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Early Driver Fatigue Detection from Electroencephalography Signals using Artificial Neural Networks

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Abstract— **This paper describes a driver fatigue detection system using an Artificial Neural Network (ANN). Using electroencephalogram (EEG) data sampled from 20 professional truck drivers and 35 non professional drivers, the time domain data are processed into alpha, beta, delta and theta bands and then presented to the neural network to detect the onset of driver fatigue. The neural network uses a training optimization technique called the Magnified Gradient Function (MGF). This technique reduces the time required for training by modifying the Standard Back Propagation (SBP) algorithm. The MGF is shown to classify professional driver fatigue with 81.49% accuracy (80.53% sensitivity, 82.44% specificity) and non-professional driver fatigue with 83.06% accuracy (84.04% sensitivity and 82.08% specificity).**

I. Introduction

Driver fatigue is a significant problem on Australia's roads, with estimates putting the number of fatalities in which driver fatigue was a significant factor as high as 30% [1]. The Australian Transport Safety Bureau includes fatigue in the "Fatal Five" behavioral factors, alongside issues such as speeding, seatbelts, driving under the influence and distraction [1]. As a result, research into driver fatigue and its causes is an important area and has widespread benefit to the community.

Reference [2] classifies driver fatigue detection and prevention technologies into four categories.

- Readiness-to-perform and fitness-for-duty technologies. These are technologies which assess the user's ability to perform the task before they begin the task.
- Mathematical models of alertness dynamics joined with ambulatory technologies. These are technologies which mathematically predict the onset of fatigue as well as levels of alertness using models of Circadian rhythms and sleep patterns.
- Vehicle based performance technologies. For example, a system whereby a network of sensors and guidance systems (such as GPS) allow a processor within the car to calculate the level of workload the driver must devote to the upcoming section of the road [3].
- In vehicle, online, operator status monitoring technologies. It is in this category the driver fatigue classification system presented in this paper belongs.

Various techniques exist to detect the onset of driver fatigue. Real-time non-intrusive driver fatigue detection systems have been developed whereby a number of physical attributes, namely eye/gaze movement [4]-[7], head movement [8], or a combination of these indicators [9] are monitored by a video device.

An alternative method to visual monitoring of the drivers state is to monitor the drivers neurophysiologic indicators. EEG has been used to detect the onset of sleep or fatigue/drowsiness using Neural Networks [10], [11]. More specifically, EEG has been used in conjunction with statistical methods to detect the onset of fatigue in motor vehicle drivers [12].

This paper demonstrates the detection of driver fatigue using Artificial Neural Networks (ANN) in conjunction with an optimization technique named the Magnified Gradient Function (MGF) [13] to detect fatigue in professional and non-professional drivers using EEG data. Fatigue is induced in 20 professional and 35 non-professional drivers using a driving simulator at speeds less than 80km/h, the raw data is then pre-processed and fed into the Neural Network and classified.

II. Methods

A. The Magnified Gradient Function

The Magnified Gradient Function is a modification to the Standard Back Propagation (SBP) Algorithm aimed at speeding up the convergence rate by "magnifying" the gradient of the activation function. This magnification improves the performance of the derivative of the activation function over a range of values which in turn improves the convergence rate whilst maintaining the gradient descent property.

Fig. 1 shows the general form of the multi-layered neural network. One of the most convenient aspects of the MGF algorithm is that it maintains the structure of the neural network and actually requires minimal modifications to existing computational techniques.

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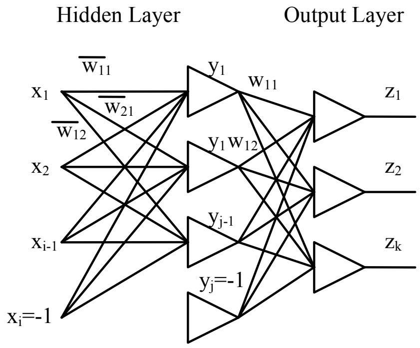

Fig. 1 Neural Network Structure

Equations (1) and (2) are the two error signal terms (delta and delta bar) which need to be modified to implement the MGF.

