Neural Network and Hidden Markov Model Classification of Schizophrenia using Eye Gaze Data

T.D. Gedeon and K.K. Kozek

Department of Information Engineering
School of Comp. Sci. & Engineering
University of New South Wales
Sydney 2052 AUSTRALIA

E-mail: tom@cse.unsw.edu.au
Facsimile: +61 2 9385 5995

ABSTRACT

Persons suffering from the condition known as schizophrenia require sophisticated medical expertise to recognise, hence there is considerable interest in classification based on objective measures of brain function. Much work has focussed on measures of electrical brain activity.

We report here on some work using neural network and hidden markov model techniques for classification on data acquired from a novel eye gaze detector developed at Westmead Hospital.

INTRODUCTION

The major advantage of eye gaze data is that when we know where the eye is looking, we know the contents of the major input channel to the brain. For example, the sequence of points of fixation for schizophrenic versus normal controls on a neutral affect face produces results which qualitatively separates the two cases. The data for this study was acquired from a novel eye gaze detector developed at Westmead Hospital. The detector uses infra-red to detect the difference between the angle of reflection from the front of the eye and the retina to determine where on screen the subject is looking.

The initial trial used 10 schizophrenic and 10 normal individuals, with 4 responses of 10 seconds duration recorded at 50 Hz, classified by a neural network on the eye gaze summary statistics.

This work extends this classification process to reliably classify the individual cases based on raw scan data.

The nature of the data required us to develop a number of novel data pre-processing techniques and appropriate network topologies. There are few very large patterns representing a time series which consists of weakly coupled sections. Our results are an improvement on previous work using EEGs (there is no previous work using eye gaze data). By an incremental process we can reduce the length of time series segments used to maintain a minimally acceptable level of classification accuracy down to single time steps. That is, we can distinquish between a schizophrenic and normal based on a single fixation and deviation from the previous fixation.

PREVIOUS WORK

Previous work has investigated the use of related soft computing techniques, being vector quantisation and simulated annealing in the classification of schizophrenic versus medicated schizophrenic patients versus normal controls using EEGs (Haig, Gordon, et al, 1995).

We have also done some work on the 'morphing' of images and the recognition of facial control points (Gedeon and Chan, 1994). The integration of this work and the classification process using eye gaze data leads to some exciting possibilities for future work, such as the production of schizoid corrected faces (faces which will look normal to a schizoid patient as judged by the parts of the image traversed by their gaze), or schizoid caricature faces (which will illustrate for normal individuals the schizoid perception of faces). We have also examined measures to determine the functional contribution of inputs to outputs of neural networks for schizophrenia classification by using a novel functional analysis of the weight matrix based on a technique developed for determining the behavioural significance of hidden neurons (Gedeon, 1996).

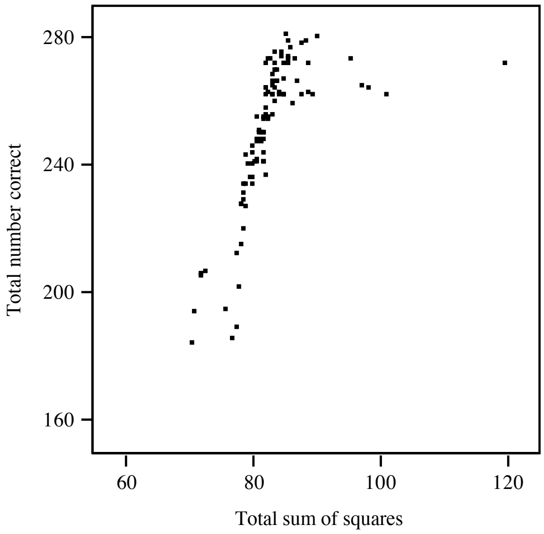
NEURAL NETWORK RESULTS

The initial network topology was 12-7-1, being twelve inputs, seven hidden neurons, and one output neurons. The data used in this section makes use only of the summary statistics of the entire data stream, with respect to fixations of gaze of 200 msec or longer.
The twelve inputs are: x and y co-ordinates; overall distance, horizontal, and vertical distance to previous fixation point; distance to previous fixation point relative to scan distance; pupil area; pupil area relative to pre and post-stimulus pupil areas; dwell time; and relative dwell time compared to the average dwell time; and finally, which image in being looked at.

