THE STUDY OF LEARNERS' PREFERENCE FOR VISUAL COMPLEXITY ON SMALL SCREENS OF MOBILE COMPUTERS USING NEURAL NETWORKS

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ABSTRACT
The vision plays an important role in educational technologies because it can produce and communicate quite important functions in teaching and learning. In this paper, learners' preference for the visual complexity on small screens of mobile computers is studied by neural networks. The visual complexity in this study is divided into five levels, including "very high" complexity, "slightly high" complexity, "medium" complexity, "slightly low" complexity and "very low" complexity. This study focuses on the age effects for vision problems in educational technologies. The age of the tested subjects distributes from 10 to 64, and is uniformly divided into 11 groups with each group composed of 30 tested subjects. For simplicity, the effects of gender, words, colors, and other visual factors are ignored. This study found that only learners of the younger and older age groups have special preference on the picture of very high complexity. Most learners prefer pictures of medium and slightly high complexity. These results are consistent with many existing studies. With the use of neural networks, only about half of the investigation data are required to predict the overall investigation results. Discussions and interpretations on the results are also given in this study. This study will be helpful in vision problems of educational technologies.
Keywords: learner, visual complexity, screen, mobile computers, neural networks

INTRODUCTION
The use and capabilities of small mobile communication devices, which include many all-in-one features, have become embedded in one's everyday life and are growing rapidly, such as pocket PCs, tablet PCs, smart mobile phones, and smart wireless sensors (Karan, Bayraktar, Gümüskaya and Karlik, 2012). Mobile devices are portable, ubiquitous and easily accessible, and are then widely used by many people. This situation implies that there is great potential to enhance learning through mobile devices (Keskin & Metcalf, 2011). The learning is one of human instincts. New learning technologies initiate new learning styles. Nowadays, mobile computers lead learners to new mobile learning environments. This then motivates us to choose the vision of mobile computers as the main topic of this study. The degree of a device's mobility determines the way it is best used in learning. A smartphone is no doubt much more mobile than a laptop, and this high degree of mobility makes it indispensible in modern learning (Franklin, 2011; Mcconatha, 2008). Traditionally, artists presented their work using non-interactive visual media. With the ongoing development of information and interactive technologies, people can create art using digital multimedia (Chang & Lee, 2010; Isman & Celikli, 2009). From a constructivist perspective, small mobile computers can be utilized to provide meaningful art information and then enhance learning experiences.

The neural network is a control theory rising in recent years (Haykin, 2009). It has attracted wide attention of researchers due to its special black-box characteristics. For example, a neural network makes inference according only to human operating experiences and control rules (Kumar, 2005). Hence, the neural network has become the new focus of various professional research areas in recent years (Ham and Kostanic, 2001). This is because various research fields can utilize neural networks to solve strongly nonlinear and complicated problems (Zhang and Zhang, 2006). Neural networks can simulate the information processing of biological neural systems, and simulate the nerve tissues and functions of the human brain. Thus a black-box system with simulated operations of perception, thought, imagination, and logic of the human brain can be constructed. The neural network can learn through given examples (i.e., known input and output data) to construct a nonlinear system model (input-output relation) for estimation and prediction. It can also be viewed as a special type of statistical techniques (Bailey & Thompson, 1990; Specht, 1991; Haykin, 2009). This study focuses on vision problems of educational technologies. The vision system is probably the most complicated system among all sensory systems (Solso, 2000). In visual cognition, the acceptance of vision communication is easier than that of textual communication. This is the reason why we choose pictures on mobile computers' screens as the research topic. We study learners' preference for visual complexity on small screens of mobile computers. In addition, this study utilizes a neural network model for analysis, and intends to predict the overall results by using fewer questionnaire samples. The goal is to know learners' preference for visual complexity on small screens of mobile computers. The results will be helpful for educational technologies.

Although scholars have studied human brains for years, there are still many secrets in the vision cognition processes of brains (Solso, 2000). Throughout the years, the two major theories for the psychology of vision, i.e., Realism Theories and Relevant Cue Hypotheses, have not reached any consensus yet (Lin, 1994). The Realism Theories suggest that the learning effects of learners increase with visual information, and learners prefer more complex visions. Pictures with rich information can arouse the interest of learners (Vartanian & Goel, 2004; Kawabata & Zeki, 2004; Hsu & Wang, 2010). In addition, picture background information can help learners to build an overall architecture and then enhances the recognition of visions. Thus, more complex vision information is favored (Dale, 1946; Antes & Metzger, 1980). However, the Relevant Cue Hypotheses suggest opposite viewpoints. They report that one's ability to process information is limited, although complex pictures are interesting. Complex pictures will increase the load on the brain. Thus interferes are occurred during the communication of pictures (Alesandrini, 1984; Dwyer, 1978; Hurt & Kirk, 1988). People are more sensitive to simple pictures than to complex pictures (Pezdek & Maki, 1988), as illustrated in Figure 1. The recognition advantage of pictures over verbal descriptions is not due to the extra details that pictures contain. Complex pictures with extra details have no advantage in recognition (Nelson, Metzler & Reed, 1974), as illustrated in Figure 1.

