Journal of the Ergonomics Society of Korea
Vol. 15, No. 2, 1996

Human performance models using neural network

Ji young Kwahk* · Sung H. Han*

ABSTRACT

A single line display menu (SDM) is widely used for the user interface of many electronic consumer products, and the designers need useful guidelines applicable to the SDM. In many studies on menus, major focus has been placed on the optimal menu structure, but only a few standard menu structures, such as 64^1, 8^2, 4^3, and 2^6, are usually tested for optimality. In many cases, however, ill defined or asymmetric structures are suggested as design alternatives. To determine the optimal menu structure, user performance should be obtained in terms of quantitative measures. Hence, a model is needed to provide a predicted value of user performance for a given menu structure. Altough several models have been proposed for ordinary menus, none is available for the SDM yet. To solve this problem a performance model was developed in this study using the neural network approach. This model is capable of providing quantitative measures of human performance for any menu structures without conducting additional experiments, which will save much time and reduce the design cost.

Keywords : human performance model, electronic consumer products, single line display menu, neural network

1. INTRODUCTION

Menu-driven interfaces are used for most softwares such as word processors, drawing packages. So many design guidelines have been proposed for a variety of issues related to the design of menus, among which major focus has often been placed upon the optimal menu structure. That is, the designers usually face the situation in which they should determine how deep

* Department of Industrial Engineering Pohang University of Science and Technology

and broad their menus should be made. Since the determination depends mostly upon the performance of the user, what the designers want to know is how well the user performs the tasks when a newly designed menu is provided with a newly designed menu in advance. Hence, a number of psychologists and human factors engineers have been suggested various forms of models in order to predict the performance of the users of menus (Card, 1982; Landauer and Nachbar, 1985; Lee and MacGregor, 1985; Paap and Roske-Hofstrand, 1986).

Menu-driven interfaces are often employed also for user-system dialogue in electronic consumer products which have many functions for user control. Unlike the software interfaces, the user interfaces of most electronic products cannot employ an ordinary display (e.g. CRT displays of 13 to 20 inches) to present menu items due to space and cost limitations. Instead, they usually employ a single line display typically made of liquid crystal (See Figure 1). Users navigate through the menu structure looking at the display, which shows menu items one at a time, using a set of control buttons, which makes the single line display menu (SDM) different from a menu on the ordinary display (ODM). The navigation through the SDM is much more complex compared to the ODM not only because the navigational path is much more complex than the ODM, but because the navigational information cannot be visualized to the user without an appropriate aid for the navigation. Han and Kwahk (1994) have compared the two types of menus and reported that different guidelines are required for the SDM. Based upon several experiments, they provided detailed guidelines for the design of a usable SDM (Kwahk and Han, 1994; Han and Kwahk, 1995).

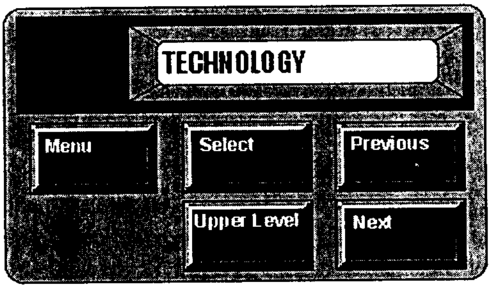

Figure 1

In their studies, a focus was placed on the optimal design of menu structure, but only the standard menu structures (i.e. 64^1, 8^2, 4^3, and 2^6) were tested for optimality in terms of user performance and preference. Although the guidelines developed in their studies are essential to the design of the SDM, they are less likely to be applied to a menu with an ill-defined or asymmetric menu structure, which can be found very often in real-world applications. As in the menus for software interfaces, however, the optimal menu structure should be determined based upon the resulting performance of the user. And a means of obtaining user performance in terms of quantitative measures for each of the optional structures is required. Although some models have been proposed for the ODM, none was found to be applicable to the SDM when they were tried.

This study was conducted to provide a performance model which is applicable to the SDM. A model was developed taking the distinctive characteristics of the SDM into account, and then the neural network approach was used to predict the parameters of the model.

