) on a screen and at the same time, to record the position of the patient reaction (Fig. 1).

Autism is a developmental disorder characterised among other things by early alterations in socialisation associated with a deficit of visual perception and/or aural and emotional expressions.

In a preliminary study on the eye-tracking trajectories of the participating patients (Fig. 1), a rudimentary statistical analysis (principal component analysis) provided interesting results on the statistical parameters under investigation such as time spent in a region of interest and attachment time. In another study involving tools from Euclidean and non-Euclidean geometry, the trajectory of eye patients also showed interesting results.

Several types of classification will be researched and implemented as part of this study. The first study (the easiest) aims to classify the results of the experiments according to two groups, namely, people with autism and people without autism. However, the test population is composed of more or less rehabilitated with autism, several groups will be proposed. In this research, the classifiers of the type ‘k-means’, ‘neural networks’ has been used in order to classifying the autism Spector disorder.

Fig. 2: Monitoring system

Material: The recordings were carried out using a look-up system comprising a computer equipped with two analogue cameras as illustrated in Fig. 1.

Following projection of images representing neutral faces or averted eyes, this system makes it possible to capture the direction, movement and position of the eyes during projection and to superimpose them in order to calculate the temporal and statistical measurements in real time using the Facelab computer tool (Fig. 2).

Stimuli: The images projected and taken into account in our study included five neutral faces, a cheerful image and a sad picture of anonymous people between 18 and 35 years of age.

Topics: Patients and controls who participated in the test were separated into two groups. The 5 autistic patients aged 18-30 years and 6 children also with autism aged 5-15 years. The 28 adult controls of the same age group and 55 healthy children aged 5-15 years.

Measures recovered by Facelab: Among the statistics provided by the FaceLab Software, we have:

- Fixing time of the image
- The number of fixations of an area of the image
- Non-image fix time
- The pupillary diameter

MATERIALS AND METHODS

In this study, we will first deal with the classification (its different types, its structures). Then we will establish the mathematical foundations of these three models: Principal Component Analysis (PCA), Neural Networks (RN).

To classify a set of objects is to assign to each one a class or category among several classes defined in advance (supervised class) or not known in advance (unsupervised class). This task is called "classification" or "discrimination" (Vapnik and Chapelle, 2000). There are two categories: those with supervised learning (automatic learning technique where one automatically seeks to produce rules from a learning database containing examples of cases already treated) and those with unsupervised learning (this method is distinguished from learning supervised by the fact that there is no output value defined a priori) (Ecker *et al*., 2010).

Supervised classification: Is $D = \{d_1, d_2, ..., d_i, ..., d_m\}$ Consider a set of data each represented by a description, $d_1, d_2, ..., d_m$ and $C = \{C_1, C_2, ..., C_k, ..., C_c\}$. A set of classes, the supervised classification assumes two functions. The first fact corresponds to any individual d_i a class C_k. It is defined by means of pairs (d_i, C_k). Given as examples to the system. The second fact corresponds to any individual d_i its description d_i. The supervised classification then consists in determining a classification procedure:

$$C_f.\vec{d}_i \rightarrow C_k$$

Which from the description of the element determines its class with the lowest error rate. The performance of the classification depends in particular on the effectiveness of the description (Chaovalit and Zhou, 2005). Moreover, if a learning system is to be obtained, the classification procedure must make it possible to classify any new example efficiently (Lee *et al*., 1999).

Unsupervised classification: Unsupervised classification is used when the class number is not known. There are two categories of unsupervised classifications: hierarchical and non-hierarchical.

In the Hierarchical Classification (HC), the created subsets are nested hierarchically in one another. We distinguish the descending HC which starts from the set of all the individuals and breaks them into a certain number of subsets, each subset then being divided into a certain number of subsets and so on. And the ascending HC which starts from the individual individuals that are grouped into subsets which are in turn grouped and so on. In non-hierarchical classification individuals are not structured hierarchically. If each individual is only part of a subset, it is called partition. If each individual can belong to several groups with the probability P(i) of belonging to group I, then we speak of overlap (Edwards *et al*., 2012).

