Application of Back-propagation Neural Network to Formulate Exercise Prescription for Taiwanese College Students

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Abstract

In this study, we attempted to apply back-propagation neural network (BPNN) to formulate exercise prescriptions for Taiwanese college students. The purpose was to realize a rapid and accurate estimation of the exercise prescription for students. Three thousand college students of both sexes aged 19–24 participated in this study. Data on five physical fitness test parameters were collected, including subjects' age, body mass index (BMI), and performance in three exercises: sit and reach, 1-minute bent-leg curl-ups, and running. The data were then randomly divided into two groups: training samples (n = 1800) and testing samples (n = 1200). Next, BPNN was utilized to estimate the exercise prescription level of the samples. The sample data was divided to examine the learning ability of BPNN. The BPNN network structure for this study encompasses an input layer (5 units), a hidden layer (5 units), and an output layer (4 units). The learning rate of the BPNN was assumed to be 0.5, and its learning cycle consisted of 850 rounds. The results indicated that the mean accuracy rate for estimating the prescription level was 93.22% for training samples and 92.38% for testing samples. In other words, the mean relative error was 6.78% for training samples and 7.62% for testing samples, both of which were within the acceptable range. These results indicate that applying BPNN to formulate an exercise prescription is feasible. Furthermore, because it is rapid and accurate, BPNN could prove to be a better option than manual assessment. Further, computer applications based on the BPNN technology can be developed to assist teachers and coaches in formulating student exercise prescriptions, thus conserving the cost and labor that would otherwise be required in the case of manual assessment.

Keywords: Physical fitness, Hidden layer

Introduction

The Ministry of Education in Taiwan has established norm-referenced standards specifying the physical fitness of male and female Taiwanese students. The authorities also encourage schools to conduct physical fitness tests for their students; this has contributed to the prevalent use of physical fitness passports in colleges nationwide. Although physical fitness tests are conducted for college students, an exercise prescription is not immediately available to them. According to the American College of Sports Medicine [1], the purpose of providing an exercise prescription is to improve one's physical fitness. Traditionally, PE teachers or coaches are responsible for formulating a prescription. They first assess a student's fitness level by manually referring to the norm-referenced chart, and then formulate a prescription. The process is time consuming and fails to offer students an immediate prescription. Without prompt feedback, students' may lose interest in fitness self-training. Additionally, most PE teachers and coaches receive little formal training in formulating exercise prescriptions [2]; consequently, it is likely that the prescriptions provided are imprecise, which may have a negative influence on student exercise training and hinder the promotion of the fitness passport project. In view of this, it is crucial that a more efficient method for formulating exercise prescriptions.

An artificial neural network is a computing system that

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includes both hardware and software [3]. Such a network consists of large quantities of simple artificial neurons that are designed to imitate the biocomputation and information processing of a biological neural network. BPNN is an artificial neural network that has learning and recalling abilities. Thus far, computing with BPNN has been successfully applied in many areas. In the analysis of biomechanics [4], for example, Barton and Lees [5] conducted a study on human gait patterns, in which they adopted BPNN to analyze leg length. BPNN has also been applied in biomedical signal analysis, such as electrocardiography [6], electromyography [7], and electroencephalography [8]. Wong [9,10] used BPNN's technique of image processing and identifying to establish an intelligent refereeing system, which can function as a supplementary tool in deciding whether or not a point is won or lost. The aforementioned previous studies demonstrate that BPNN has been widely applied in many fields. Nevertheless, BPNN has seldom been applied to studies on physical fitness or for the estimation of personal exercise prescriptions. The extensive use of BPNN for other applications inspired the authors to conduct this study.

According to the American College of Sports Medicine [1], the following basic elements should be taken into consideration when formulating a prescription: body composition, muscular flexibility, muscular strength and endurance, and cardiorespiratory endurance [11]. At present, Taiwanese college students' physical fitness level are determined according to five parameters: age, body mass index (BMI), performance in sit and reach, performance in 1-minute bent-leg curl-ups, and performance in running. Chiu [12] once adopted a BPNN algorithm to handle the data from the fitness testing of adult females in order to estimate their fitness level. The results revealed that BPNN was effective and efficient in assessing the fitness level. However, without exercise prescriptions, one's fitness cannot be enhanced effectively. In this study, we attempted to explore the possibility of adopting BPNN to formulate exercise prescriptions, with the aim of formulating students' exercise prescription level rapidly and accurately. It is expected that the designed BPNN algorithm can be used to develop a computer software; such an application would allow exercise prescriptions to be formulated more quickly compared to manual assessment, and human error would be reduced or eliminated.