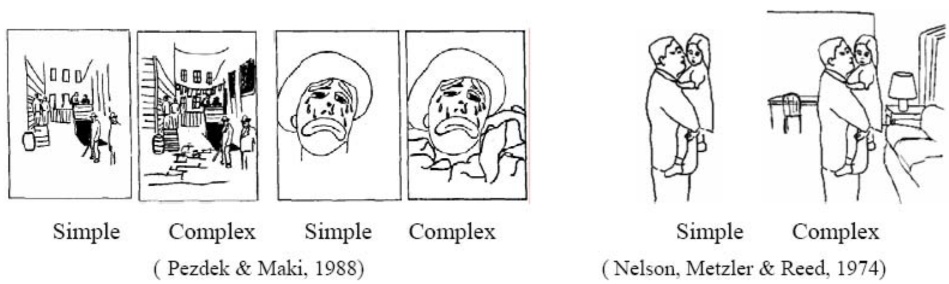


Figure 1. Examples of pictures in both simple and complex forms.

In this paper, investigations by questionnaires are first given. The testing pictures in this study are mostly drawings with black and white outlines. The visual complexity means the density of conveyed visual information in the picture. Higher picture density makes the image more complex, and vice versa. Visual complexity contains the amount of interior details in a picture and background information (Wang, 2002). Many studies have discussed the relationships of pictures to cognition and attention, emphasized the importance of picture information (Saunders, 1994; Micklos, 1982), (Rieber, 1994), and used the inverted U-shaped function to explain the relationship between pictures and learners (Wang & Hsu, 2009; Dwyer, 1978), as shown in Figure 2.

METHOD

Research Method & Procedure

Initially, this study conducted a questionnaire survey, and collected data from subjects of various age groups. Next, data were analyzed by statistical operations and modeled by neural networks. Finally, the discussion and interpretation about learners' preference for complexity is given. This study utilized the neural network to model learners' preference for visual complexity on small screens of mobile computers. Wang (2002) found that the gender factor would not influence the preference for visual complexity. Therefore, this study only considered the age factor. The subjects of this study were 10-64 years old, and were divided into 11 age groups in units of 5 years. They were chosen by using the stratified random sampling method, including 10-14 years old, 15-19 years old, 20-24 years old, 25-29 years old, 30-34 years old, 35-39 years old, 40-44 years old, 45-49 years old, 50-54 years old, 55-59 years old, and 60-64 years old. Each age group consisted of thirty subjects, and thus there were totally 330 subjects surveyed by questionnaires. Pictures with five different levels of complexity were utilized to test the subjects. Each subject was asked to answer a questionnaire and chose his favorite picture among the five testing pictures. The goal is to obtain the percentages (%) of preferences of various age groups for mobile computer pictures with different levels of complexity. These investigation results are further modeled by neural networks. In the learning phase of neural networks, investigated data of the 6 odd age groups (Groups #1, #3, #5, #7, #9, and #11) were selected from the 11 age groups to serve as the training samples. After the neural network is trained, results of all the 11 age groups were predicted by the neural-network model. Neural networks may have many types of architectures. The neural-network architecture utilized in this study is the RBF-NN (radial basis function neural network) model, which is composed of weighted Gaussian function bases (Christodoulous & Georgiopoulos, 2001). This type of neural-network architecture can model strongly nonlinear problems through only simple algebraic operations. Since the learners' preference for a picture is inherently strongly nonlinear behavior, the RBF-NN model becomes a good candidate for modeling such a problem.

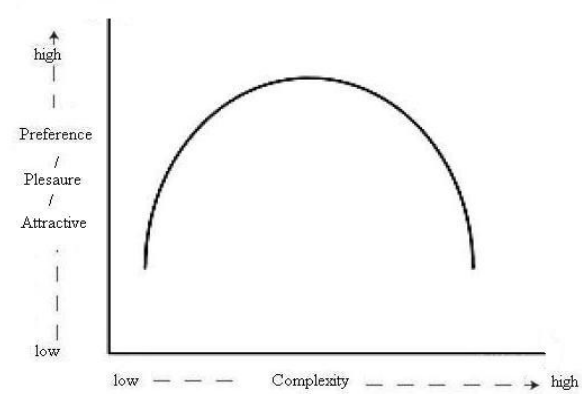


Figure 2. Te inverted U-shaped function for visual complexity.

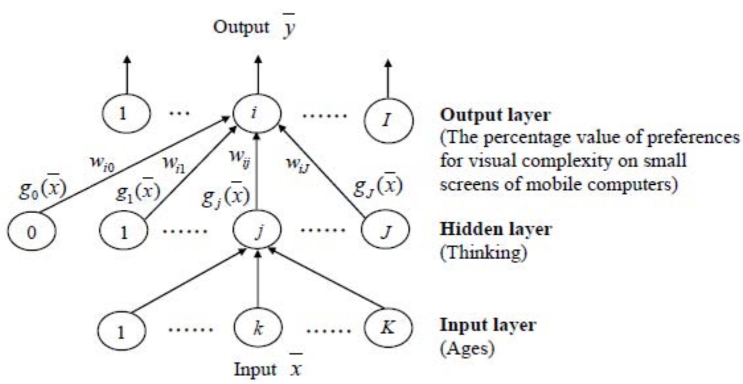


Figure 3. Architectures for the RBF-NN Model.

