THE DEVELOPMENT OF A NEURAL NETWORK MODEL TO IMPROVE THE RELIABILITY OF THE DEMAND/EFFORT MODEL FOR EVALUATING HIGHWAY SAFETY

Bongjo Jung, Senior Researcher, Korea Expressway Corporation, chungbj@ex.co.kr

Seongkwan Mark Lee, Senior Researcher, KEC, smlee4@gmail.com

Jae-Soo Kang, Chief Director, Chung-Seok Engineering

Myeong-Soon Jang, Professor of Transportation Eng. Dept., Hanyang University

ABSTRACT

Traffic accidents on highways are likely to happen when there is an unbalance in the complex relationships among the key elements such as road geometries, driver related factors, and mechanical performances.

The Demand-Effort Model (DEM), which evaluates highway safety, can be explained by the unbalance, which occurs when the level of requests on the driver's attention to the road environment exceeds that of the response from the driver. This study suggests a new model that improves the reliability of the current DEM through a reinterpretation of physiological signals with the help of the Neural Network Model (NNM).

The data were collected from 149 subjects, who drove test vehicles on the Yongdong, Honam, and Seohaean Expressways in Korea. Three important results could be drawn from the recursive tests as follows; ① Only 5 out of 10 parameters of the physiological signals which are currently used were proven to be meaningful through the Normality Test, Cluster Analysis, and Mann-Whitney Analysis. ② The revised DEM, which internally uses the NNM, showed more reliable results than the existing DEM. Group 1, which is based on the new DEM, showed 80 % accuracy in measuring the level of the driver's efforts, however, that of Group 2, based on the current DEM, was 74.3 %. ③ Field tests on the Honam Expressway showed a lower 'correct rejection' with the new DEM (40.5 %) than the old DEM (58.8 %).

The DEM is designed as a quick and easy way to determine highway safety prior to a minute road safety audit (RSA) by a professional audit team. Therefore a new DEM, which is based on the NNM, needs to be considered since it showed higher reliability and lower errors.

Keywords: Demand-Effort Model, Neural Network Model, Highway Safety

INTRODUCTION

Traffic accidents on the roads are classified into human factors, road and environmental factors, and vehicle factors and the traffic accidents have been known to occur via individual factors or through discordance in the relationships between such mixed factors.[1)]
When the traffic accidents that occurred on the highways, for three years from 2000 to 2002 inclusive, were classified by the occurrence factors, the traffic accidents that occurred in relation to driver error reached 82.7 %, i.e. 9,517 cases in a total 11,505 cases. Notably, it is known that drivers make mistakes in situations where they perform complicated tasks with excessive exposure to external environments or, in contrary situations. Most traffic accidents were caused by driver factors but it is difficult to establish efficient traffic measures to minimize drivers' mistakes due to microscopic and insufficient studies on the various drivers' factors.
The causes of traffic accidents that describe the relationship between the road environment factors and the drivers' workload to meet such factors has been defined in the model to compare system demand and driver performance suggested by Blumenthal M(1968)[2)] . In the study on the relationship between stimuli and workload conducted by Wilson, J. R. & Corlett, E. N. (1996)[3)] , the mental workload of workers was increased to smoothly perform the work when stimuli from the surroundings were high and Fuller, R. (2000)[4)] reported the "Task-Capability Interface Model" to describe that accidents occur when the tasks demanded by the road and traffic environment are larger than the drivers' capability[5)], and that safe driving is possible when the drivers' capabilities are larger than the tasks demanded. Thomas C and Hankins[6)] et al. (1998) identified whether HR[7)], HRV[8)], blinking, EEG α waves, and θ waves are explanatory of the measurement of the pilots' mental load and Alexander Gundel[9)] et al. (1995) evaluated private pilots' drowsiness during night flights by checking EEG α waves, θ waves, β waves, δ waves, and EOG.
Jeong-Ryong Kim (2002, 2003)[10)] suggested a demand-effort model to evaluate highway risks based on the relationship between the demand level by the road environment and the effort level that is the workload to the drivers shown during driving in the road environment, by analyzing the workload to drivers. Bong-Jo Jeong (2005) pointed out that existing demand-effort models had problems in their basic assumptions about the normal distribution of biological signals and suggested useful analysis parameters.
Jeong-Ryong Kim (2002) used 10 parameters consisting of two size values for EOG-H and GSR and eight inclination values for EOG-H, EOG-V, SKT, GSR, the left frontal lobe β/α, the right frontal lobe β/α, the central lobe θ, and the parietal lobe θ collected from 139 persons on the three sections comprising the high accident section on the Yeongdong Expressway, the moderate-accident favorable linear section on the other expressway, and the low-

1) Workload given to drivers depending upon the complexity levels of the roads and traffic environments
2) Electroencephalograph
3) Electrooculomotorgraphy
4) Galvanic Skin Response
5) Drivers' performances to be applied depending upon the complexity levels of the roads and traffic environments
6) Skin temperature
7) Heart rate
8) Heart rate variation
9) Fast Fourier Transform
10) Electrocardiograph

accident favorable linear section on the Seohaean Expressway. When a normality test was conducted using Shapiro-Wilk to these 10 biological signal parameters, the inclination of the frontal lobe EEG only showed normal distribution among the 10 parameters at low-effort level on the Seohaean Expressway; on the Yeongdong Expressway, the incline values of the right frontal lobe, the central lobe, and the parietal lobe EEG only showed normal distribution at moderate-effort level and the inclination values of the right frontal lobe and the parietal lobe EEG only showed normal distribution at the high-effort level. As it was assumed that the biological signal parameters of existing models had normal distribution properties, the existing models required modification.

