OPTIMIZATION OF NEURAL NETWORK ARCHITECTURE FOR THE APPLICATION OF DRIVER FATIGUE MONITORING SYSTEM

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ABSTRACT

Apart from heart disease and stroke, road crashes are identified as the top killer in Malaysia, claiming an average of 19 deaths per day in 2014. The majority of these traffic fatalities are attributed to the human errors, such as fatigue driving. Current law enforcement on speed and alcohol cannot effectively tackle the driver fatigue issues. In order to overcome the aforementioned critical scenarios, an embedded electronic monitoring system is proposed to alert the driver when there is a tendency of the driver falling asleep. In this paper, the study focus on the development of artificial neural network (ANN) based classifier to recognize whether the driver falls into fatigue condition. Typically, a ANN model consists of more than one parameter, e.g. number of hidden neurons, different type of activation functions, learning algorithms and etc. Instead of trial an error approach, a design of experiment (DOE) technique called factorial design is employed to investigate in details the contribution of the above factors towards the prediction accuracy of the constructed ANN model. Among the investigated factors, the learning algorithm and activation function has a significant effect ($p<0.05$) on the ANN prediction performance. Throughout the study, the best optimized ANN architecture achieves 94.7% of fatigue detection accuracy.

Keywords: artificial neural network, fatigue monitoring system, design of experiments, factorial design.

INTRODUCTION

The critical situation of road crashes had been highlighted globally in the past decade. According to a report issued by World Health Organization, the annual cost of road crashes worldwide is up to USD $518 billion [1]. Due to the fact, the organization had gave a serious warning that the road traffic injuries are predicted to rank at the 5th leading cause of death by 2030 if no urgent and effective measures taken.

Among the causes of deaths and injuries on the roads, driver fatigue is one of the top leading causes, besides of speed and alcohol use. Typically, the current measures implemented such as law enforcement and road safety campaign are proven useful to reduce the traffic mortality rate by raising the drivers' awareness regarding the importance of safe driving on the roads. Nevertheless, these approaches are not effective enough to tackle the issue of driver fatigue. Since 2011, some of the leading automotive industries realize the importance of Advance Driver Assistance System (ADAS) to assists and prevents the driver involved in fatal road accidents. Among the features introduced in the ADAS system, such as collision and lane departure warning, one of the functions is to detect the fatigue behaviour and ensure the driver do not fall into drowsiness condition.

In this article, several preliminary investigations related to the development of driver fatigue warning system are presented. The highlights of the studies are listed as follows:

(1) The potential of using biometrics data, i.e. heart rate as a classification feature of artificial neural network (ANN) for fatigue detection is investigated.
(2) The optimization of ANN architecture using 2-way factorial design is presented.

The rest of the article is organized as follows. Section 2 briefly presents some previous related works. Section 3 details the experimental setup for statistical design. Section 4 provides the experimental results and finally Section 5 concludes the works done.

PREVIOUS WORKS

Generally, current techniques developed to detect and predict the fatigue condition can be divided into two main monitoring categories, which are driving behaviour and driver behaviour. The monitoring of driving behaviour evaluates the performance of driver based on the steering wheel movement, lane deviation and etc. The decrements of the driving performance from time to time may indicate the driver fall into fatigue or drowsiness. On the other hands, the monitoring of driver behaviour can be further divided into two classes depends on the detected feature, either visual or non-visual. Some of the visual features reported for the fatigue detection are eye blinking rates and yawning [2]. The extracted visual features from camera are further analyzed using machine visions techniques. While for the non-visual features such as heart rate and frequency of breaths, the obtained signal from the sensors can be processed and analyzed using various classification algorithms such as support vector machine (SVM), ANN, and etc. The decision from the algorithm indicates whether a subject falls into fatigue or not. Typically, most of the reported studies regarding the fatigue detection are still in the beginning of development stage. In fact, the solution for driver fatigue monitoring system still not widely available in the market. In this study, the potential of using heart rate as feature and ANN as classifier to detect fatigue behaviour are investigated in details.

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Generally, ANN is a computation model with the capability of learning, recognizing and classifying specific object through training. It is fair to say that the ANNs have big advantages in solving complex problems that involves organizing, classifying, optimizing or summarizing data [3]. When the ANN model for a specific application was successfully trained and developed, the model consist only direct arithmetic calculations that can be programmed on the controller devices for embedded real-time applications.