Principle Component Analysis (PCA): From the matrix, M [m×n] of the data (m is the number of observations and n represents the number of parameters), we project the data in a reduced-size basis to establish two groups. To do this, we began by reducing the variables of the matrix M by choosing a threshold to retain only those that express a significant difference (Constantino *et al*., 2004; Uddin *et al*., 2013).

- Role of the PCA
- Study the linkage (correlation) between the variables
- Project the observations following new axes results of linear combinations of the initial variables, reduction of dimension and obtaining new coordinates
- Change to a new orthonormal basis to implement data variances

RESULTS AND DISCUSSION

Result of classification in adults: For adult data, we have an M matrix [182.73] (182 = 154 controls+28 autistic). For a threshold, equal to 10, only 15 parameters are retained, the matrix becomes: M[182,15]. The results of the manual classification are given in Fig. 10. Two groups are formed:

- One group contains 6 autistic subjects out of 28 and 127 out of 154
- A second group contains 22 autistics among 28 and 27 of 154

Finally, the test performed to classify people with autism gives: a sensitivity of 78.6% and a specificity of 82.47%. We recall that sensitivity is defined:

$$Se = VP/(VP+FN)$$

Where:

VP = The true Positive
FN = The False Negative

The specificity is defined by:

$$Sp = VN/(FP+VN)$$

Where:

VN = The true Negative
FP = False Positives (Fig. 3)

Result of classification in children: For children, we have an M matrix [433,73] (433 = 393 controls+40 autistic). For a threshold equal to 10, only 19 parameters are retained, the matrix becomes: M[433,19]. The results of the manual classification are shown in Fig. 3. Two groups are formed:

- One group contains 5 autistics among 40 and 376 out of 393
- A second group contains 35 autistics patients of 40 and 17 of 393

Finally, the test performed to classify people with autism gives: a sensitivity of 87.5% and a specificity is 95.7%.

The results obtained after the application of the PCA method show a fairly good classification for adults and a very good classification in children. On the other hand, out of 73 criteria, only 15 were retained in adults and 19 in children (Fig. 4).

Thus, by displaying the correlation circle for adults (Fig. 4) and for children (Fig. 5), it can be said that among the parameters selected by the most discriminating ACP method are the following:

- Percent time nonfixated related to time tracked
- Percent time nonfixated
- Gaze point count/total fixation duration in zone