It was required to classify the parent groups of the biological signal parameters into 3 levels and, in this study, cluster analysis was performed to group by similar-tendency data. As a result, the 4 parameters consisting of the inclination values of SKT, GSR, the left frontal lobe β/α, and the central lobe θ that had small numbers of samples among the 10 parameters were excluded and Mann-Whitney analysis was performed to verify whether each of the biological signal parameters had the same grouping tendency at each level; when the Chi-Square value was less than 0.001 at a 95 % confidence level, an alternative hypothesis was applied instead of a null hypothesis to verify that the median value had statistical significance. As the result of the analysis, the inclination value of EOG-V only showed 0.4694 of the Chi-Square value at all the three high, moderate, and low effort levels among the six biological signal parameters, thus denying the alternative hypothesis, and the median values of the remaining 5 parameters showed statistical significances at each level at a 95 % confidence level. In conclusion, it was decided to use five parameters, consisting of the size values for EOG-H and GSR and the inclination values for EOG-H, the right frontal lobe β/α, and the parietal lobe θ, among the 10 biological signal parameters, in determining the drivers' effort levels

NEURAL NETWORK MODEL

Construction of a Neural Network

The actions of man are the response to a stimulus set. Man learns through experiencing various situations and the learned memory obtained through past experiences is used as the decision-making data for new stimuli. The artificial neural network is the algorithm for inducing the response to stimuli by artificially configuring a network of the systems between such stimuli and responses.

As the biological signal parameters used in this study are the response values of drivers' biological signals to external stimuli, they are independent but influence one another among the biological signal parameters and, as the response types of individual drivers are very diverse, it is practically limiting to model the relationship between the biological signals through the quantitative and measurement process.

The biological signal parameters are the drivers' responses to external stimuli and they also respond to stimuli from other biological signal parameters. The sets of individual biological signal parameters are finally expressed as the whole responses by the drivers. This process of the mutual stimulus levels and the contribution levels to the responses among the biological signal parameters would be able to be modeled using the artificial network.

In this study, a multi-layer perceptron (MLP) structure artificial network was used to evaluate the effort levels using the drivers' biological signal parameters and a back propagation algorithm was also used. The mutual stimulus levels and the contribution levels to the responses among the biological signal parameters were modeled as a multi-layer perceptron structure consisting of an input layer to input five biological signal parameters, three hidden layers consisting of 5 neurons in the interim, and an output layer consisting of 1 neuron, using the artificial network.

The multi-layer perceptron used in this study consists of an input layer to input five biological signal parameters, three hidden layers consisting of 5 neurons in the interim, and an output layer consisting of 1 neuron (Figure 1). When the quantity of the hidden layers is increased, the convergence may be accelerated and a stable neural network may be configured but the output obtained after inputting may not be sufficiently sensitive resulting in errors in evaluating risk levels. If the quantity of hidden layers is too small, the network may show a rapid convergence process as well as sensitivity but the possibility of divergence becomes high; therefore, three hidden layers were used because this number is usually considered to be appropriate. At the output layer, the output values are obtained in the range from zero (0) to 1 for each of the three neurons meaning high, moderate, and low effort levels and the effort of the neuron showing the largest value was considered as the final output.

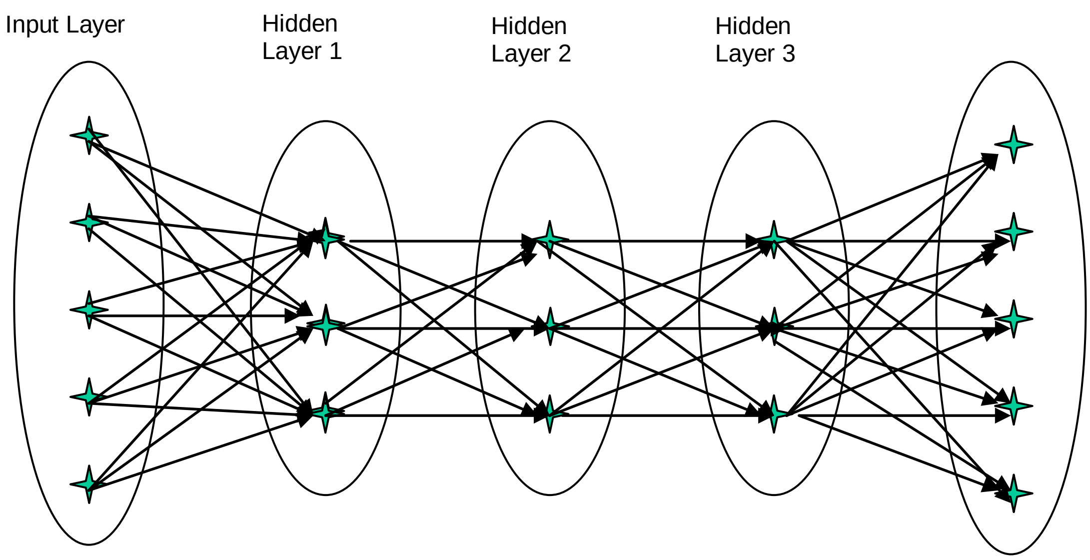

Figure 1 - The Multi-Layer Perceptron structure used in this study

That is, the mutual relationship between the biological signal parameters and the contribution level to the responses may be used in the respect that the past learning effect is used as the memory of the past to the stimuli by the present biological signal parameters using the recognition/decision system consisting of the weights among the individual neurons that are

the configuration units of the neural network and the associative memory device that is equivalent to the brain of man.
The adjustment of the connection weights (w_{ij}) of the constructed neural network was performed in terms of the credit assignment problem and, in case of an assignment of credit to the errors, the errors were reduced by the error back propagation method; the learning process of the error back propagation consists of the feed forward step for operation from the input layer to the output layer and the feed backward step for correction from the output layer to the input layer as shown in Figure 2. The afore-mentioned process repeats the operation until the neural network system is converged with no divergence, that is, the output value comes into the error allowance range of the target value. When the output value is converged into the error allowance range, learning is terminated.
The initial weight was randomly set in the range from zero (0) to 1 and the connection weight (learning strength) was set so that the learning was terminated when the connection weight was within ±0.01 of the error allowance of the target value (0~1) and the learning output value (0~1). The Sigmoid function was used as the output function, the maximum learning times were set as 50,000, and divergence was prevented by feedback to the initial step if convergence is not done after divergence. Although the trained output value reached the error allowance, learning was performed more than 10,000 times to verify the possible divergences.