Nevertheless, the performances of ANN system highly depend on training. In a typical ANN architecture, there are several parameters that need to be defined, i.e. number of neurons in a hidden layer, number of hidden layer, activation function of each neuron and also the training algorithms. Many experiments and tests need to be conducted to find the best architecture with optimized performance. Instead of trial and error approach, the study presents a technique called factorial design to investigate the effect of each parameter in ANN model and minimize the amount of tests that need to be conducted to determine the best ANN architecture.

EXPERIMENTAL SETUP

In this article, the training data of ANN consists of 700 heart rate dataset which collected from 10 male subjects aged between 23 and 24. Each heart rate dataset has two variables, i.e. reference heart rate and testing heart rate. The reference heart rate is taken to eliminate the variability of different heart rate possessed by different people. These two variables form the two neurons in the input layer of the ANN. The output layer consists of only one neuron to indicate the results of recognition whether the driver falls into the fatigue group for every instance of input data presented to input neurons. A threshold value of 0.5 is introduced to the output layer of ANN. The final obtained result is either "1" if the calculated number of the output neuron is greater than the threshold value, indicates fatigue detected or "0" if the output less than 0.5, means the driver heart rate is in normal condition. The ANN was trained using built-in function in MATLAB.

Besides of the input neurons and output neuron, the performance of the ANN affected by the architecture of the hidden layer lies between the input and output layer. There are no any rules of thumb to define the amount of hidden neurons required in the hidden layer. Several tests need to be conducted to resolve the best architecture. Similar things go to the number of hidden layer and the activation function of each neuron. In this article, a technique called factorial design based on the statistical principle was conducted to minimize the amount of testing through the verification on how the changes in some parameters affect the performance of constructed ANN model.

In this study, the factorial design analyze on the 3 factors which suggest results to the different performance of ANN training on the response. The 3 specified factors are the number of hidden neurons, activation functions of each neurons and learning algorithms. On the other hands, the response of investigations is indicated by the success rate in the prediction of fatigue behaviour. Total of 300 collected heart rate dataset, which differs from the training data was served as the testing data. The null hypothesis of the experiment is each of the 3 investigated factors and their interactions has no significant effect on the response. Besides of the selected factors, another parameter which may have effect on the response, i.e. number of hidden layer is fixed to 1 since there are only two input neurons in this case of study.

Due to the nature and requirement of the factorial design, the variables of the 3 selected factors are reduced to 2 levels, designated as (+1) and (-1) for the use in the analysis of variance (ANOVA) model [4,5]. The definition of each factor is shown in Table-1. The first two columns list down the selected primary investigated factors while the last two columns represent the factor levels implemented in the factorial deign analysis.

Table-1. Factors level in 2 level factorial design.

Factor	Label	Factor Level	
		Low (-1)	High (+1)
Number of hidden neurons	A	3	5
Neurons' activation function	B	"logsig"	"purelin"
Learning algorithms	C	Trainlm	Traingd

In order to evaluate the selected 3 factors at 2 levels, a 2 level factorial design with 8 experiments (8 degree of freedom) are carried out in randomized fashion. The principle of randomization is applied to avoid statistical distortions. In addition, each of the tests is replicated twice to estimate the experimental error for the verification of the statistical significance of the effects [6]. The design matrix and the responses of the factorial design conducted in this study are illustrated in Table-2. The collected responses and statistical design are further analyzed using Minitab.

Table-2. Design matrix and responses of factorial design.

Exp.	Factor			Response	
	A	B	C	Y_1	Y_2
1	-1	-1	-1	0.947	0.947
2	-1	+1	-1	0.930	0.927
3	-1	+1	+1	0.000	0.000
4	-1	-1	+1	0.834	0.813
5	+1	-1	-1	0.947	0.947
6	+1	+1	-1	0.940	0.930
7	+1	+1	+1	0.000	0.000
8	+1	-1	+1	0.840	0.877

EXPERIMENTAL RESULTS

In general, the factorial analysis is capable to evaluate how much the influence of each factor (A, B, and C) and also their interactions (AB, AC, BC, and ABC) on the response. In the present study, the significant effect of

ARPN Journal of Engineering and Applied Sciences

the factor can be determined by comparing the values of effect for each factor with the calculated experimental error. Since the conducted test is replicate twice for the same factor levels, the variance (S^2) and the experimental error (S) can be calculated using the equation listed below:

$$S^2 = \frac{1}{2^k(n-1)}\left(\sum S_i^{\,2}\right);\ S = \sqrt{S^2}$$

where k = the number of factors (3) and n = the number of replications (2).