Figure 3 shows architectures for the RBF-NN model. In Figure 3, the K nodes (chosen as K=1 in this study) of the input layer represent age, which is normalized into the range of 0 to 1. The hidden layer has J nodes, which serve as the thinking process of a neural network. The J is chosen as J=10 in this study. The output layer has I nodes (chosen as I=5 in this study) representing the output functions, which are percentages (%) of preferences of various age groups for testing pictures with five different levels of complexity. According to Christodoulous & Georgiopoulos (2001), the output of the RBF-NN can be expressed as

$$y_i = w_{i0} + \sum_{j=1}^{J} w_{ij} g_j(\bar{x}),\ i = 1, 2, \ldots, I, \tag{1}$$

where

$$g_j(\bar{x}) = e^{-\frac{1}{2}(\bar{x}-\bar{v}_j)^T \bar{\bar{\Sigma}}_j^{-1} (\bar{x}-\bar{v}_j)},\ j = 1, 2, \ldots\ldots, J, \tag{2}$$

represents the nonlinear transform relation between input-layer and hidden-layer variables. In Eq. (2), $\bar{v}_j$ denotes the mean vector for Gaussian functions in the hidden layer, and $\bar{\bar{\Sigma}}_j$ denotes the auto-covariance matrix. The training procedures of the RBF-NN are described in the following (Christodoulous & Georgiopoulos, 2001).

* Step 1: Select initial values for the weights (w_{ij}) from hidden to output layers. These weights are chosen to be small random values. Select initial values for the centers of the Gaussians in the hidden layers. These centers are randomly chosen from the training data. Select initial values for the diagonal elements of the covariances of the Gaussian functions. These variances are all chosen to be equal to some constant.
* Step 2: Present the p^{th} input pattern at the input layer of the RBF-NN.
* Step 3: Utilize Eq.(1) and Eq.(2) to calculate values for nodes in hidden and output layers of the RBF-NN.
* Step 4: Compare the actual output $y_i(p)$ at the output layer and the described output $d_i(p)$ for i = 1, 2, …, I. If $y_i(p) = d_i(p)$ for 1 i I, go to step 5. If $y_i(p) \neq d_i(p)$ for some i, proceed to change the weight or parameter values as follows

$$\Delta w_{ij} = \eta [d_i(p) - y_i(p)] g_j[\bar{x}(p)], \quad (3)$$

$$\Delta \bar{v}_j = \eta g_j[\bar{x}(p)] \sum_{i=1}^{I} [d_i(p) - y_i(p)] \cdot w_{ij} (\bar{x}(p) - \bar{v}_j) \cdot \quad (4)$$

* Step5: If $p=P_T$ and the cumulative error is smaller than a pre-specified threshold, we consider the training completed. If $p=P_T$ and the cumulative error is larger than a pre-specified threshold, then we return to Step 2 starting with the first input pattern of index p=1. If $p \neq P_T$, we return to Step 2, by increasing the pattern index p by one.

After the neural network is trained by some learning samples of $\bar{x} \to \bar{y}$ according to the above procedures, all the weights w_{ij} (i = 1, 2, …, I; j = 0, 1, …, J) will be determined. Therefore, the prediction of $\bar{x} \to \bar{y}$ will be given by Eq.(1). That is, the trained RBF-NN can model the mapping of $\bar{x} \to \bar{y}$. In particular, the trained neural network can predict data of $\bar{x} \to \bar{y}$ that do not belong to the training data sets.

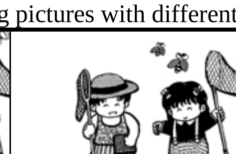
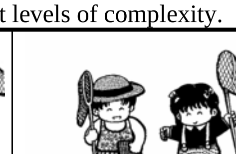
Research Samples

The samples in this study are drawings with black and white outlines, of single scenario without text, as shown in Table 1. There are five testing pictures with different levels of complexity in Table 1, as described in the following.

(1) Picture A: Very high complexity image, with detailed descriptions of figures, objects, scenarios, and backgrounds.
(2) Picture B: Slightly high complexity image, with detailed descriptions of figures, objects and scenarios, but background is slightly simplified.
(3) Picture C: Medium complexity image, with detailed descriptions of figures, objects, and scenarios, but only the most important background information is maintained.
(4) Picture D: Slightly low complexity image, with only descriptions of character details.
(5) Picture E: Very low complexity image, only outlines of characters are retained.

The above five testing pictures are entered into a mobile computer with a small screen (Figure 4). The experimental screen size is 102mm × 62mm (Figure 5). Figure 6 shows the experiment for a subject.

Table 1. The five testing pictures with different levels of complexity.

				
Picture **A**	Picture **B**	Picture **C**	Picture **D**	Picture **E**
Very high complexity	Slightly high complexity	Medium complexity	Slightly low complexity	Very low complexity

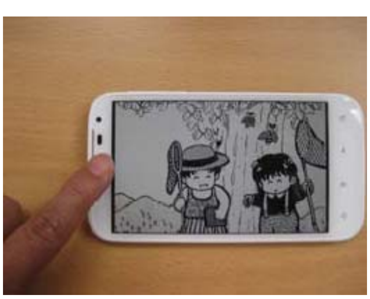


Figure 4. The sample picture is entered into a mobile computer with a small screen.