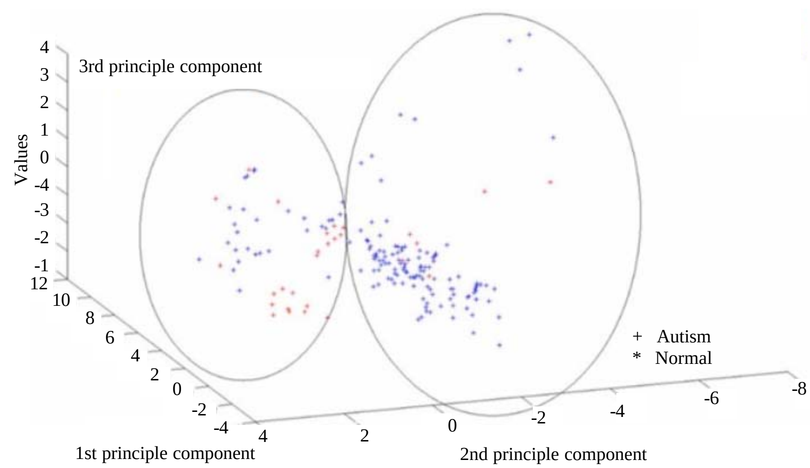

Fig. 3: Classification in adults

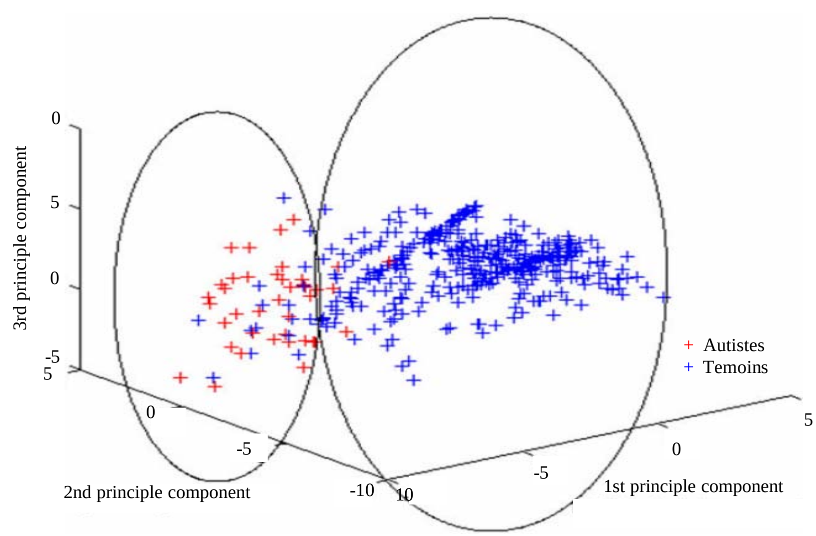

Fig. 4: Classification in children

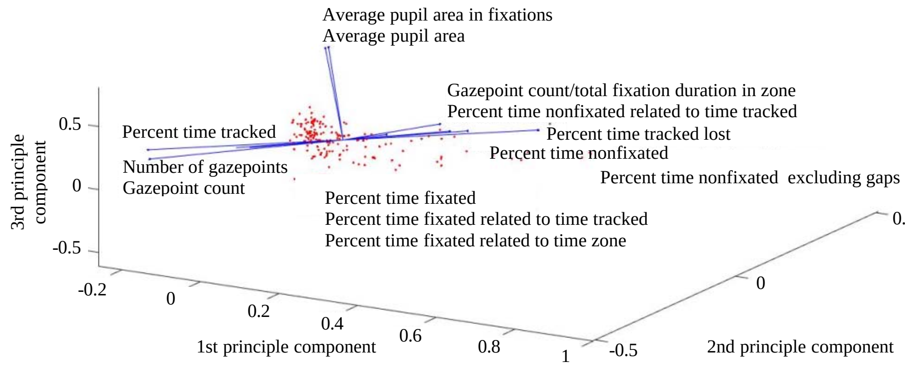

Fig. 5: Adult correlation circle

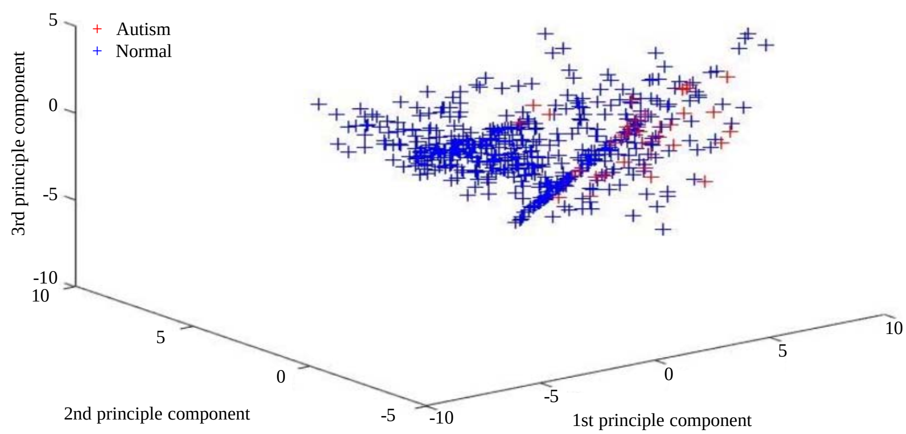

Fig. 6: Children correlation circle

- Percent time nonfixated related to time tracked
- Percent time nonfixated excluding gaps
- Number of gaze points
- Percent tracking time lost
- Average pupil area in fixation
- Percent time nonfixated related to time tracked
- Average pupil area

Finally for both children and adults, the performance of classifiers is good, since, there is on average 80% sensitivity for about 90% specificity (Fig. 6).