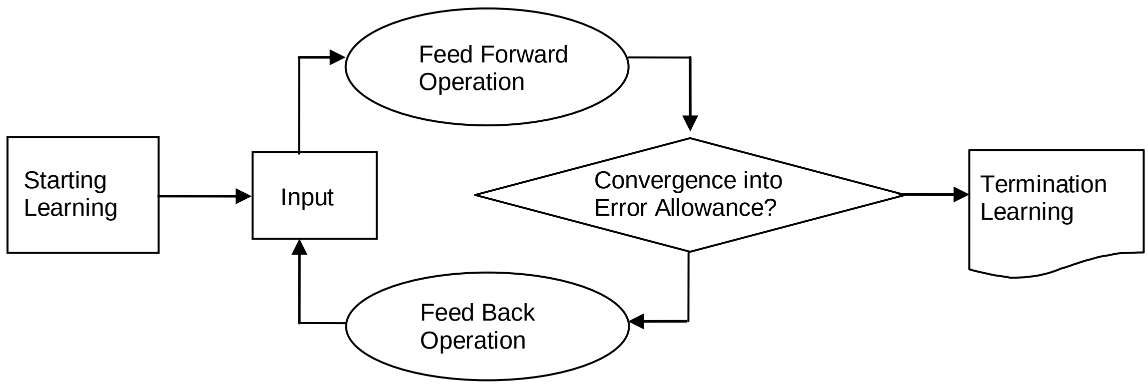

Figure 2 - The learning process of the feed forward/backward steps of the artificial neural network

Collection and Processing of Biological Signal data

Biological signal data was collected using the biological signal parameters collected from the 139 subjects having at least 3 years of actual operation experience on the high accident section of the Yeongdong Expressway, the moderate-accident favorable linear section of the other expressway, and the low-accident favorable linear section of the Seohaean Expressway when constructing the demand/effort model. Random sampling was adopted to analyze the biological signal parameters of the subjects and the subjects were randomly classified into Group 1 and Group 2 consisting of 50% of the subjects, respectively.
The sets of the biological signal parameters of the subjects were used in determining the standard value of each effort level and the valid range of each parameter of the biological

parameters and in evaluating the effort level for each biological signal parameter of the subjects, through the statistical analysis of each biological signal. Group 1 was used in constructing the patterns for the biological signal parameters for the neural network to learn, constructing the operation memory data using the learned data, and verifying the effort-level determination method for Group 1. Group 2 was applied in determining the effort levels by Group 2 based on the effort-level determination model and the operation memory data constructed using Group 1 and was used in evaluating such determinations.

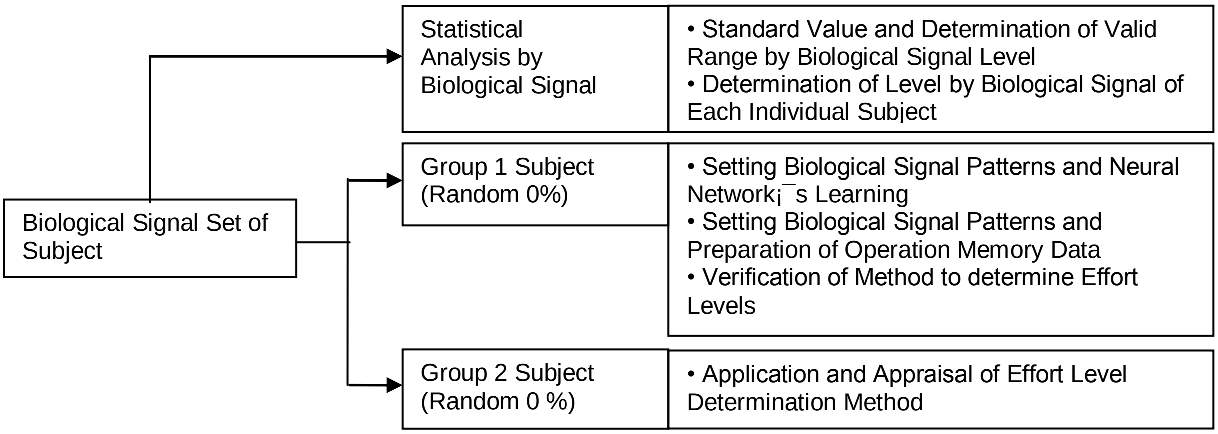

Figure 3 - Substantial utilization method of collected data

Setting the Patterns of Biological Signal Parameters

As the types, levels, and units of the five biological signal parameters collected from the subjects were different one another, the biological signal parameters were patterned by the multi-subject optimization method and the five types of biological signal parameters for each subject were made into a 5D signal-group vector $F(x)$. Then, the distances and direction of the biological signal parameters for each subject for each biological signal parameter belonging to the signal group were set as the values between zero (0) and 1 if they were not less than the arithmetic mean of the maximum and minimum parameter values, i.e. the space where the parameter value exists, or as the value between -1 and zero (0) if the values are not more than the arithmetic mean. The direction of each element of the input vectors and the input patterns stored in the operation memory device were compared and consistent patterns were selected.

