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A Model for the Health Index of the Elderly People Forecasting Based on Rfid

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Abstract: With more and more attentions to the aging population problem socially, many monitoring systems have been built to diagnose the health of the old people by the internet. However, there are few systems and methods to forecast or perceive the change of their health by low cost while monitoring and tracking the activity of the aged people for nursing and no model for describing the health index of the elderly people. Making use of the statistical data of the aged people living from the monitoring system based on RFID, this study builds a model to describe the states of the elderly health by the health index. The data from the RFID mainly include the times of physical activities for living, such as dining, going to the toilet, sleeping and so on. According to the natural relations between the activity and the health of the elderly people, the functions of the health index are designed for the model. According to the reflection between the index and the health states, it analyzes the data with a BP neural network and forecasts the health index of the old person in the bead-house. The experiments show that it provides a real-time, low-cost decision support to forecast and perceive the health states of the elderly for their managers and family members.

Key words: Health index; forecasting, RFID, BP neural network, bead-house, elderly people

INTRODUCTION

Since, the aging population is increasing in china, more and more attentions have been paid to the supporting, nursing, especially monitoring the health states of the elderly in the society (Xuan and Zhao, 2011). Thus, the problem how to perceive the states of the elderly health has arisen which plays an important role in nursing the elderly. Some health diagnosing system for internet with the specialized sensors of physiology are used to diagnose the people's health; however, there is some lack of the functions for forecasting the elder's daily health and warning in these systems which is also the greatest concern for the bead-house managers and the elderly family members.

There are many systems of health monitoring for the elderly, such as a monitoring system based on Wireless Body Area Network (Xuan and Zhao, 2011; Zhang, 2011). The system can be used to determine the physical states of the elderly by collecting electrocardiography, blood pressure and other physiological parameters of older people through the sensor technology and then analyzing it by some medical institutions such as hospitals and community service centers. Afterwards, Lin Z. H developed an intelligent remote health diagnosis system based on video (Lin and Xie, 2008). This system mainly takes the camera, physiological parameter instruments as a client at home and detects physiological data to diagnose the physical health of people by the videos. Since, these systems require specialized sensors of physiology and other devices such as video to deliver the patient's information to the doctors for diagnosing, the perceived cost is relatively higher than the system based on RFID and also the range of application belongs to the outpatient system, so they are not suitable for the daily management of the bead-house.

To forecast the states of the older people's health from the daily activities by lower cost, this study presents a method to solve it. Firstly, a model is designed to describe the states of the elderly health by a numerical index. It results from the data of the daily life activities upon the statistics and reflects the health states according to the basis of medicine and behavior (Anderson *et al*., 2012). The data are collected from a tracking and monitoring system for the elderly based on RFID (Zhong and Li, 2013). Secondly, a BP neural network is built for analyzing and forecasting the elderly health index (An *et al*., 2013; Ren and Wang, 2013; Cen and Liu, 2011; Li and Xing, 2012; Liu and Li, 2012). Lastly, the simulation experiments have been done and discussed for the results. It shows that can provide a real-time, low-cost decision support to hold the health state of the elderly people for their managers and families.

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DESIGN OF HEALTH INDEX MODEL

Effect factors of health and the number of daily activities for the elderly: The elderly health is affected by numerous factors. Researches by medicine specialists show that the change of people's regular life order always means physically ill. Usually the times of the physical activities for living can indicate a person's health (Anderson *et al*., 2012). The times of daily activities especially like the dining, sleeping and going to the toilet is taken as the principal factors to affect the elderly health obviously. On the other hand, the times of leisure activities, such as watching TV, walking, sporting outdoors and so, on, are taken as the secondary factors. According to the statistical and analytical records of the activities every day for six months among 30 elderly people, the factors average values a day are confirmed while an older person is in the optimal health states which is that the dining is 3.9 times a day, the sleeping is 1.9 times a day, the toilet is 9.7 times a day. These are just standard values for referencing because a different person or a different environment may influence health differently.

However, different factors effect on health differently, so these weights are set to the unique factors for affecting the health levels. On the basis of medical expert's viewpoint, it is apt to set the weight of dining as 0.35, the weight of sleeping as 0.2, the weight of toilet as 0.3 and the weight of other leisure activities as 0.15. In order that the leisure activities can be detected conveniently by RFID, they are divided to playing chess, taking a walk, batting, watching TV, reading and so on and their weights are, respectively set to be 0.02, 0.03, 0.07, 0.02 and 0.01. The health factors of the elderly, their average values and effect weights are listed as the Table 1 and the Table 2.