$$\delta_k = (d_k - z_k)\left[\frac{\partial z_k}{\partial v_k}\right]^{\frac{1}{S}} \tag{1}$$

$$\bar{\delta}_k = \left[\frac{\partial y_j}{\partial \bar{v}_j}\right]^{\frac{1}{S}} \sum_{k=1}^{K} \delta_k x_{kj} \tag{2}$$

This magnification improves the error gradient behaviour in two ways. Firstly, when x is approaching zero, $f'(x,S)$ is relatively close to the value of $f(x)$, where as when x is sufficiently large, i.e. z and y approach zero or one, the value of $f'(x,S)$ compared to $f(x)$ is increased greatly. The result of this magnification of the derivative function is shown in Fig. 2, where the original value of S=1 represents the SBP algorithm and values ranging from S=2 to 100 are shown.

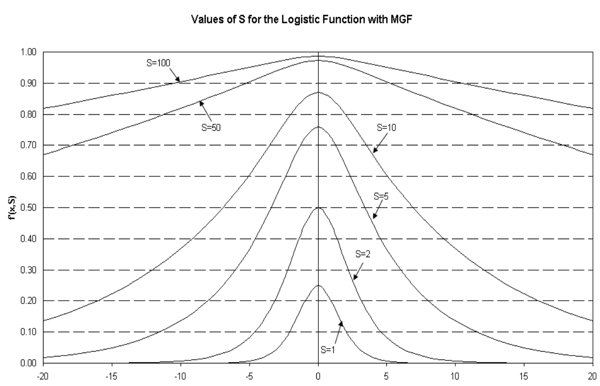

Fig. 2 $f'(x,S)$ for values of S=[1-5]

B. Data Collection and Neural Network Structure

Samples are collected from 20 professional truck drivers (44 ± 11 years) and 35 non professional drivers (34 ± 21 years). All participants gave written consent for the study which was approved by the institutional ethics committee.

Each of the 55 participants uses a driving simulator continuously, whilst their face is monitored, until fatigued. Fatigue is judged by an expert based on eye and head movements, and once it is determined the participant is in a solid fatigued state, the data collection is stopped.

The early driver fatigue classification proposed in this paper uses EEG data collected using the International 10-20 electrode from a total from 19 sites on the head. These sites are F1, F2, F7, F8, F3, F4, T3, T4, C3, C4, T5, T6, P3, P4, O1, O2, FZ, CZ and PZ. Samples are recorded at 256Hz and separated into one second epochs.

The raw time domain data collected is transformed using a Fast Fourier Transform (FFT), with a 4-term Blackman–Harris window and a 2-Hz cut-off high-pass filter were used to reduce low frequency artifact, and divided into four bands for analysis, alpha (8-13Hz), beta (14-26Hz), delta (0.4-4Hz) and theta (4-7Hz). The sum of magnitudes within each individual band is calculated and sixty of these one second windows are concatenated to form a vector, with example patterns shown in Fig. 3 and Fig. 4 which show fatigued and non fatigued samples respectively. A total of 10484 these vectors were collected and used to train the neural network.

These samples are then randomly sorted into the training, validation and test sets in the ratio of 3:1:1 respectively as shown in Table I.

TABLE I
DISTRIBUTION OF SAMPLES ACROSS TRAINING, VALIDATION AND TEST SETS FOR BOTH PROFESSIONAL AND NON-PROFESSIONAL DRIVERS

Driver Class	***Training Set***	***Validation Set***	***Test Set***
Professional	1573	524	524
Non-Professional	923	307	307