Table-3. Calculation of variance.

Responses		Average	Variance (S_i^2)
Y_1	Y_2		
0.947	0.947	0.9470	0.0000
0.930	0.927	0.9285	4.5e-6
0.000	0.000	0.0000	0.0000
0.834	0.813	0.8235	0.0002
0.947	0.947	0.9470	0.0000
0.940	0.930	0.9350	5e-5
0.000	0.000	0.0000	0.0000
0.840	0.877	0.8585	0.0007
Sum of Variance			0.00096

The calculated values of S^2 and S in this case study are 0.00012 and 0.011 respectively. Based on the calculated experimental error, the standard deviation of the effects is calculated as below:

$$S(effect) = \frac{2S}{\sqrt{n2^k}} = \frac{2(0.011)}{\sqrt{2.2^3}} = 0.0055$$

According to the t-distribution, for the confidence level of 95% and the degree of freedom of 8, the tabulated value for factor t is 2.31, thus the confidence interval of the effects is:

$$effect(95\%) = S(effect) * t_{95\%,8} = 0.0127$$

Through the obtained results, the effects which have value above 0.036 are concluded as significant with 95% of confidence level. From the ANOVA results (shown in Table-4) generated in Minitab, it could be observed that the factors B, C and B*C are significant with their effects (second column) higher than the standard deviation for a 95% interval of reliability (0.0127).

Table-4. ANOVA results of full factorial model.

Term	Effect	T-value	P-value
A	0.0104	1.89	0.095
B	-0.4281	-78.18	0.000
C	-0.5189	-94.76	0.000
A*B	-0.0071	-1.30	0.229
A*C	0.0071	1.30	0.229
B*C	-0.4129	-75.40	0.000
A*B*C	-0.0104	-1.89	0.095

S = 0.01095; R-Sq = 99.96; R-Sq(adj) = 99.93%

The indicated P-value (forth column) further verify the results. The P-value of the identified factors that have significant effect on the response is all less than the chosen α value (0.05). The smaller number of the P-value represents the greater strength of evidence.

Among the principal factor, learning algorithms which labeled as factor C has the most significant effect followed by the activation function labeled as factor B. On the other hands, the number of hidden neuron labeled as factor A is not statistically significant. Moreover, for the second order factors, besides of the interaction between factor B and C, all others factors are not significant. The effect of third order interaction factor (A*B*C) is also not significant in this case of study. The details of the effect for each factor can be observed from Pareto chart (shown in Figure-1) and the normal probability plot (shown in Figure-2).

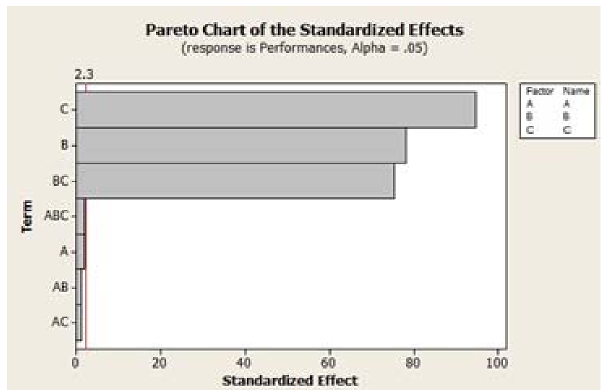

Figure-1. Pareto chart.

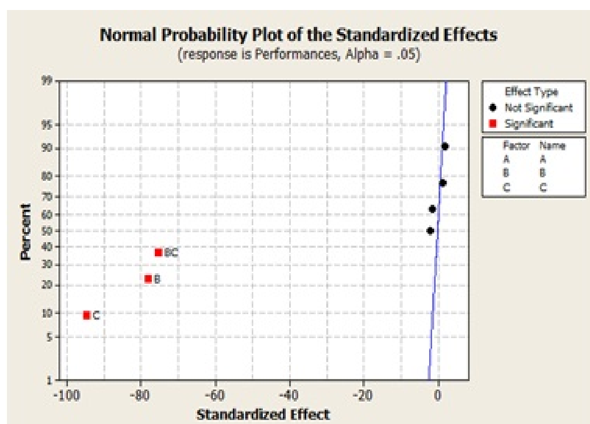

Figure-2. Normal probability plot.