2. PERFORMANCE MODEL

The optimum tradeoff function of depth versus breadth of the hierarchical menu structure was determined by specifying $u(n)$, the user response time to select one item from n possible items at a specific level. Two functional relationships between response time and menu breadth were proposed, among which a linear relationship proposed by Lee and MacGregor (1985) has more relevance to the SDM compared to the logarithmic one, since, though extremely important, the results from the study of Landauer and Nachbar (1985) are criticized because their study was mainly confined to the laboratory conditions particular to their studies (Norman, 1990). The linear model is represented by the following equation:

$$u(n) = E(n)t + k + \alpha$$

where $E(n)$ is the expected number of menu items read, t is the reading time per item, k is the key press time, and α is the computer or system response time. Since they assumed constant symmetric trees with N terminal nodes, the relationship between depth d and breadth n was given as $d = \log_n N$, which was multiplied by $u(n)$ to yield the total response time. The linear model sometimes is not appropriate at all, since it ignores the decision time part of the response time and the reading time itself may not be constant within or across menu levels (Norman, 1990).

Those models proposed for the ODM, however, are not applicable directly to the SDM for the following reasons: Firstly, the response time within or across depth levels was assumed to be constant, which may not be true in some cases. For example, users may be faster in reading the items since they are familiar to those items in the top-level menu which they have seen more frequently than the lower menus; Also some users may be slower in determining whether to choose the current item or not in the upper level menus since they cannot figure out the class inclusion relationship between the currently displayed item and the target than in the lower level menus. Secondly, the response time at a level $u(n)$ was multiplied by menu depth d (i.e. $\log_n N$) to get the total response time, which is impossible when the depth cannot be specified as such. Thirdly, items in a depth level can be scanned by saccadic movement in the ODM, while additional button pushes are required in the SDM, which is one of the most critical differences between the SDM and the ODM

Hence, a new model is proposed for the SDM as shown in the following equation:

$$\text{Search Time} = \sum_{i=1}^{Depth} \{ E(n_1)(t_1 + k + \alpha) \}$$

where $E(n_i)$ is the expected number of menu items read in level i, t_i is the reading time per item, and k and α are key-press and system response time, respectively, which were assumed to be constant.

3. PREDICTION OF E(n_i) AND t_i USING NEURAL NETWORK

Different from previous studies in which both $E(n_i)$ and t_i were assumed to be the same in all depth levels, they were estimated taking the breadth n, depth d, and level i into account by using the neural network in this study.

3.1 Network Structure

Two separate networks were constructed in order to predict $E(n_i)$ and t_i in this study. A three-layered multi-layer perceptron (Haykin, 1994). was used in each network which had three input nodes and one output node. The input nodes were breadth n, depth d, and level I, and the predicted values of $E(n_i)$ and t_i were the output of each network (See Figure 2).

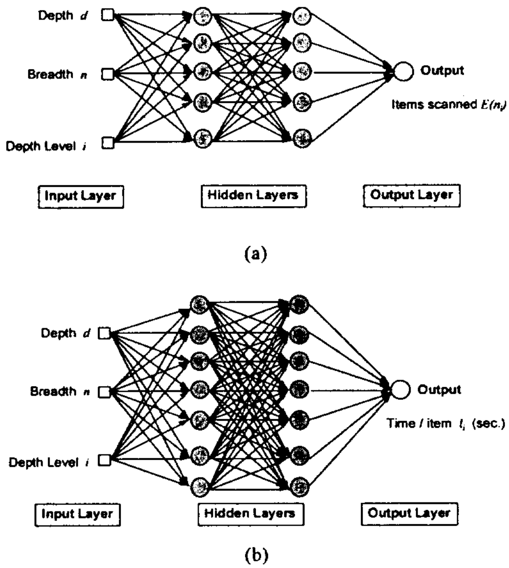

Figure 2

3.2 Learning

The method of backpropagation with a momentum was used in learning (Haykin, 1994). A total of 500 sets of data collected through the experiment conducted by the authors in the prior study (Han and Kwahk, 1995) were used as the input-output patterns of the training set. Out of the 500 sets of data, 350 chosen randomly were used in network training and the remaining 150 were used in cross validation. For more detail on the experiment, see Han and Kwahk (1995). Different activation functions were used in the hidden and in the output layer: A logistic function was used for nodes in the hidden layers, while a linear function was used for those in the output layer. The size of network and the parameters of learning were determined with regard to the results of cross validation. The number of epochs and the values of two learning parameters, η and α are summarized in Table 1 together with the corresponding values of mean squared error (MSE) of learning and cross validation.