Methods

Subjects

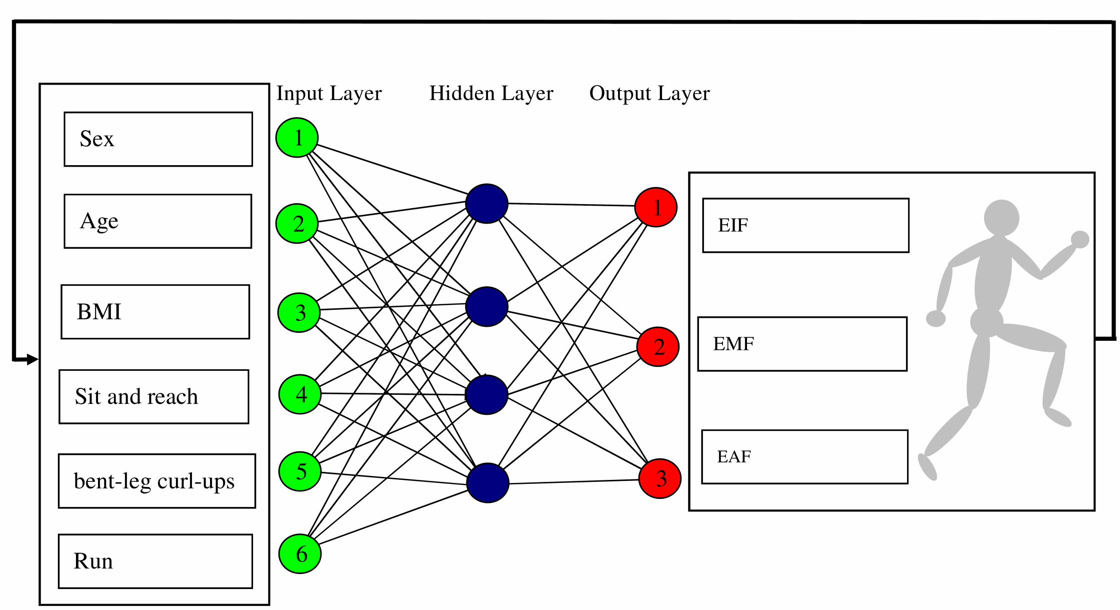

Figure 1. BPNN structure

Study subjects were 3000 students from National Taiwan University (age: 19–24; weight = 57.2 ± 9.8 kg; height = 158.5 ± 8.4 cm). The required data consisted of five parameters: age, BMI, and performance in three exercises: sit and reach, 1-minute bent-leg curl-ups, and running (males: 1600 m; females: 800 m). These data function as the input vectors of BPNN. To examine the learning ability of BPNN and its viability for estimating exercise prescription level [3], the researchers randomly divided the samples into two groups: training samples and testing samples. The number of training samples was 1800 (males: 1047; females: 753). The number of testing samples was 1200 (males: 735; females: 465).

BPNN structure

In this study, the BPNN structure comprises three layers: an input layer, a hidden layer, and an output layer (Fig. 1). There are six nodes for the input layer's neuron $(x_i, i=1,2,..,6)$, four nodes for the hidden layer's neuron $(q_j, j=1,2,..,4)$, and three nodes for the output layer's neuron $(y_k, k=1,2,3)$. BPNN's learning ability is examined by exploring how BPNN converges. The root of the mean square error (RMS) obtained from the function $(E(1/2)[\sum(d_k - y_k)^2])$ is used to judge the convergence of BPNN [13-15]. In the formula, the symbol d_k

represents the target output vector.