Figure 5. The experimental screen size.

Figure 6. The experiment for a subject.

Limitations

There are some limitations in this study, as shown in the following.

(1) The sample pictures of this study are homemade and are simple. Practically, pictures on a mobile computer are complex and have many styles. For simplicity, this study focuses on pictures of only one style.
(2) For simplicity, pictures of this study are monochrome. Practically, pictures on a mobile computer are colored.
(3) For simplicity, pictures of this study are static. Practically, pictures on a mobile computer are moving.
(4) For simplicity, pictures of this study contain only icons. Practically, pictures on a mobile computer contain both icons and text.
(5) For simplicity, surveys are made on only 330 subjects form the Southern Taiwan. To improve the accuracy, much more subjects should be tested in the future.

EXPERIMENTAL RESULTS

Following the above investigation procedures, experimental data are recorded and statistically analyzed. Table 2 shows the percentages (%) of preferences of various age groups for mobile computer pictures with different levels of complexity. For clear illustration, the data in Table 2 are further plotted in Figure 7.

Table 2. Percentages (%) of preferences of various age groups for mobile computer pictures with different levels of complexity.

Group	Group #1	Group #2	Group #3	Group #4	Group #5	Group #6	Group #7	Group #8	Group #9	Group #10	Group #11
Ages	10-14 years old	15-19 years old	20-24 years old	25-29 years old	30-34 years old	35-39 years old	40-44 years old	45-49 years old	50-54 years old	55-59 years old	60-64 years old
Preference for Picture A (%)	19.79	18.18	17.03	14.60	17.69	16.44	13.34	12.88	14.01	17.03	21.67
Preference for Picture B (%)	22.24	24.10	25.10	25.25	24.05	23.20	24.83	23.36	23.56	23.34	20.31
Preference for Picture C (%)	24.80	26.38	27.95	26.88	24.92	25.33	25.36	26.82	24.33	25.13	25.22
Preference for Picture D (%)	21.64	19.07	16.59	17.27	16.84	18.24	19.30	19.09	20.19	18.88	20.00
Preference for Picture E (%)	11.98	12.16	13.63	15.79	16.23	16.42	17.38	17.51	18.02	16.10	12.79

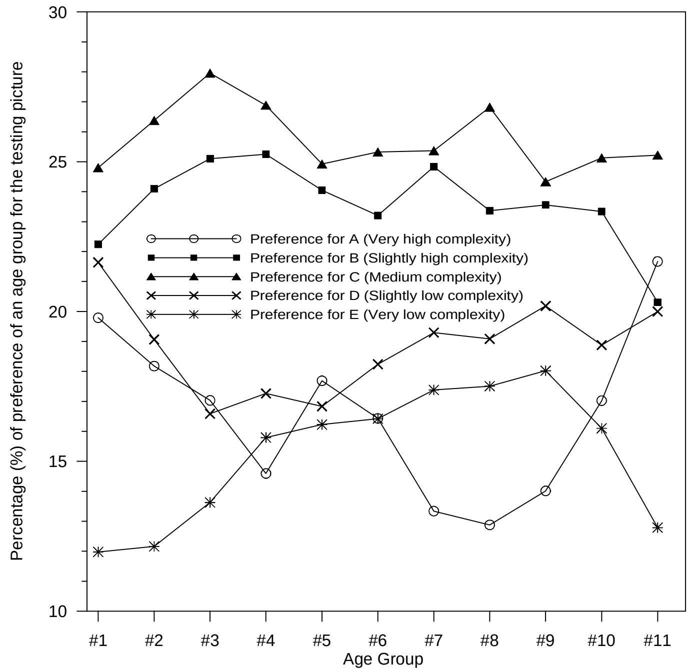


Figure 7. Tendency chart for percentages (%) of preferences of various age groups for mobile computer pictures with different levels of complexity.

Next, the RBF-NN is utilized to model and then predict the results of Table 2 or Figure 7. During the learning phase of RBF-NN, data of Groups #1, #3, #5, #7, #9, and #11 from Table 2 are chosen as training samples, as shown in Table 3. The detailed learning procedures have been mentioned above. After the RBF-NN is trained, it can predict the overall investigation data.

Table 3. Training data sets of the RBF-NN --- odd groups of Table 2.

Group	Group #1	Group #3	Group #5	Group #7	Group #9	Group #11
Ages	10-14 years old	20-24 years old	30-34 years old	40-44 years old	50-54 years old	60-64 years old
Preference for Picture A (%)	19.79	17.03	17.69	13.34	14.01	21.67
Preference for Picture B (%)	22.24	25.10	24.05	24.83	23.56	20.31
Preference for Picture C (%)	24.80	27.95	24.92	25.36	24.33	25.22
Preference for Picture D (%)	21.64	16.59	16.84	19.30	20.19	20.00
Preference for Picture E (%)	11.98	13.63	16.23	17.38	18.02	12.79

Table 4 shows the comparison between RBF-NN predictions and questionnaire survey results. The absolute error in Table 4 means the absolute value for difference between the RBF-NN prediction and questionnaire survey. It is defined as "Absolute error (%) = | RBF-NN prediction (%) - questionnaire survey (%) |". From Table 4, it reports that the maximum error value is 3.64%, the minimum is 0.06%, and the average error value is 1.627%. These results are very accurate and reasonable. Comparisons between RBF-NN predictions and questionnaire survey results for individual testing pictures are plotted in Figure 8 to Figure 12.