And then, the input patterns to be compared and the directions in the operation memory device were inspected by the weighted sum method in terms of the extended multi-subject optimization method; the shortest distance of the vector space between the first selected patterns was measured and the pattern having the smallest value was finally selected. The pattern selection procedure is shown in Figure 4. Finally, the selected pattern was stored in the pattern group configured from the operation memory device shown in Figure 5 and each effort level (low, moderate, or high) was stored in the operation storage.

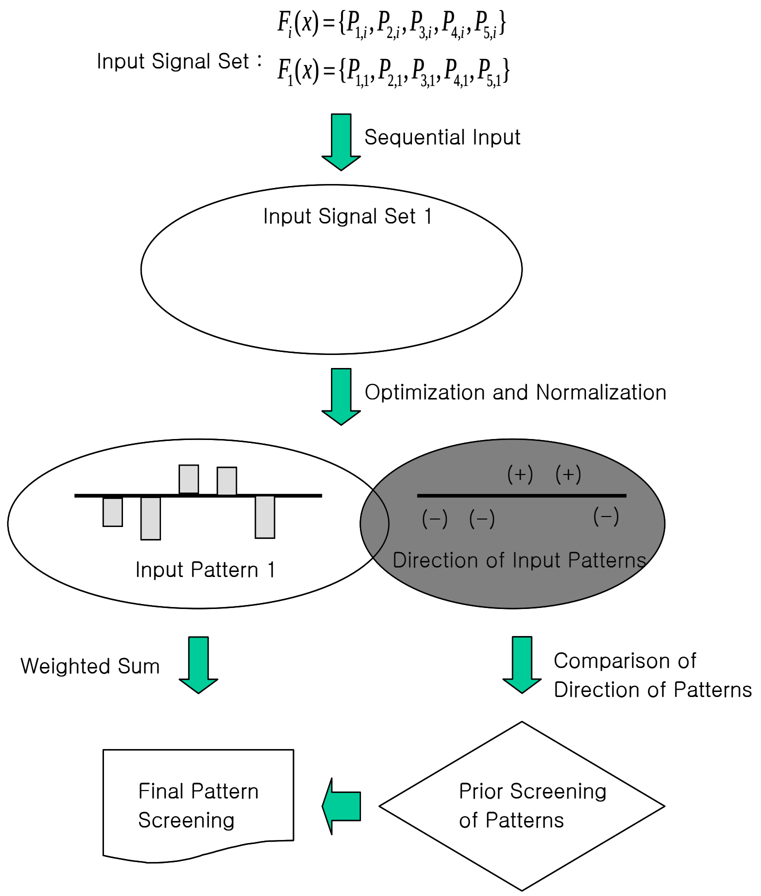

Figure 4 - Screening and processing patterns

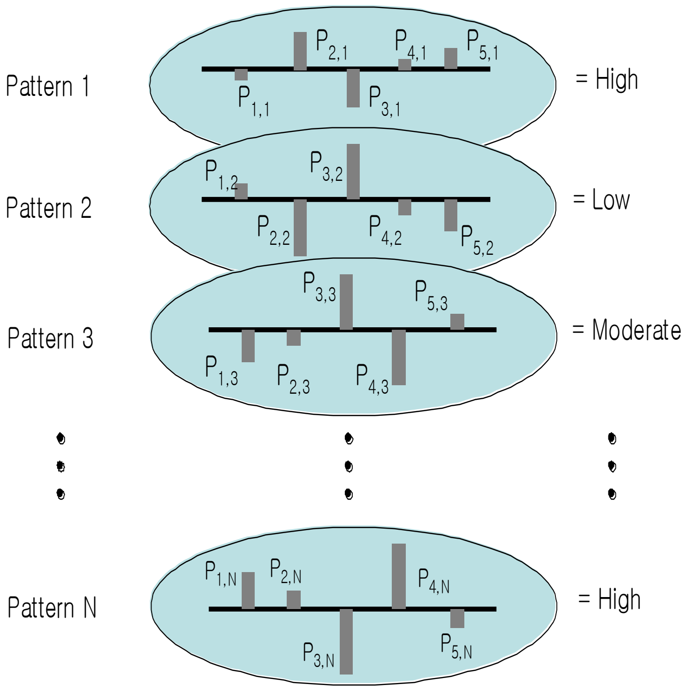

Figure 5 - The signal group after the patterning process

Determination Procedure

At Step 1 for determination, the values were converted into to the effort levels for each biological signal parameter for each subject. At Step 2, the pattern for each biological signal parameter was constructed and the neural network' learning and operation memory device was constructed. At Step 3, the effort level for each biological signal parameter was determined. In the case of an invalid biological signal parameter pattern, a filtering process was performed; in the case of a valid pattern, Step 1 and Step 2 were performed for addition to the operation memory. The construction of the data for determination of effort levels, the verification of effort-level determination model, and the application and evaluation of the effort-level determination model were performed by the procedures and contents shown in Figure 6.