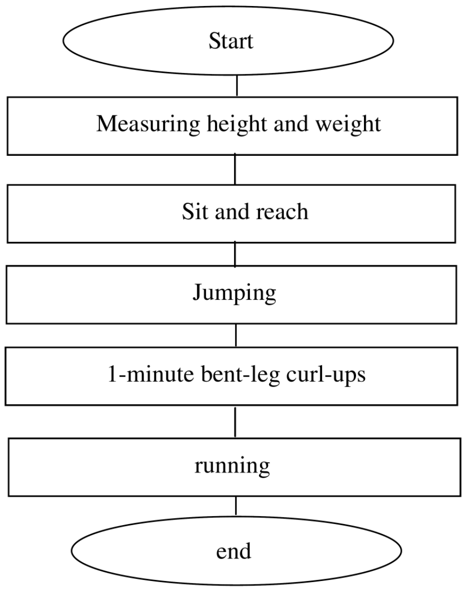

Figure 2. procedure of fitness test

In order to make BPNN's learning algorithms converge to an acceptable range, the input vectors $(x_i, i=1,2,..6)$ and target output vectors $(d_k, k=1,2,3)$ need to be standardized. In this study, the value of each vector was presumed to be between 0 and 1 [13]. For example, the vectors of training samples were presented or converted as follows: for the input vectors $(x_i, i=1,2,..6)$, x_1 represented gender, its input value was 1 for males and 0 for females; x_2 represented age, and the input value: age/100; x_3 represented BMI, and the input value: BMI./100; x_4 represented the performance in sit and reach, and the input value: total number of sit and reach/100; x_5 represented the performance in 1-minute bent-leg curl-ups, and the input value: total number of 1-minute bent-leg curl-ups/100; x_6 represented the performance in running, and the input value: seconds/1000. When standardizing the target output vector d_k (k=1,2,3) to make each input value fall between 1 and 0, the researchers referred to the fitness program of the American College of Sports Medicine [1] and categorized the exercise prescription into five levels. The value was thus 0.2 for level 1, 0.4 for level 2, 0.6 for level 3, 0.8 for level 4, and 1.0 for level 5 (Table 1).

The output vector y_k $(y_k, k=1,2,3)$ was defined as follows: y_1 represented the exercise prescription for improving muscular flexibility (EIF); y_2 represented the exercise prescription for muscular fitness (EMF); and y_3 represented the exercise prescription for aerobic fitness (EAF) (Fig. 1). Based on the fitness program of the American College of Sports Medicine [1], each output vector was categorized into five levels. The established value for each level is listed in Table 1.

Data collection

Complying with the requirements of the Republic of China's Physical Fitness Passport, this study conducted physical fitness testing on participants. First, participants were asked to fill out an exercise safety questionnaire. Next, their height and weight were measured. They were then tested on sit and reach, 1-minute bent-leg curl-ups, and running (Fig. 2). The above procedure was strictly followed because if the steps were reversed, participants might not be able to perform normally on certain testing exercises.

Data analysis

In this study, the C++ computer program language was edited to design BPNN algorithms so that BPNN could be used to execute learning and recalling computations. After learning computation was executed with BPNN on training and testing samples, the resulting mean square error was used to judge if the BPNN network converged well. Finally, recalling computation was conducted on training and testing samples to see if it was feasible to apply BPNN in estimating exercise prescriptions.

Results

Data of five parameters involved in the fitness testing of 1800 subjects served as the training samples of BPNN. The data of the other 1200 subjects served as the testing samples of BPNN. The training samples went through 850 learning cycles, and the learning rate was presumed to be 0.5. It was found that the RMS was 0.0135 (Table 2). After the testing samples went through 850 learning cycles, the RMS was found to be 0.0123 (Table 2).

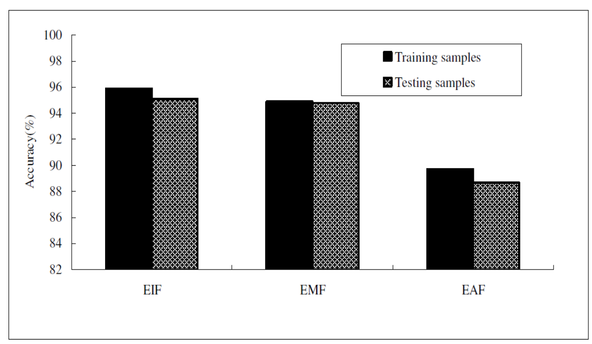

Figure 3. Accuracy rate in estimating male exercise prescription

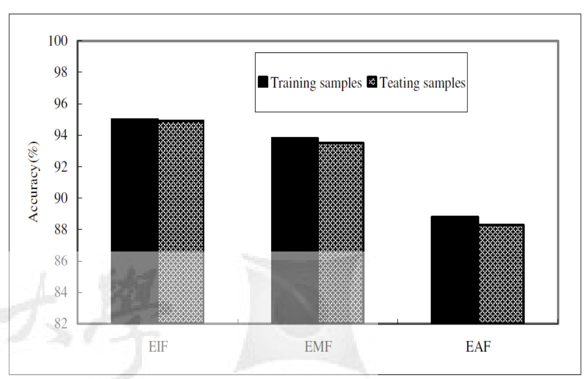

Figure 4. Accuracy rate in estimating female exercise prescription

After adopting BPNN to estimate the prescription level of male training samples, the results indicated that the accuracy rate was 95.9% for EIF, 94.9% for EMF, and 89.7% for EAF (Fig. 3), which meant that the mean accuracy rate was 93.50%. For male testing samples, the accuracy rate was 95.0% for EIF, 93.8% for EMF, and 88.8% for EAF (Fig. 3), with a mean accuracy rate of 92.53%.