The single output classifies by values above/below 0.5 whether the particular patterns belongs to a normal control or schizophrenic patient. Note the this problem is particularly hard, as the network needs to determine a classification based on the current eye gaze location and the difference from the previous one.

The network was trained using error-backpropagation (Rumelhart, Hinton and Williams, 1986). All connections are from units in one level to units in the next level, with no lateral, backward or multi-layer connections. Each unit is connected to the units in the preceding layer by a simple weighted link. The network is trained using a set of input patterns with desired outputs, using the back-propagation of error measures.

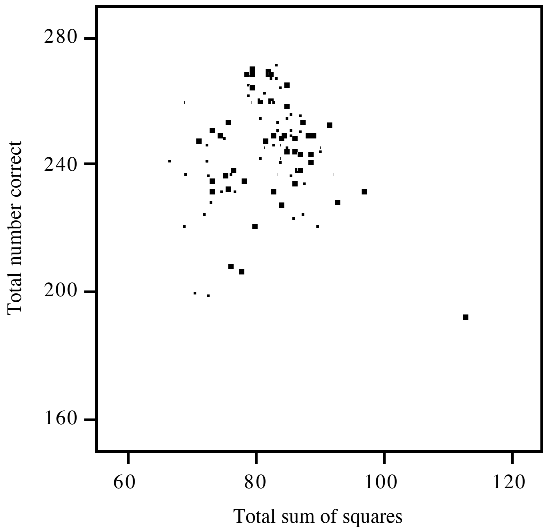
The network is tested using a validation set of patterns which are never seen by the network during training and thus can provide a good measure of the generalisation capabilities of the network. Thus all results quoted in this section are for the test set. The following diagram shows the number of correct classifications versus the total sum of squares error measure during training.



The anti-correlation of the total sum of squares (tss) value and the number of patterns correctly classified demonstrates the degree of difficulty of the classification problem for the network. There are a number of inputs which are providing irrelevant information, and the network was trained using the sum squared error measure: when the network provides a better result in terms of low tss, the number of correctly classified patterns is reduced.

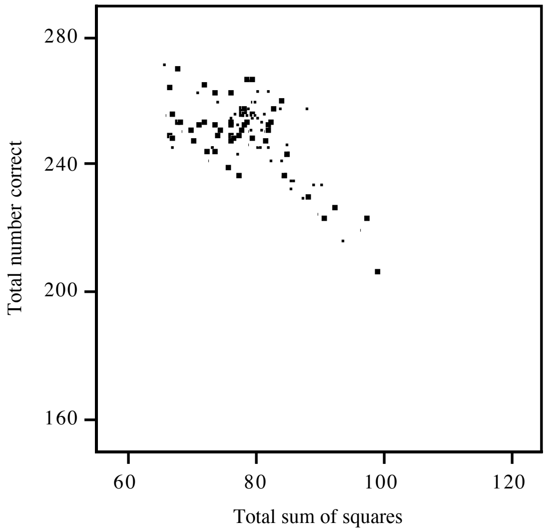
The following two graphs demonstrate two techniques (Gedeon, 1996) for analysing the significance of neural network inputs, by eliminating the inputs identified by the technique as least significant (contributing least to the solution) and showing the improved pattern of performance produced.

W

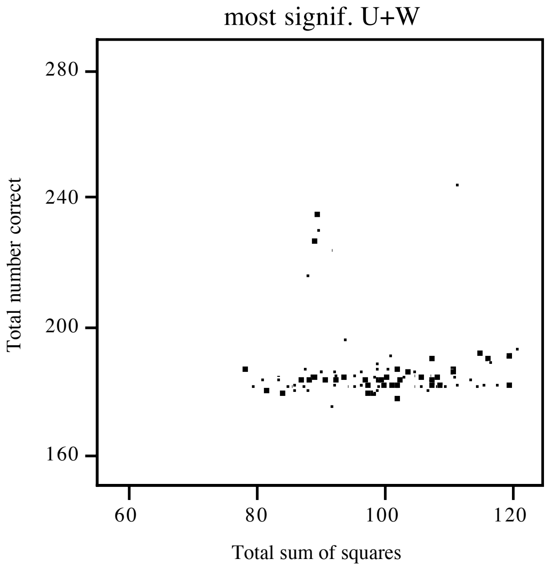


This diagram has shown that the anti-correlation has been removed, and a slight correlation introduced. Note that the overall number correct is significantly improved.