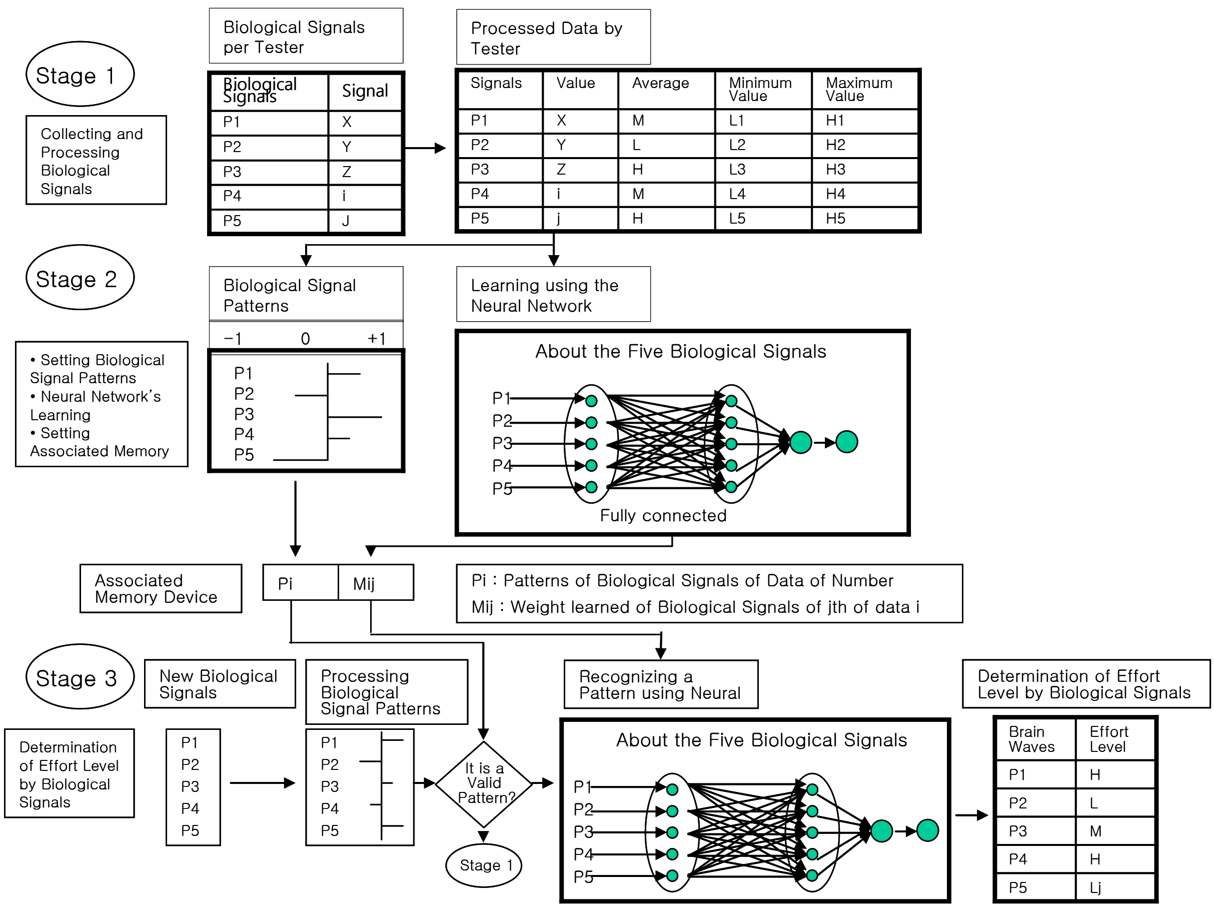

Figure 6 - The effort-level determination process using an artificial neural network

Verification of the Neural Network Algorithm

The input values and target values were fixed to verify the application suitability of the constructed neural network structure, the operation input model of the input value, a 5 % -error value of the original input value, a 15 % -error value of the original input value, and a 30 % -error value of the original input value were created, and the tendencies of convergence and divergence were evaluated in the case of convergence to the target value depending upon the situation when changing the quantity of the layers from one to three.

Figure 7 shows the tendencies that the errors of the input values are dependent upon the quantity of the layer(s); the output value was gradually increased up to 5 % of the input error in the case of one or two layers but was reduced when the input error exceeded 5 %, indicating that back propagation shows an irrevocable tendency in the neural network structure. When three hidden layers existed, the output was gradually increased as the input error increased. Figure 8 shows the diagram for expecting the change tendency of the output; the output value was gradually increased up to 5 % of the input error in the case of one or two layers but was reduced when the input error exceeded 5 %, indicating very strong fluctuation. When three hidden layers existed, the output was gradually decreased and then stabilized as the input error increased.

In terms of the sensitivity, the cases having one or two hidden layers might be considered to be excellent but more weights were placed on the entire stability of the neural network structure and the reliability of output; therefore, cases having three hidden layers were selected for the neural network structure of this study to generate non-fluctuating and revocable output

For the verification of the constructed algorithm, the biological signal parameter analysis of the subjects was performed using Group 1 consisting of 50% randomly-selected subjects based on the random sampling method of the 139 subjects to set the patterns of the biological signal parameters for the neural network's learning, construct the operation memory data using the learned data, and verify the effort-level determination method and Group 2 was used in evaluating the effort levels of Group 2 with application in determination based on the constructed effort-level determination model and operation memory data.

The determination accuracy of the effort levels to individual biological signal parameters ($\{P_1,...,P_5\}$), the accuracy of the amount of the pattern data for each biological signal parameter, and the determination accuracy of the total effort levels for the 5 biological signal parameters of i of the individual biological signal parameters set (P_i) were verified using each subject group ($P_i = \{P_1,...,P_5\}$) in Group 1.

As the result of verification, the determination accuracy of the effort level for each biological signal parameter was 96.5 % at the low level, 100.0 % at the moderate level, and 98.3 % at the high level. The accuracy by the number of each biological signal parameter pattern(s) was found to be 80 % or higher as shown in Fig. 9. Especially, when 10 or more biological signal parameter patterns were set, 93 % or higher accuracy was shown. The accuracy of the effort level with the integration of individual biological signal parameters was 81.8% or higher; the more the biological signal parameter patterns, the higher the accuracy.