Table 4. Comparison between RBF-NN predictions and questionnaire survey results.

Group		Group #1	Group #2	Group #3	Group #4	Group #5	Group #6	Group #7	Group #8	Group #9	Group #10	Group #11
Ages		10-14	15-19	20-24	25-29	30-34	35-39	40-44	45-49	50-54	55-59	60-64
Preference for Picture A (Very high complexity)	Questionnaire survey (%)	19.79	18.18	17.03	14.60	17.69	16.44	13.34	12.88	14.01	17.03	21.67
	RBF-NN prediction (%)	16.89	17.57	14.78	15.22	16.08	16.18	14.88	12.16	14.08	14.94	22.40
	Absolute error (%)	2.90	0.61	2.25	0.63	1.61	0.25	1.54	0.72	0.06*	2.09	0.73

Preference for Picture B (Slightly high complexity)	Questionnaire survey (%)	22.24	24.10	25.10	25.25	24.05	23.20	24.83	23.36	23.56	23.34	20.31
	RBF-NN prediction (%)	24.89	25.57	23.70	23.62	22.01	25.36	27.34	21.82	22.38	20.19	21.81
	Absolute error (%)	1.16	1.47	1.40	1.63	2.04	2.16	2.51	1.54	1.18	3.15	1.50
Preference for Picture C (Medium complexity)	Questionnaire survey (%)	24.80	26.38	27.95	26.88	24.92	25.33	25.36	26.82	24.33	25.13	25.22
	RBF-NN prediction (%)	25.96	24.87	28.89	28.54	21.80	21.94	27.91	27.99	27.96	22.85	27.31
	Absolute error (%)	1.16	1.50	0.93	1.66	3.13	3.38	2.55	1.17	3.64*	2.27	2.10
Preference for Picture D (Slightly low complexity)	Questionnaire survey (%)	21.64	19.07	16.59	17.27	16.84	18.24	19.30	19.09	20.19	18.88	20.00
	RBF-NN prediction (%)	18.61	18.29	18.45	17.58	17.47	20.73	16.91	21.68	23.00	17.20	19.75
	Absolute error (%)	3.03	0.78	1.86	0.31	0.64	2.49	2.39	2.59	2.81	1.68	0.25
Preference for Picture E (Very low complexity)	Questionnaire survey (%)	11.98	12.16	13.63	15.79	16.23	16.42	17.38	17.51	18.02	16.10	12.79
	RBF-NN prediction (%)	13.70	13.10	13.10	18.06	16.64	16.92	19.34	18.24	15.40	16.62	14.66
	Absolute error (%)	1.72	0.94	0.53	2.27	0.41	0.49	1.96	0.73	2.62	0.51	1.87
※ Absolute error (%) ＝ | RBF-NN prediction (%) － Questionnaire survey (%) |												

DISCUSSION

Image is generated by a computer to blend with the environment to enhance the visual experience. Visual complexity is a multiple concept that combines picture attributes with picture variables. Thus, it does not merely refer to the density of picture composition, but is also influenced by many different factors, such as picture size, line, style, form, and color. This study discussed the amount of interior details inside a picture and its background information. The learners' preference affected by age factor is discussed. Table 5 shows the results from Table 4 sorted by total subjects' preference for testing pictures. From Table 5, it indicates that learners most prefer the picture with medium complexity (Picture C, survey: 25.74%), followed by the picture of slightly high complexity (Picture B, survey: 23.58%). The possible reasons are as bellows. First, the two testing pictures (C & B) contain moderate amount of vision elements and appropriate amount of information communication. They conform to an acceptable degree of visual capacity without increasing visual and cerebral loads. Second, the two testing pictures (C & B) are not too crowded so that the picture subject is clear at a glance. That is, they have the most comfortable density degree for visual elements. Third, the two testing pictures (C & B) have proper guiding functions and strong communication and transmission abilities.

The data in Table 5 also indicate that learners most dislike the picture of very low complexity (Picture E, survey: 15.27%), followed by the picture of very high complexity (Picture A, survey: 16.61%). This implies that the picture with too much or too little information is disadvantageous to visual communication in learning. The possible reasons why learners dislike the picture of very low complexity (Picture E) are as bellows. First, the picture of very low complexity is plain with tedious and empty senses so that it is not interesting to the learners. Second, learners feel that the picture of very low complexity is incomplete with no visual strength or feeling of quantity. Third, the picture subject is unclear, and provides insufficient stimulation for the learning. The possible reasons why learners dislike the picture of very high complexity (Picture A) are as bellows. First, the picture of very high complexity contains too many details unrelated to the subject and thus the normal learning is influenced. Second, the subject content cannot be highlighted in a short time due to too much information. This is disadvantageous to visual communication and learning. Third, learners can process only a part of the information when they are presented with a very complex picture. Thus the remaining information will be neglected and meaningless.