Based on the generated ANOVA results, it is not necessary to design a full factorial model. The interaction factors that are not significant can be neglected in the reduced model. Thus only factor A, B, C and their interactions are included in the reduced model. Factor A is included to maintain the hierarchical model. The ANOVA result for the reduced model is summarized in Table-5.

ARPN Journal of Engineering and Applied Sciences

Table-5. ANOVA result of the reduced model.

Term	Effect	T-value	P-value
A	0.0104	1.62	0.133
B	-0.4281	-67.01	0.000
C	-0.5189	-81.21	0.000
B*C	-0.4129	-64.62	0.000
Lack of fit			0.151

S = 0.01278; R-Sq = 99.93; R-Sq(adj) = 99.90%

Typically, the lack of fit (LOF) error arises when some term are removed from the term incorrectly [7]. The null hypothesis of the LOF test state that the removed term is null effect. Since the indicated P value is greater than 0.05, the null hypothesis is accepted, means that the removed factor do not influence on the response and indicate no bias on mean square error (MSE).

Since the interaction of factor B and C shows significant effect on the response, the interaction plot between factor B and C is examined instead of their main effect plot. The interaction plot is illustrated in Figure-3. From the interaction plot, it can be observed that the both level of factor B perform almost equally when factor C is at low level. In other words, when Levenberg-Marquardt is used as ANN training algorithm, the activation function for neurons can be set as either sigmoid or linear transfer function. However, when factor B is defined at high level, there is a significant reduction in performance if factor C is set at high level, means that gradient descent training algorithm cannot be implemented together with linear activation function because it will diminish the neural network performance.

Finally, the best architecture of ANN in this case of study can be easily observed from the cube plot (shown in Figure-4). The best performance of ANN is achieved when the defined factor is set at A+ (3 hidden neurons), B- (logsig activation function) and C- (trainlm algorithm) or A- (5 hidden neurons), B- and C-, for an average predicted performance of 0.9470 (94.7% success rate).

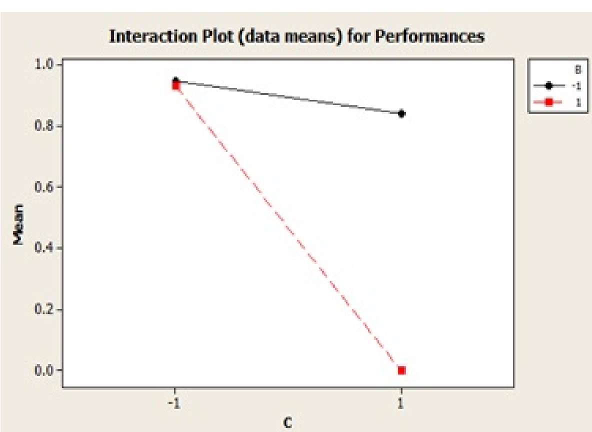

Figure-3. Interaction plot between factor B and C.

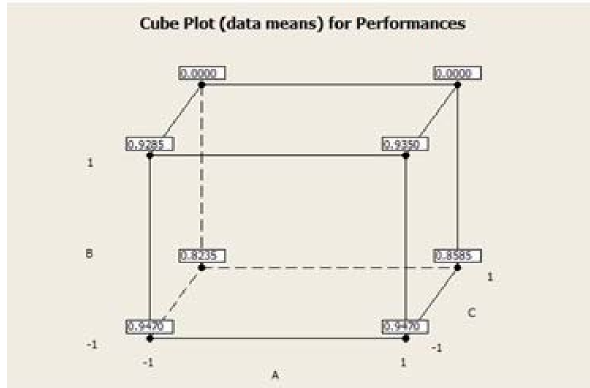

Figure-4. Cube plot for ANN performances.

CONCLUSIONS

In the present study, a framework of ANN model had been developed for the prediction of fatigue behavior. The presented work is focus on the techniques to obtain the best ANN architecture for the specific application using factorial design approach. The performance of fatigue prediction through the combination of ANN and heart rate as the recognition feature show promising results, as the success rate for all configurations of factors is above 80%, except for the case when traingd and purelin activation function was used together. In addition, the application of factorial design shows satisfactory results on the investigation of the influences or effects of experimental parameters. The conducted analyses provide a useful guidance and play an important role in optimizing the ANN parameters. In this case of study, the training algorithm has the strongest effect on the ANN success rate, followed by the neuron activation function. The highest success rate (94.7%) achieved when Levenberg-Marquardt is used as training algorithm together with sigmoid activation function, regardless of the amount of hidden neurons (either 3 or 5).

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