The algorithm was applied in the process to determine the effort level for each biological signal and the integrated effort levels of the individual biological signal parameter set, of Group 2, using the biological signal patterns, the neural network algorithm, and the neural network's operation memory data provided using Group 1 was constructed. The determination accuracy of the effort level for each biological signal parameter was 94.3 % at the low level, 97.8 % at the moderate level, and 90.9 % at the high level indicating that the applicability of the effort level algorithm constructed in this study was very high.

The accuracy depending upon the number of biological signal parameter patterns was found to be at least 80.0 % when 20 or more parameter pattern data existed as shown in Figure 9; the more the pattern data for each parameter and each effort level, the higher the effort-level determination ability.
The diagram below shows the accuracy of the entire effort levels of the subjects when Group 2 was applied; the accuracy by effort level was 76.2 % at the low level, 55.6 % at the moderate level, and 95.5 % at the high level; differences were found by effort level but the entire effort level was found to be 74.3 % indicating the appropriateness in determining the effort levels of the subject groups at any point or segment of the expressways.
As the output values of the multi perceptron neural network used in this study were input with normalization into the range of 0~1 using the sigmoid function, the output values near to zero (0) and 1 were not sensitive and should be modified to the input/output values between about 0.15~0.85. The multi perceptron neural network that connects all the neurons between layers was used; as the studies regarding the relationships that exist among the biological signals and what influence is given were insufficient, all the neurons were connected. It is thought that, because the entire risk levels were measured using the biological signals from 139 subjects and multi determinations were applied to the same road sections, although a wrong determination was made due to concentration in the individual local optimum, there might be no problem in determining the risk levels.

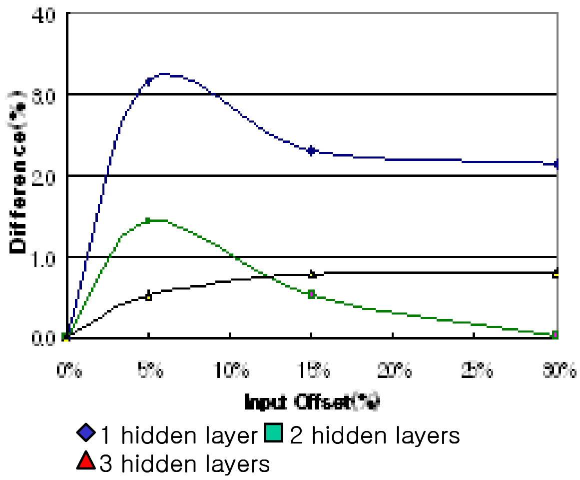

Figure 7 - Change rate of output

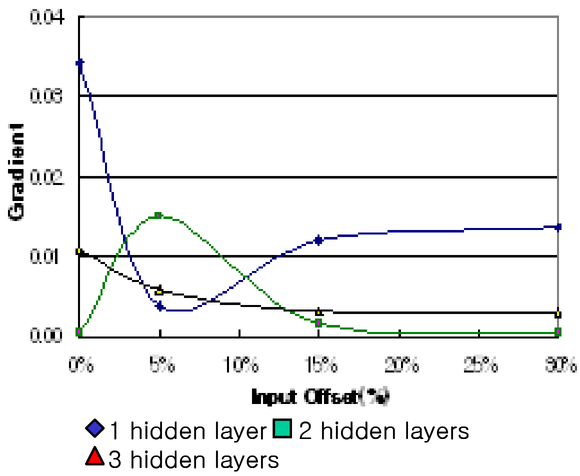

Figure 8 - Change in gradient

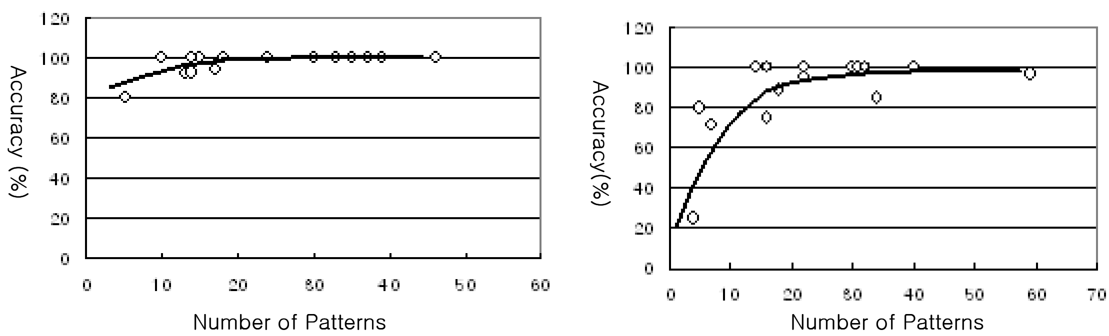

Figure 9 - Accuracy of parameter level by the number of patterns

APPLICATION

Collection of Drivers' Biological Signals

The section (Jeonju IC → Hoedeog JCT) on the Honam Expressway was selected as the test section based on the field survey, geometrical structure, and traffic data analysis. The length of the section for data collection was decided as about 78 km in consideration that it was efficient for the measurement equipment to collect the signals within 1 hour after collection. As this section had two or more accidents in the recent 5 years and its geometrical structure was not significantly improved, the history of past accidents and the response data of the drivers could easily be compared and analyzed.

In case of the studies of the human factors, it is accepted to collect and analyze data collected from 5~10 persons due to difficulty in the collection of data. The field running experiment was performed once a week using 10 subjects; the subjects were prohibited from drugs, smoking, coffee, and alcohol before performing the experiment and the subjects were to participate in the experiment with no accumulated fatigue. The subjects were selected in consideration of the ratios of the drivers by the periods of their driver's license acquisition.