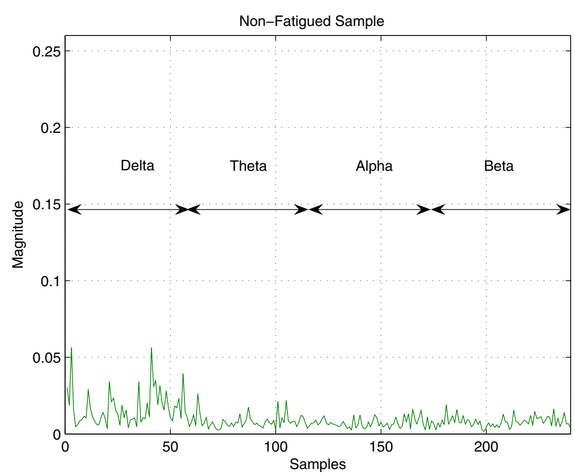

Fig. 3 Non-Fatigued EEG data sample

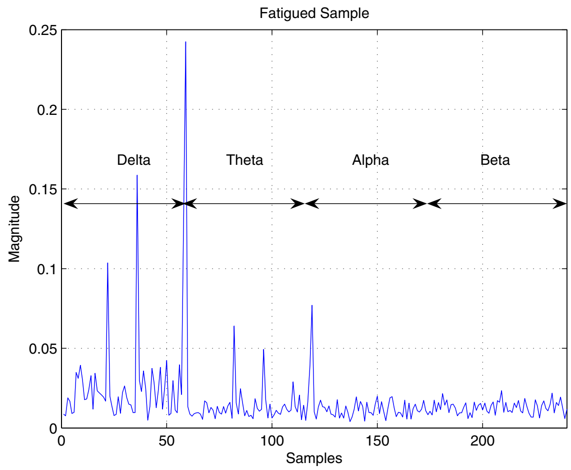

Fig. 4 Fatigued EEG data sample

The input layer of the neural network consists of 61 neurons, the hidden layer has five hidden neurons and the output layer consists of two neurons, representing the two possible classifications. Both the input and hidden layers are augmented with a bias neuron of -1.

Two separate neural networks were trained during the fatigue training experiments; one with professional drivers and one with non professional drivers. Multiple networks were trained in parallel, keeping starting weights, the learning and momentum rates, as well as data sets static between networks but changing the value of S. Each network was trained over 5000 cycles, and an early stopping point selected from the minimum value of the validation cycle error to ensure generalization. The system weights from this early stopping point are used with the test set to obtain the overall accuracy of the network.

III. Results

A. Professional Drivers

From the professional driver validation set shown in Fig. 5, we can see that the minimum error lies at the 493 cycle point, with an S value of S=2. Fig. 6 shows the cycle error for SBP (S=1) and S=2.

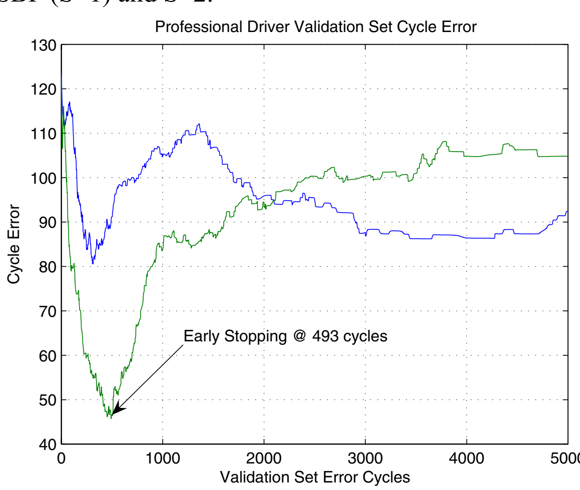

Fig. 5 Professional Driver Validation Set Cycle Error

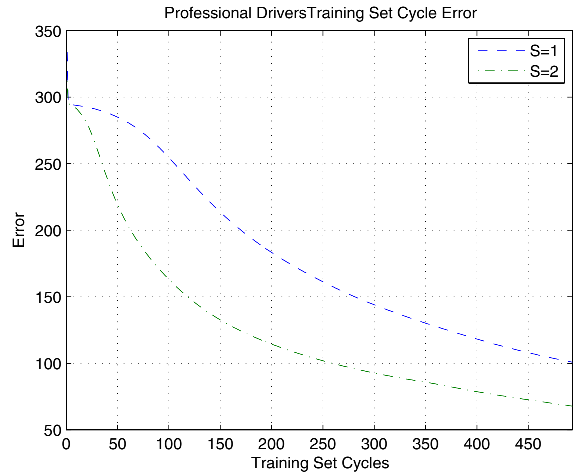

Fig. 6 Professional Drivers Training Set Cycle Error

B. Non-Professional Drivers

From the non-professional driver validation set shown in Fig. 7, we can see that the minimum error for the lies at the 183 cycle point, with an S value of S=2. Fig. 8 shows the cycle error for SBP (S=1) and S=2.