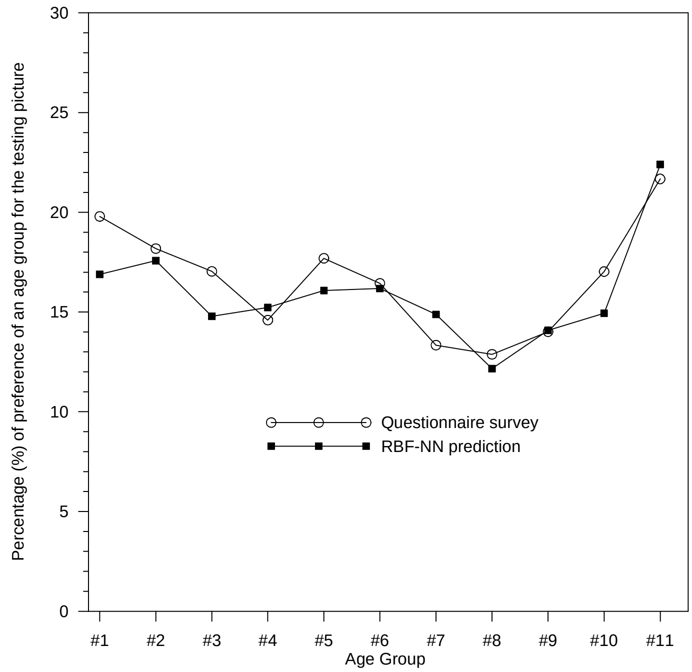


Figure 8. Comparison between RBF-NN predictions and questionnaire survey results --- Picture A (Very high complexity).

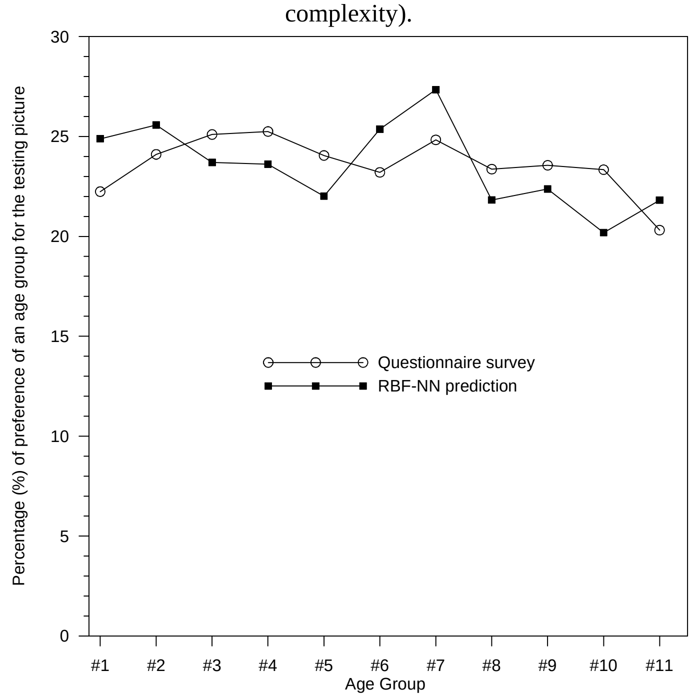


Figure 9. Comparison between RBF-NN predictions and questionnaire survey results --- Picture B (Slightly high complexity).

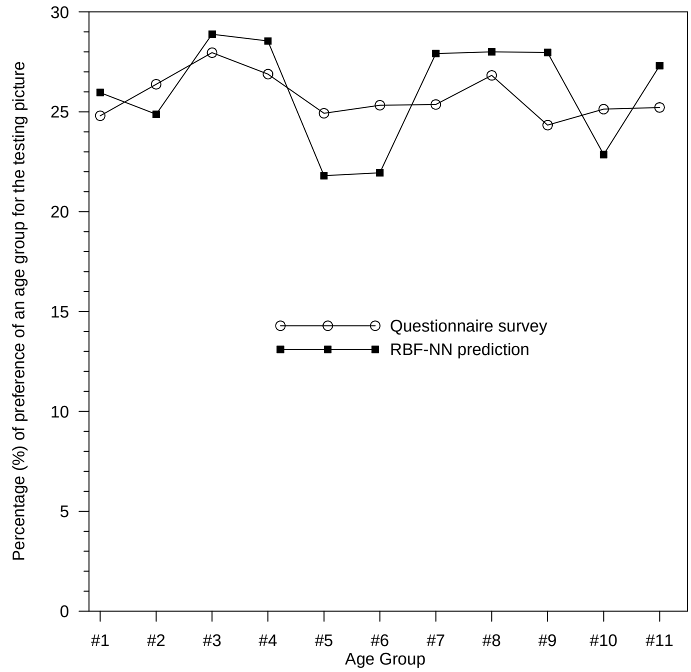


Figure 10. Comparison between RBF-NN predictions and questionnaire survey results --- Picture C (Medium complexity).