Neural networks: The idea is to automate classification without the presence of an operator. This method of supervised classification consists in choosing the architecture of the neural network and then to carry out an apprenticeship. In this research, we will apply two types of architecture: the perceptron and the multilayer perceptron for adults as well as for children.

Perceptron: After having chosen the architecture of the neural network: perceptron, it is necessary to carry out an apprenticeship to determine a separationsurface.

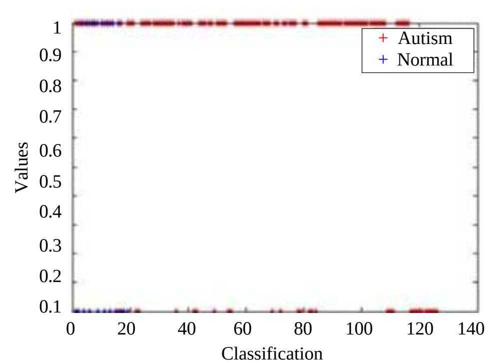

Fig. 7: Classification of adults by applying the perceptron (0: autistic, 1: healthy

Result in adults: In this part, we chose to train the neural network from 9 autistic and 9 normal. The following graph is obtained in Fig. 7 which represents two groups:

- A group of 19 contains 12 true autistic and 7 false autistics
- A second group 145 contains 103 true normal and 42 false normal

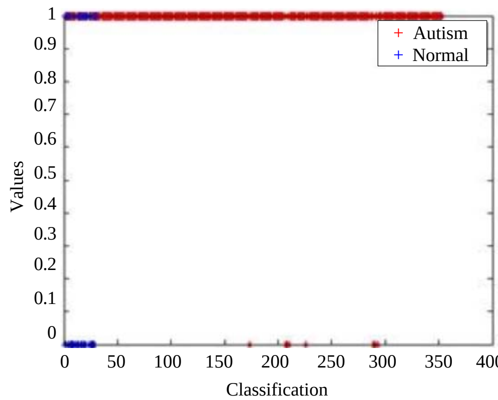

Fig. 8: Classification of children by applying the perceptron (0: autistic, 1: healthy)

The sensitivity is 63% and the specificity is 71%.

Result in children: For the children, we trained the network with 12 autistics and 12 normal. Two groups are formed:

- A group of 28 contains 18 true autistic and 10 false autistics
- A second group of 381 contains 366 true normal and 15 false normal

The sensitivity is 64% and the specificity is 96%. The performance of this detector/classifier is average in terms of sensitivity. On the other hand, it is very specific. Note that by selecting 50% of the drive groups, the sensitivity and specificity reached 57.89 and 84.21%, respectively (Fig. 8).

Perceptron Multilayers (PML): The application of the neural network method with the multilayer perceptron architecture requires the choice of the number of hidden layers (Hacker *et al*., 2013). We started with 2 layers then with 3. Learning was done with 12 autistics and 12 normal persons (for adults and for children):

- Result in adults
- Result in children

By comparing the perceptron with the multilayer perceptron, we found that the results obtained for the first structure are more significant than the second one, knowing that two groups could be discriminated. Finally, since, the complexity of the multilayer perceptron is greater than that of the perceptron, the perceptron will then be preferred (Fig. 9-12).