Tabel 1. Summary of learning results

	# Epochs	η	α	MSE (Learning)	MSE (Cross Validation)
$E(n_i)$ Model	2000	0.01	0.01	0.0724	0.0913
t_i Model	2000	0.1	0.1	0.2971	0.3420

4. RESULTS AND DISCUSSION

In order to test the prediction performance of the model developed in this study, named NN model, the predicted search time of the NN model was compared to the average search time obtained from the experiment. The predicted search time based on the conventional linear model proposed by Lee and MacGregor (1985) was also computed for comparison. See Table 1 for the computed results, and Figure 3 shows the comparison results in a graphical form. The total search time for each menu structure was computed using the predicted values of $E(n_i)$ and t_i obtained from the neural network in the NN model. And the average values of $E(n)$ and t were used to compute the total search time for the conventional model.

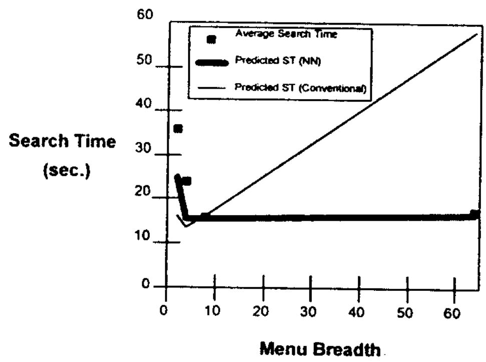

Fig 3

Table2. Predicted search times : NN model vs. Conventional

Menu Structs	Depth Level	NN Model $E(n)$	NN Model t_i	NN Model ST_1	Conventional Model $E(n)$	Conventional Model t	Conventional Model ST_2	Ave. ST of Experiment
64^1	1	22.47	0.74	16.52	32.5	1.80	58.59	17.0
8^2	1	4.63	1.42	15.58	4.5	1.80	16.22	15.7
	2	4.95	1.82					
4^3	1	2.70	1.48	15.56	2.5	1.80	13.52	23.9
	2	2.85	1.84					
	3	3.01	2.10					
2^6	1	1.84	1.57	24.72	1.5	1.80	16.22	35.6
	2	1.90	1.83					
	3	1.97	2.03					
	4	2.03	2.17					
	5	2.09	2.30					
	6	2.14	2.41					

The model developed in this study has several advantages listed below:

- The prediction accuracy was improved by considering the depth, breadth, and depth level information together in computing $E(n_i)$and t_i.
- Since the neural network approach was used, it was not necessary to guess the functional relationship among depth, breadth, depth level, and the two parameters $E(n_i)$ and t_i.
- Because of the robust property of the neural network, the model can also give a reasonable prediction value for new input patterns that have never seen by the network during the training. For example, predicted search times can be obtained for unbalanced menus like 16×4 and 4×16 menu structures, or even more ill-defined ones.

5. CONCLUSION AND FUTURE STUDIES

The model developed in this study will provide quantitative measures of human performance for any menu structure without conducting additional experiments, which will save much time and, as a result, reduce the design cost. However, more data collection is necessary to make the model more accurate.

The results of this study are expected to have an immense impact upon the design of menus for user interfaces of many electronic consumer products. Furthermore, a new paradigm of using the neural network in predicting the human performance was suggested in this study. It is a more powerful tool for the researchers in this area, allowing them to bypass the difficult process of inferring the underlying functional relationships. In addition, it is a strong advantage that there is no need to make assumptions of parameter distributions. Often the unrealistic assumptions lead to false conclusions in a conventional statistical analysis.

REFERENCES

[1] Card, S.K. (1982). User perceptual mechanisms in the search of computer command menus. Proceedings of Human Factors in Computing Systems, 190-196.

[2] Han, S.H. and Kwahk, J. (1994). Design of a menu for small displays presenting a single item at a time. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, CA: Human Factors and Ergonomics Society.

[3] Han, S.H. and Kwahk, J. (1995). Single Line Display Menu. Proceedings of the Human Factors and Ergonomics Society Annual Meeting, CA: Human Factors and Ergonomics Society.

[4] Kwahk, J. and Han, S.H. (1994). Menu structure for single-line displays, Proceedings of 3rd Pan-Pacific Conference on Occupational Ergonomics.

[5] Landauer, T.K. and Nachbar, D.W.

(1985). Selection from alphabetic and numeric trees using a touch screen: Breadth, depth and width. CHI-85 Proceedings, 73-78.

[6] Lee, E., & MacGregor, J. (1985). Minimizing user search time in menu retrieval systems. Human Factors, 27, 157-162.

[7] Norman, K.L. (1990). The Psychology of Menu Selection: Designing Cognitive Control at the Human-Computer Interface. NJ: Ablex.

[8] Paap, K.R. and Roske-Hofstrand, R.J. (1986). The optimal number of menu options per panel. Human Factors, 28, 377-385.