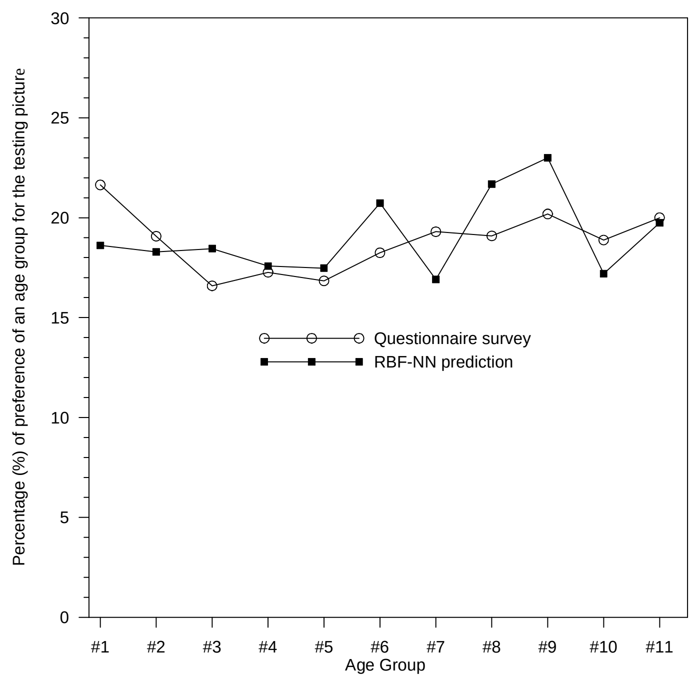


Figure 11. Comparison between RBF-NN predictions and questionnaire survey results --- Picture D (Slightly low complexity).

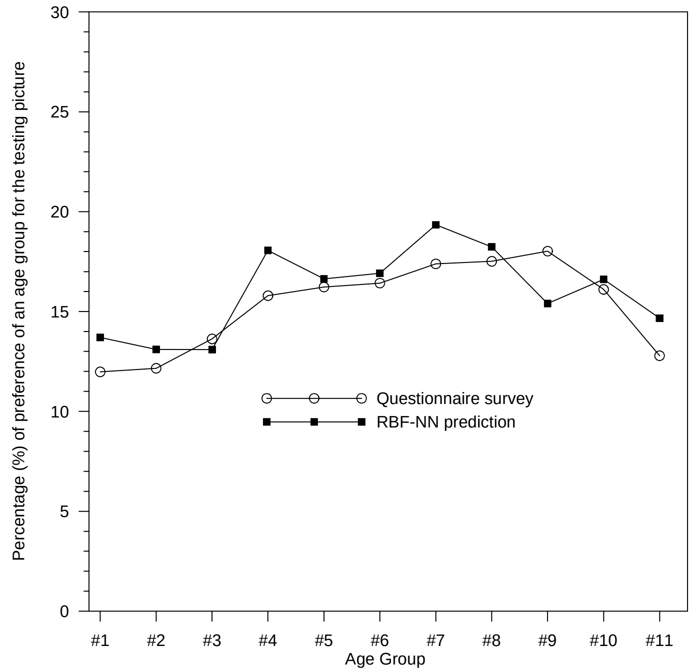


Figure 12. Comparison between RBF-NN predictions and questionnaire survey results --- Picture E (Very low complexity).

Table 5. Results from Table 4 sorted by total subjects' preference for testing pictures.

Testing Picture					
Sorted by Subjects' Preference	1	2	3	4	5
Visual complexity	Medium complexity	Slightly high complexity	Slightly low complexity	Very high complexity	Very low complexity
Picture number	Picture C	Picture B	Picture D	Picture A	Picture E
Questionnaire survey (%)	25.74	23.58	18.83	16.61	15.27
RBF-NN prediction (%)	26.00	23.52	19.06	15.93	15.98
Absolute error (%)	2.14	1.80	1.71	1.22	1.28

The complexity of a picture has significant influences on cognitive learning and these influences are tightly related to age (Micklos, 1982). Although most subjects disliked the picture of very high complexity, there were special groups of learners preferring this picture. According to Figure 8, the learners in younger and older age groups most liked the picture of very high complexity, and the preference curve is slightly U-shaped. The learners of the group "60-64 years old" (group #11) and the group "10-14 years old" (group #1) specially prefer the picture of very high complexity. The possible reasons for this phenomenon are as follows. First, the picture of very high complexity has visual integrity, and is then vivid, lively, entertaining, and vital. Second, learners sometimes selected a picture according to their psychological perceptions for different psychological conditions. Thus the learners of older and younger age groups may psychologically select their preference without basing on visual factors. Third, the learners in younger and older age groups did not like comfortlessness, loneliness or emptiness. This will influence the choice of preference for pictures. This finding is consistent with the Realism Theories, which assert that the learning effect of pictures increases with visual complexity. Only a few researchers, e.g., McDougall & Reppa (2008) think that viewers prefer simple pictures. Figure 12 shows that neither the older nor the younger learners like the picture of very low complexity. The curves of Figure 12 are slightly inverted U-shaped. The older and younger learners may have some similarities in psychology (Siegler & Alibali, 2005; Peng, 2008). In general, they are mentally empty, afraid, dependent, and short of a sense of security. Detailed pictures provide viewers more entertainment (Tsai, Chang, Chuang & Wang, 2008), and hence

they preferred the picture of very high complexity.
Figure 13 shows the tendency chart for Table 5, which is plotted with respect to levels of complexity for testing pictures. Note that the curve in Figure 13 is approximately inverted U-shaped. This is consistent with Figure 2, which is the viewpoint of numerous scholars studying visual complexity (Berlyne, 1974; Chang & Wei, 2002; Hsu & Wang, 2010; Tucha et al., 2009; Hurt & Kirk, 1988; Angert, 1980). Taking a general view of Figure 13, the final finding of this study is similar to the viewpoint of Relevant Cue Hypotheses, but different from the viewpoint of Realism Theories. From the curve of Figure 13, the maximum value occurs at the medium level of complexity (Picture C, survey: 25.74 %). In addition, the learners preferring pictures of medium complexity and slightly high complexity are about half of total subjects. Wang (2002) found that the subjects thought that the optimum computer screen picture only needed to emphasize the important part of the picture, and thus excessive detail description was unnecessary. For learning, pictures of medium complexity generally have better learning effects, and higher relative learning efficiency (Antes & Metzger, 1980).