A Galloper V6 was used as the experimental vehicle with installation of the equipment to collect the driver's biological signals and to monitor the surrounding environmental information. An MP100 was used to collect the driver's biological signals because it is widely used in collecting signals from the autonomic nerves and central nervous systems of man. The electrodes for collecting biological signals from the driver in the running vehicle were attached by the 10-20 Method of the international brain-wave academy (international brain wave, IFCN). An electrode was attached between the index finger and the middle finger to measure skin conductivity. Electrodes were attached near to the right and left crown tops to measure eye movement and electrodes were attached at the top and lower parts of the right eye to measure the vertical movement of the eye.

The 10 subjects were informed not to take alcohol or drugs on the previous day of the experiment and were to take meals 2 hours before performing the experiment. When the subjects arrived, they were briefed about the purpose and procedure of the experiment and heard the precautions related with the experiment. When the driver had had sufficient time for adaptation, biological signals were collected in the stabilized status and the stabilization state was visually checked, and verbally checked with questions.

The experiment was performed between 14:00 and15:00 on fine weekdays from 20 May to 21 June 2002. The experimental vehicle was maintained at 95 - 100 km/h in the 2nd lane if possible and passing was permitted to satisfy the 90 -100 km/h experiment condition. 20 minutes of prior driving time was given to the driver for sufficient adaptation to the vehicle before entering into the signal collection section. Five kinds of biological signals consisting of the β/α inclination on the right frontal lobe, the θ inclination on the parietal lobe, GSR size, and the inclination of EOG-H were collected every 2 seconds from the drivers who were judged to have the right characteristics for effort-level analysis.

Processing Biological Signal Data

Sampling data was arranged at the appropriate intervals to meet the purpose of the analysis and each 5 raw data were gathered to make one analysis-unit data using the raw data collected every 2 seconds in the section (Jeonju IC → Hoedeog JCT) on the Honam Expressway. Jeong-Ryong Kim (2002) suggested 10 seconds in his study as the efficient unit time for the analysis of biological signal analysis. As a result, a total of 171 biological signal data were obtained for each parameter in the section (Jeonju IC → Hoedeog JCT) using 10 subjects. The collected raw data was first filtered to remove signal noise from the collected biological signals by the biological signal analysis method used in the existing demand-effort models. In the filtering process, a high pass filter was 0.5 Hz and low pass filter was 30 Hz. Processing was performed in this order: FFT analysis → power value calculation → calculation of the relative power spectrum values (α, β, and θ waves) → calculation of the biological signal variances (β/α, relative energy coefficient, and root mean square) → calculation of the biological signal parameter values (slope, amplitude).

Evaluating Highway Safety Using the Demand/Model with the Application of a Neural Network

There is no clear statement on the determination of the demand levels in the demand/effort model of Jeong-Ryong Kim (2002) and the mental stress was defined as the demand asked of the drivers to drive safely in the expressway running environment. There would be various methods to determine the demand levels but this study was conducted based on the model of Jeong-Ryong Ghang (2002); this model is a domestically developed microscopic traffic-accident expectation model having the geometrical structure and traffic volume of the roads as independent variables for 4-lane expressways and was developed for the Honam Expressway.

Figure 10 shows the curve fitting result and demand levels by road classification in exponential functions when the model was applied. The sections were classified by the method of Bong-Jo Jeong (2005) who classified the boundary values of the upper/lower levels by the demand level using PD-2000 (a commonly-used road design inspection program). As a result, 14 high-demand places, 128 moderate-demand places, and 29 low-demand places were obtained.

The effort levels on the 171 unit analysis points in the section (Jeonju IC → Hoedeog JCT: 87 km) on the Honam Expressway were determined by the effort level determination method using the neural network. When this result was simply compared with the demand levels deduced from the neural network model, a total of 29 sections consisting of 3 high-demand sections, 24 moderate-demand sections, and 2 low-demand sections were evaluated as inappropriate with traffic safety problems.

When this result is compared with the actual traffic accident data, 1 high-demand section was consistent in terms of traffic accident occurrence and another 2 sections had no traffic accidents. For moderate-demand sections, 14 sections had traffic accidents and 12 sections had no traffic accidents.

For low-demand sections, 1 section had traffic accident(s) and 1 section had no traffic accidents. In terms of the total of 171 sections studied, 6 sections, among the 29 inappropriate sections that took 16.9 % of the share, showed traffic accidents with a 55.2 % accident rate and a 44.8 % no-accident rate; the rate of no accidents in the appropriate sections was 40.5 %. When the analysis was performed by the effort level determination method by Jeong-Ryong Kim (2002) using the maximum/minimum value ranges, 9 inappropriate sections were found and, among them, the accident rate was 66.7 % and the no-accident rate was 33.3%; for the 34 appropriate sections, the accident rate was 58.8 % and the no-accident rate was 41.2 %.
If it is emphasized that the road managers should more actively extract and improve the traffic-accident risk points, it would be reasonable to determine such points aiming at the minimization of correct rejections. In case of the effort level determination method by the neural network analysis applied in this study, the risky road sections are actively determined with expectation of 29 places, which shows about 3 times the places of other methods, and the more interested correct rejections were found in 40.5 % compared with the 58.8 % in the existing models, indicating that the traffic accident risk evaluation model is appropriate in terms of the purpose of development. Also, it would meet the usage of road risk expectation models for expert groups to roughly determine the road risk prior to performing detailed road safety inspections.