After adopting BPNN to estimate the prescription level of female training samples, the results demonstrated that the accuracy rate was 95.1% for EIF, 94.8% for EMF, and 88.9% for EAF (Fig. 4), which meant that the mean accuracy rate was 92.93%. For female testing samples, the results revealed that the accuracy rate was 94.9% for EIF, 93.5% for EMF, and 88.3% for EAF (Fig. 3), with a mean accuracy rate of 92.23%.

The mean relative error in estimating training samples' prescription level with BPNN was 6.50% for males and 7.07% for females. The mean relative error in estimating testing samples' prescription level with BPNN was 7.47% for males and 7.77% for females.

Table 1 Target output vector $\boldsymbol{d_k}$ and output vector $\boldsymbol{y}_k$

Prescription levels		1	2	3	4	5
EIF	$\boldsymbol{d_1}$	0.2	0.4	0.6	0.8	1.0
	$\boldsymbol{y}_1$	(0.1,0.3]	(0.3,0.5]	(0.5,0.7]	(0.7,0.9]	(0.9,1.1]
EMF	$\boldsymbol{d_2}$	0.2	0.4	0.6	0.8	1.0
	$\boldsymbol{y}_2$	(0.1,0.3]	(0.3,0.5]	(0.5,0.7]	(0.7,0.9]	(0.9,1.1]
EAF	$\boldsymbol{d_3}$	0.2	0.4	0.6	0.8	1.0
	$\boldsymbol{y}_3$	(0.1,0.3]	(0.3,0.5]	(0.5,0.7]	(0.7,0.9]	(0.9,1.1]

Table 2. Root of mean square (RMS) for BPNN learning computation of training samples and testing samples

Samples	Number	RMS
Training samples	1800	0.0135
Testing samples	1200	0.0123

Table 3. The relative error found in estimating the exercise prescription level

Prescription	Training samples		Testing samples	
	Males (%)	Females (%)	Males (%)	Females (%)
EIF	4.1	4.9	5.0	5.1
EMF	5.1	5.2	6.2	6.5
EAF	10.3	11.1	11.2	11.7
mean relative error	6.50	7.07	7.47	7.77

Note:The mean relative error was 6.78% for training samples and 7.62% for testing samples. That is, the mean accuracy rate was 93.22% for training samples and 92.38% for testing samples.

Discussion

The physical fitness of college students is a major concern for many nations. As such, the formulation of precise exercise prescriptions for students to follow in order to improve their fitness is an issue of significant urgency. In Taiwan, it is PE teachers that are currently responsible for drawing up prescriptions. Normally, the teachers assess students' fitness level by manually referring to the norm-referenced chart. Next, they plan the prescription in accordance with the fitness level. Several drawbacks can be identified in this process. First, the process is time consuming and thus lacks efficacy. Second, errors are more likely to occur when the assessment is made manually. Third, prescriptions may differ from teacher to teacher with no unity or correspondence among them [2]. Under these circumstances, the usefulness of the manual prescription is questionable.

Convergence of BPNN

RMS is the index used to examine the convergence of BPNN. When BPNN converges well, then BPNN is considered to have reliable learning ability. In this study, 1800 training samples and 1200 testing samples were processed with BPNN algorithms. It was found that the RMS was 0.0135 for training samples and 0.0123 for testing samples (Table 2). Yeh [3] conducted BPNN on 150 subjects to test its learning ability. The RMS was 0.0491 for training samples and 0.0737 for testing samples, both of which are much larger than the RMSs found in this study (Table 2). This significant difference verified that the BPNN of this study converged well and had good learning ability. Only when three requirements are met will such acceptable convergence occur: (1) sufficient and generalized samples, (2) even distribution of sample ages to make them representative, and (3) precision and consistency of keyed-in subject data [13].

Level estimation with BPNN

The mean relative error in estimating the prescription level was 6.50% for male training samples and 7.07% for female training samples. The mean relative error in estimating prescription level was 7.47% for male testing samples and 7.77% for female testing samples (Table 3). Yeh [3] conducted a study with 300 training samples and 200 testing samples. In his study, the mean relative errors were 37% and 42%, respectively, which were much larger than those in our study. The errors were also larger than any of the relative errors found in estimating the EIF, EMF, and EAF levels in this study (Table 3). This phenomenon clearly verified that the output vectors estimated in this study correspond to the target output vectors. That is, the BPNN estimation results were reliable and acceptable. Although very small mean relative errors still exist when estimating the prescription level with BPNN, they can be minimized. It is suggested that two methods to minimize the errors be adopted in future studies. Researchers in the future can try to increase the number of samples to achieve an even distribution of samples, or they can increase the number of neurons of BPNN's hidden layer [16].