After comprehensive discussion, it was found that the influencing factors in the preference of learners for visual complexity could be divided into objective and subjective factors. The objective factors for complexity depend on the structure of a picture. They include the picture line thickness, style, manifestation, shape, size, information content, and elements' distribution. While the subjective factors for complexity depend on individual differences of learners. They include learners' psychology, life background, personal preference, visual system difference, learning background, and age. In particular, the age has the most significant influence (Travers & Alvarado, 1970). The objective factors shall be observed using the subjective factors. Thus different learners will have different cognition results. Existing studies reported that the objective factors and the subject factors for complexity are correlated (Attneave, 1957; Chipman & Mendelson, 1979) and interactive (Strother & Kubovy, 2003). The above factors are listed in Table 6.

Table 6. Factors affecting learners' preference for visual complexity.

Structure of a picture (objective factors)	Individual differences of learners (subjective factors)
* line thickness of a picture * style of a picture * manifestation of a picture * shape of a picture * size of a picture * information content of a picture * elements' distribution of a picture	* psychology of learners * life background of learners * personal preference of learners * learning background of learners * age of learners * visual system of learners

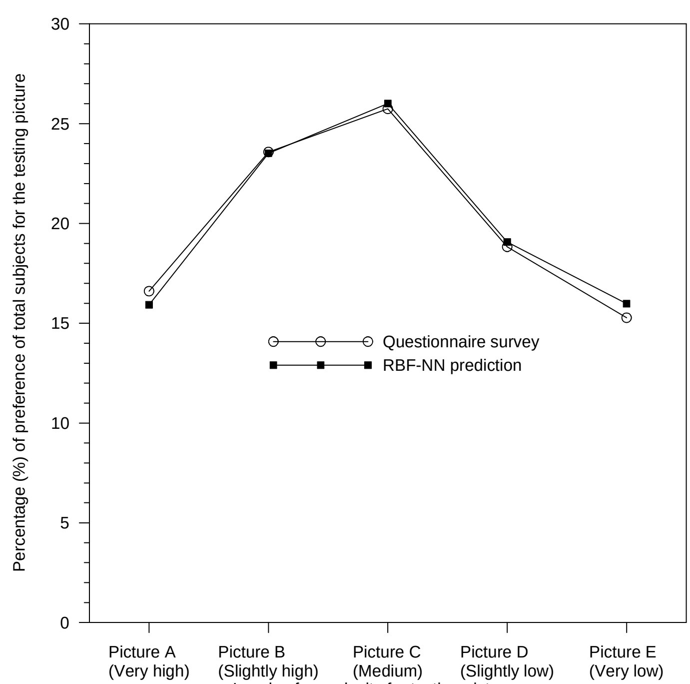


Figure 13. Tendency chart for Table 5, which is plotted with respect to levels of complexity for testing pictures.

CONCLUSIONS

The neural network has been widely used in engineering science, and its nonlinear modeling and predicting abilities have been proven. In this study, the RBF-NN has been successfully applied to visual communication of educational technologies. The average absolute error of prediction is only 1.627%, which is very accurate. With the use of RBF-NN model, only about half of investigation data are required to predict the overall investigation results. This will greatly reduce the investigation efforts. The important problems in this study are age, human vision acuity, and visual information processing capacity, which will affect learners' preference. Thus the learners will have logical decisions and different preference. This study found that learners' preference for pictures has differences and obviously varies with age. This is because learners have their favorite perception modes with differences in psychological cognition, and thus preference occurs in different age groups. The visual complexity of this study is the visual evaluation of integrity composed of many internal elements. Discussions regarding the visual complexity of mobile computers have been given in this study. Learners in different age groups will have different visual acuities and visual information processing capacities. Under the influences of both objective and subjective factors for complexity, learners will select their preferences for picture compositions by personal perception. This study found that only the learners of the younger and older age groups have special preference for pictures of very high complexity. Most learners prefer pictures of medium complexity, followed by pictures of slightly high complexity. This finding is consistent with the results of Dwyer (1978) and Berlyne (1974). In addition, our results are consistent with the viewpoints of Relevant Cue Hypotheses, which present the picture preference distribution as an inverted U-shaped curve. The vision is very important in educational technologies. It produces quite important functions and has already become indispensable arts of teaching materials. When educators choose and determine the type of vision for teaching materials, they should not base choices on their own aesthetic conceptions. To enhance learning effects, educators should choose the suitable vision according to learners' preference. This study will be helpful in vision problems of educational technologies.

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