Classification		Low	Moderate	High
Linear Part	Main Line	< 0.86	0.86 ~ 6.42	6.42 <
	In/Out Line	< 1.24	1.24 ~ 9.03	9.03 <
Curved Part	Main Line	< 0.67	0.67 ~ 4.94	4.94 <
	In/Out Line	< 1.06	1.06 ~ 8.26	8.26 <
Smoothly Curved Part	Main Line	< 0.42	0.42 ~ 3.11	3.11 <
	In/Out Line	< 0.50	0.50 ~ 4.00	4.00 <

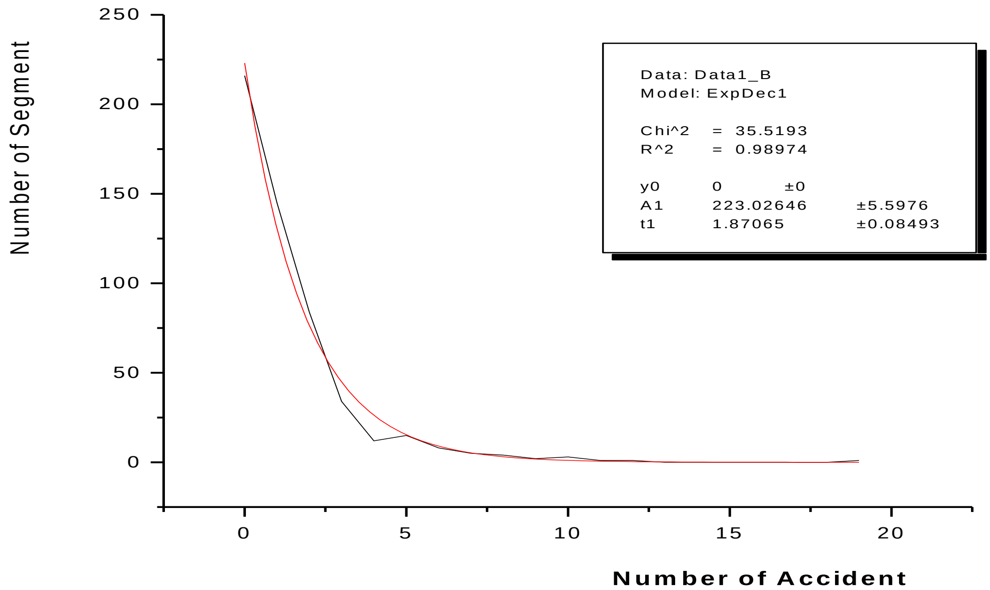

Figure 10 - The standard values of the traffic accident estimation model for determining the curve fitting result and demand levels on the main line part of smoothly curved lines

CONCLUSION

Although most of road traffic accidents have been found to be related with human factors, most of the efforts to reduce traffic accidents have been concentrated on improving the geometrical structures of road facilities or improving vehicle performances due to insufficient studies on the driver factors. This study was aimed at the fact that serious problems are generated in traffic safety due to discordance in the drivers' mental workload and road environment demand levels on the drivers, in order to consider the human factors of the drivers as the important factors in evaluating the road risk. Various biological signals to evaluate the drivers' mental workload and the analysis methods to process them were surveyed using previous studies. Through this survey, the properties of the biological signal parameter values collected from the drivers during driving were identified and mental workload was evaluated, suggesting a new method to evaluate road risk. Through this study, conclusions were obtained as described below.

Firstly, the problems in the 10 biological signal parameters suggested in the existing models were indicated and 5 useful biological signal parameters suggested based on statistical analysis.

Secondly, as the neural network is a flexible nonlinear model and has a powerful pattern recognition function, the accuracy of effort level evaluation was found to be very high in the biological signal groups of nonlinear and integrated organic substances. The accuracy of the entire effort levels of each subject in Group 1 used in constructing the neural network was as high as 80.0 % or higher and the accuracy of the entire effort levels of each subject in Group 2 was 74.3 %.

Thirdly, when the road risk was compared between the demand-effort model using a neural network and existing models based on the 171 unit analysis points in the section (Jeonju IC → Hoedeog JCT: 87 km) on the Honam Expressway, Correct rejections were found in 40.5% of the neural network model and in 58.8% of existing models. If the evaluation of road risk by the demand-effort model is assumed not to be the final one but to be the intention for the rough determination of road risk prior to a detailed road safety inspection, the method for using the neural network showing fewer correct rejection would be considered in order to meet the aim of the demand-effort model.

In spite of the proven performance of this study in determining the road risk with the collection of drivers' biological signals during driving, additional studies would be required in this area to deduce more reliable results to be applied in the field. Firstly, the biological signals used in this study were EEG, EOG, and GSR. As found in previous studies, it is needed to develop the parameters for applying various biological signals related with cardiac actions such as ECG as the important factors during driving and to more clearly and credibly explain the drivers' driving properties in each wave type of the EEG.

Secondly, biological signal measurement sensors and analysis methods should be developed for the identification and practical application of the drivers' mental and physical workload using the biological signals.

Thirdly, more data should be collected to determine the effort levels that were the major factor of this study and the determination of the optimum boundary values for each parameter should be supplemented to be used in determining the effort levels.

Fourthly, existing demand-effort models do not make any specific suggestion in determining the demand levels. The method to determine the demand levels is assigned to the successive researchers in order meet the purposes of their studies. Just as with the determination of effort levels, the expectation model for determining demand levels simply reflects the geometric structures and traffic properties of roads only and it would be difficult to verify the climatic and environmental factors. Therefore, it would be required in successive studies to suggest the methods for determining more reliable demand levels with a reflection of various conditions at the development stage of expectation models.
This demand/effort model is meaningful in the respect that the road risk is evaluated from the standpoint of the drivers who generate most of the causes of traffic accidents. It's the initial stage of the study and, if the study is continued in the future in spite of some limitations, this kind of study would be positioned toward a new research area related with traffic safety.

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