U



The above diagram demonstrates the correlation hoped for, with higher total correct classifications than the original base case.
To prove the point, the performance of the network can be eliminated completely by eliminating the inputs which are the most significant.



The above experiment on the summary statistics using neural networks demonstrate that schizophrenic patients and normal controls can be classified using the eye gaze data.

To use the full data set, however, we need to be able to make use of the time-varying component of the signals. The qualitative classification we started with was also based on the time sequence information.

We have chosen to use Hidden Markov models to attempt to classify the raw scan-path data.

HIDDEN MARKOV MODEL RESULTS

Hidden Markov models (HMMs) were trained on the time sequence of eye gaze scan data.

The raw data is a sequence of 500 observations (10 seconds sampled at 50 Hz), being the horizontal and vertical positions of the point the pupil is pointing at on the screen, and the pupil area. Thus we have a sequence of 3D points.

Additional post-processing has been done to eliminate invalid observations, due to either huge jumps in position or positions outside the picture. Also, to account for possible biased calibration of the eye gaze detector, data points in each sequence of observations is adjusted by the average of valid eye positions in one second before the image presentation. (The images are also only shown when the subject has fixated on the targeting dot in the centre of the screen for at least one second.)

For each of the three dimensions T_j, find values $t_{i,j}$ for $i = 1,\ldots,T_j$ such that $i/(T_j+1)$ of samples have the j-th coordinate less or equal to $t_{i,j}$.

These thresholds divide the sample space into $S = (T_1 +1)*(T_2 + 1)*(T_3 + 1)$ disjoint compartments. Each point of the sequence can be replaced by the label of the compartment it falls into.

We then train two HMMs, one for the schizophrenic patients and one for the normal controls. The number of hidden nodes was arbitrarily set at 5, and repeated with the value of 10.

The HMMs are used on the test examples, to produce the diagnosis based on the probability that each test sequence was recognised by the relevant HMM. The results are 5 to 10% worse than the best neural network solution, and there appears to be little correlation between the results obtained and the number of bins or the number of hidden nodes used. This suggests that further preprocessing is required, such as used for the summary statistics for the neural network.

CONCLUSION

The results we have obtained indicate that the task is possible, and provide some indications for future work. Nevertheless, the results are not as yet suitable for clinical distinction between schizophrenic patients and normal controls.

There are a number of potential reasons for this, beyond the usual problems of noisy data collected from the real world. The two most obvious problems are the inherently subjective nature of the clinical diagnosis of schizophrenia, and the presence of two variables. That is, the schizophrenic patients are medicated, while the normal controls are not medicated.

It is not feasible to record eye gaze data from unmedicated schizophrenics for two reasons, being the difficulty of recording, and secondly the ethical problems with withholding medication for experimental purposes. It is similarly ethically impossible to acquire data on the eye gaze behaviour of medicated normal controls.

We are focussing some attention into finding similarities between the schizophrenic and control data, so as to be able to more clearly identify deviations from these norms and hence provide more reliable or distinctive data for the classification task.

REFERENCES

Gedeon, TD and Chan, SK "Image transformation by recognising facial control points," *Proceeding of the World Congress on Neural Networks*, vol. 1, 1994.

Gedeon, TD "Indicators of Input Contributions: Comparing Functional measures," *Proceedings IEEE International Conference on Digital Signal Processing (TENCON'96)*, pp. 520-525, Perth, 1996.

Haig, AR, Gordon, E, Rogers, G and Anderson, J "Classification of single-trial ERP sub-types: application of globally optimal vector quantization using simulated annealing," *Evoked Potentials*, 31 pages, 1995.

Rumelhart, DE, Hinton, GE, Williams, RJ, "Learning internal representations by error propagation," in Rumelhart, DE, McClelland, (eds.) *Parallel distributed processing*, vol. 1, MIT Press, 1986.