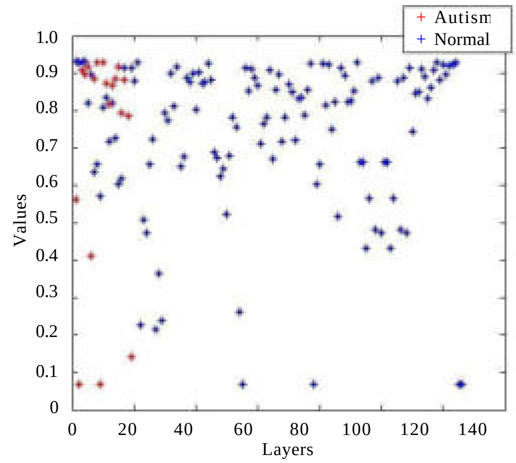

Fig. 9: For two hidden layers

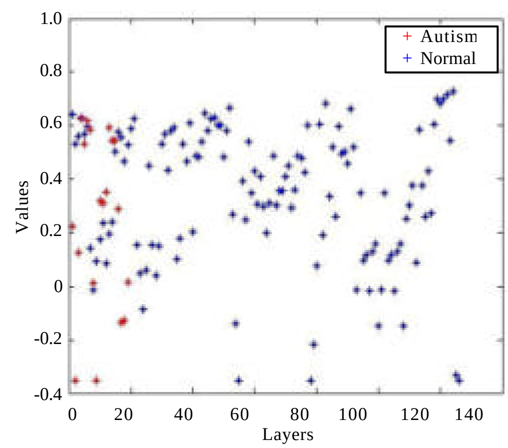

Fig. 10: For 3 layers hidden

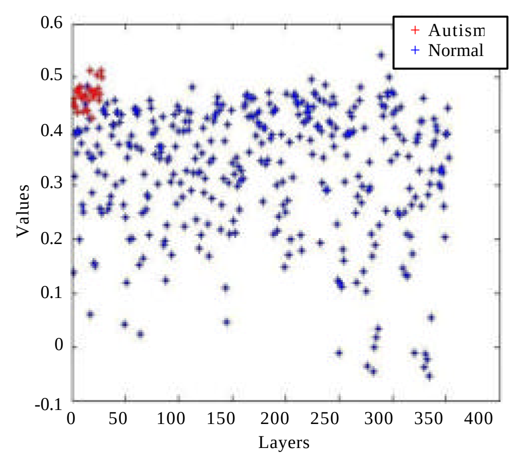

Fig. 11: For two hidden layers

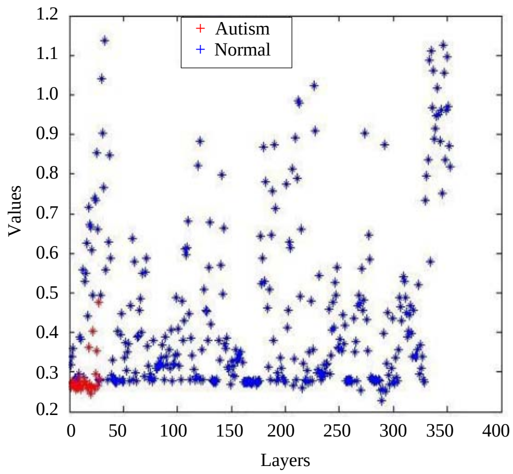

Fig. 12: For 3 layers hidden

CONCLUSION

Since, the early 1970's, the eye-tracking technique has been used to study eye movements in typical people. However, it has only been in the last decade that this technique has been developed for use with autistic people (Jrad *et al*., 2011). This technique allows us to measure several parameters that will facilitate the discrimination of people with autism.

In this research, three methods of classification are studied, applying their mathematical foundations, their applications as well as their advantages and disadvantages. Applying the principal component analysis to adult and child data reduced the number of variables from 73-15 for adults and 73-19 for children.

For the neural network method, we have opted for two structures: the first is the simplest called the perceptron and the second is the multilayer perceptron. The results obtained show that the monolayer perceptron is more adapted to these data than a multilayer model. The last method used is the "support vector machine" technique. This approach gave the best performance in terms of sensitivity/specificity. Automatic classification tools that can allow a cohort time tracking to evaluate for example, the degree of rehabilitation or the therapy put in place.

In this research, we applied the three classification methods: the principal component analysis which enabled us to know the most discriminating criteria or parameters. Then, we applied the two supervised methods: neural networks and support vector machine to classify our data. At the beginning, we used 73 parameters and then we reduced this number. The performances of the best detectors/classifiers are good with sensitivities to neighborhoods of 80% and specificities to around 90%. We advocate SVM as a supervised automated classifier.

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