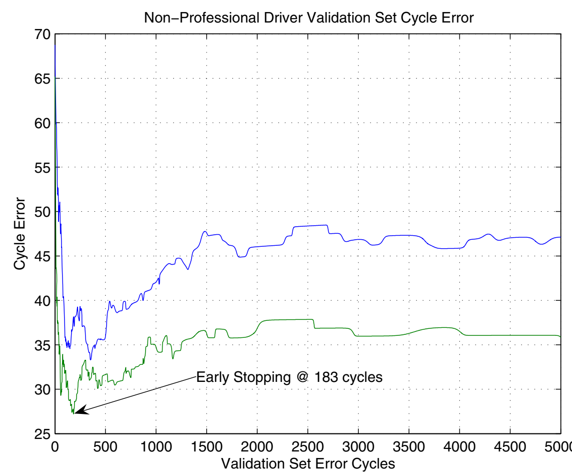

Fig. 7 Non-Professional Driver Validation Set Cycle Error

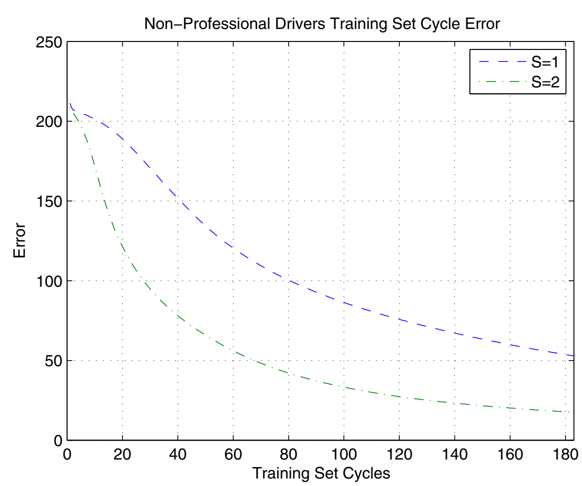

Fig. 8 Non-Professional Drivers Training Set Cycle Error

Overall test set classification rates are shown in Table II as well as sensitivity and specificity.

TABLE II
CLASSIFICATION PERFORMANCE OF NEURAL NETWORK CLASSIFIER FOR EEG FATIGUE DETECTION ON THE TEST SET. ALSO SHOWN ARE SENSITIVITY (TRUE POSITIVE) AND SPECIFICITY (TRUE NEGATIVE) PERCENTAGES, WITH A POSITIVE MEANING FATIGUE IS DETECTED.

Driver Test Set	***Sensitivity***	***Specificity***	***Overall Accuracy***
Professional	80.53%	82.44%	81.49%
Non-Professional	84.04%	82.08%	83.06%

IV. DISCUSSION

A number of interesting points are raised in both the professional and non-professional drivers' results. For the training of both of these networks a very low learning rate of 0.05 and a momentum rate of 0.7 were used to avoid oscillations as the system error, E_c, approaches zero.

Both professional and non-professional networks have a similar overall classification rate, with Table II showing a rate of 81.49% for professional drivers and 83.06% for non-professional drivers. The sensitivity and specificity of both networks were approximately even, which suggests that the network is similarly equipped to detect the driver is in a fatigued state (true positive), or a non-fatigued state (true negative).

No major difference was observed between the classification rates of professional drivers versus non professional drivers. This is interesting since one of the major questions asked before undertaking this research was whether fatigue classification in professional drivers was more difficult than non-professional drivers. The results presented above, although not definitive, do not seem to suggest that there is no difference between the fatigue characteristics (in terms of classification accuracy) between professional and non professional drivers. Further study is required and a methodology must be developed to statistically determine if this is the case.

V. CONCLUSION

In this paper, we have presented a technique for improving the speed of convergence for multi-layered feedforward neural networks. The MGF holds exciting possibilities in terms of minimizing training times in terms of iterations, whilst adding minimal computational complexity and therefore having little impact on the wall clock training time.

The MGF was applied to the real-world classification problem of classifying driver fatigue EEG data and showed reductions in training times, when compared to the SBP, a factor of 2-3. It was also shown that classification of driver fatigue, both in professional and non professional drivers is possible with a high degree of accuracy with rates in the 81-83% region obtained. It is also clear from the results that additional room is available in the classification rates of driver fatigue and some future directions have been outlined as a way of moving toward achieving this.

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