After using BPNN to estimate male training samples' level in EIF, EMF, and EAF, it was found that the mean accuracy rate was 95.9%, 94.9%, and 89.7% respectively (Fig. 3). For male testing samples, the mean accuracy rate was 95.0% for EIF, 93.8% for EMF, and 88.8% for EAF. For female training samples, the mean accuracy rate was 95.1% for EIF, 94.8% for EMF, and 88.9% for EAF. For female testing samples, the accuracy rate was 94.9% for EIF, 93.5% for EMF, and 88.3% for EAF. The accuracy rate for prescription level estimation approximated that in another study by Chiu [12] on estimating the level of muscular flexibility, muscular strength, and cardiorespiratory endurance with BPNN. In the study by Yeh [3], the mean accuracy was 71.4% for 300 training samples and 69.5% for 200 testing samples. In comparison with the result of this study, the mean accuracy rate obtained in this study was much higher. This demonstrated that adopting BPNN can render reliable exercise prescriptions.

It was also found that the mean accuracy rate was 93.22% for estimating training samples' prescription level and 92.38% for testing samples, with mean relative errors of 6.78% and 7.62%, respectively (Table 3). The results confirmed that BPNN can be applied in estimating the levels of EIF, EMF, and EAF.

Conclusions

In this study, BPNN was applied to estimate the exercise prescription level as a replacement for manual assessment. The research results confirm that the application of BPNN is effective and feasible. It is suggested that the technology can be used as a basis for the development of a computer application. It will be of great use in assisting PE teachers and coaches to formulate exercise prescriptions because BPNN software can conserve much of the cost and time involved in manual assessment.

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References

[1] M.P. Susan, P.B. Madeline and F. Barry, *ACSM fitness book*, Human Kinetics Publishers, Inc, 2002.

[2] Chih-Chin Hsu, Alice May-Kuen Wong, Principles of Exercise Prescription for the Elderly, *Formosan J Med*, 7:396-403, 2003.

[3] I.C. Yeh, *Applications of artificial neural Networks*, Taiwan: Scholars Books Co., Ltd., 2002.

[4] W. I. Schöllhorn, Applications of artificial neural nets in clinical biomechanics, *Clinical Biomechanics*., 19: 876-898, 2004.

[5] J. G. Barton and A. Lees, An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams, *Gait & Posture*., 5: 28-33, 1997.

[6] M. Yuchi and J. Jo, Heart rate prediction based on physical activity using feedforwad neural network, *International Conference on Convergence and Hybrid Information Technology*, 344-350, 2008.

[7] B. Pandey and R. B. Mishra, An integrated intelligent computing model for the interpretation of EMG based neuromuscular diseases, *Expert Systems with Applications*., 36: 9201-9213, 2009.

[8] F. Dumana, A. Erdamar, O. Erogul, Z. Telatar and S. Yetkin, Efficient sleep spindle detection algorithm with decision tree, *Expert Systems with Applications*, 36: 9980-9985, 2009.

[9] P. K. C. Wong, Developing an intelligent assistant for table tennis umpires," *Proceedings of the First Asia International Conference on Modelling and Simulation*, 2007.

[10] P. K. C. Wong, "Developing an intelligent table tennis umpiring system: identifying the ball from the scene, *Second Asia International Conference on Modelling and Simulation*, 445-450, 2008.

[11] C. C. Chiu, Establishing the diagnosis model of male college students' physical fitness with artificial neural network, *Journal of Physical Education in Higher Education*., 6: 1-12, 2004.

[12] C. C. Chiu, Application of Back-propagation Neural Network to Categorization of Physical Fitness Levels of Taiwanese Females, *Journal of Medical and Biological Engineering, 31(1): 31-35*

[13] C. T. Lin and C. S. Lee, *Neural Fuzzy Systems*, America: Prentice Hall, Inc, 1996.

[14] S. T. Welstead, *Neural Network and Fuzzy Logic Applications in C/C*, Canada: John Wiley and Sons, Inc, 1994.

[15] D. B. Rao and H. V. Rao, *C++ Neural Networks and Fuzzy Logic*, New York: MIS press, 1995.

[16] J. Hertz, A. Krogh and R. G. Palmer, *Introduction to the*

Theory of Neural Compution, Addison-Wesley Publishing Company, Inc, 1991.

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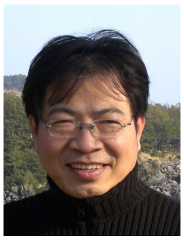

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