Design the function of the health index: Since, the fact that every factor has its own effect on the elderly health, the health index value should be the sum of effect values by all factors of the activities, respectively. The function of the health index for the elderly is designed as three parts based on multi-parameter: The first part is the contribution of effects by all factors, the second part is the contribution of effects on the factors each other and the third part is the error value. The Eq. is as shown in 1:

$$F(x) = \sum_{i=1}^{n} w_i f(xi) + \sum_{i=1,\, j=1}^{n} \rho_{ij} g(x_i, x_j) + \varepsilon \quad (1)$$

In the Eq. above:

$$\sum_{i=1}^{n} w_i f(x_i)$$

is the sum of the contribution that each factor affects the health of the elderly and:

$$\sum_{i=1,\, j=1}^{n} \rho_{ij} g(x_i, x_j)$$

is the sum of the component for the mutual influence between the factors and ε is the adjustment inaccuracy of the function's error. Where w_i is the weight of each factor which is given as in Table 1 and Table 2, $f(x_i)$ is the function of the health index which is contributed by the each factor and its value range is [0,1], P_{ij} is the influence coefficient between the different factors each other and if $i = j$ then $P_{ij} = 0$ else if $i \neq j$ then $Pij \in [-0.01, 0.01]$, $g(x_i, x_j)$ is the function of the mutual influence between the selected factors.

The basic function of the model is fixed but how to design $f(x_i)$ and $g(x_i, x_j)$ is not easy. Firstly considering the $f(x_i)$, it is divided into two parts, the health parameters of the principal factors and the secondary factors. According to the data from RFID, the elderly health index influenced by the principal factors is as showed in Fig. 1, it will fluctuate around the reference average values within the normal range in most cases.

Table 1: Principal factors of affecting the elderly health, average times a day and weights

Principal factors	Dining	Sleeping	Leisure activities	Toilet
Effect weight	0.35	0.20	0.15	0.30
Average value for reference	3.9 times/day		1.9 times/day	9.7 times/day

Table 2: Secondary factors of affecting the elderly health and their weights

Leisure activities	Chess	Walk	Batting	Reading	Watch
Effect weight	0.02	0.03	0.07	0.02	0.01

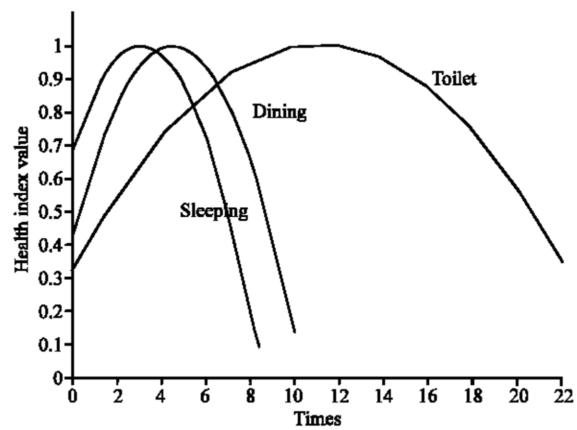

Fig. 1: Health index of contributions by principal factors

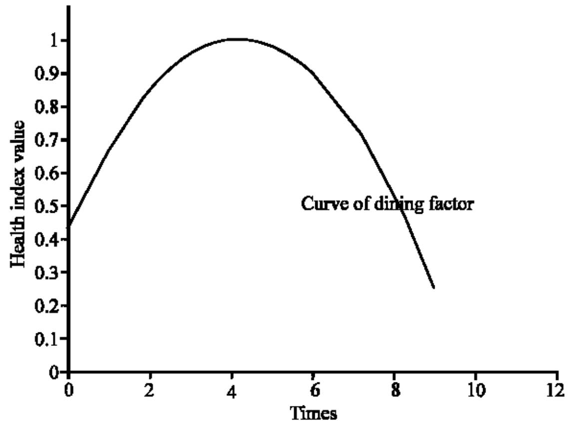

Fig. 2: Health index curve of the dinging factor

Usually, the canteen of the bead-house will not open too many times for dining and the dining times of the elderly range the interval [0,6] a day, a healthy old people often has 3-5 times meals a day, so his health index value is close to the peak value (1.0). Its curve of rule is given as Fig. 2. Similarly, the value of the sleeping times is between [0,10] and the times interval [1,4] is as a health state; the value of the toilet times is between [0,21] and the times interval [7,15] is as a health state.

Assume that the health status can be described by the health index and its value varies between the interval [0,1], then the smaller the health index, the less vigorous the elderly are and vice versa. The relationship between the value of the three principal factors and the health index has shown in Fig. 1. They have similar graphs and health status is sensitive to the change of the times of each activity, so the health index is described by using the unified form, as shown in the Eq. 2:

$$f(x_i) = \frac{-\alpha_i (x_i - \delta_i)^2 + \beta_i}{\beta_i} \tag{2}$$

where, δ_i is the average value as the reference standard value of a principal factor, α_i and β_i are variable parameters which are set by the actual situation of a principal factor affecting the elderly health.

For example as Fig. 2, when $x_i = \delta_i = 3.9$, the health index should be the maximum 1 and the change of the function curve is not discernible between the interval [3, 5]. But when x_i is not in this interval, the function value will be sensitive to the change of the value of x_i, it declines rapidly means that the health status is rapidly deteriorating. In the normal condition of the activity times, it is essential to make sure that $f(x_i) \geq 0$. Thus, Let $\alpha_1 = 6, \beta_1 = 208$, the health index curve of the dining factor can be obtained as in the Fig. 2. In a similar way, as for sleeping, let $\alpha_2 = 7$, $\beta_2 = 201$ in the health index function and for the toilet, let $\alpha_3 = 5$, $\beta_3 = 903$ in it, the overlay curves of rule have shown in Fig. 1.

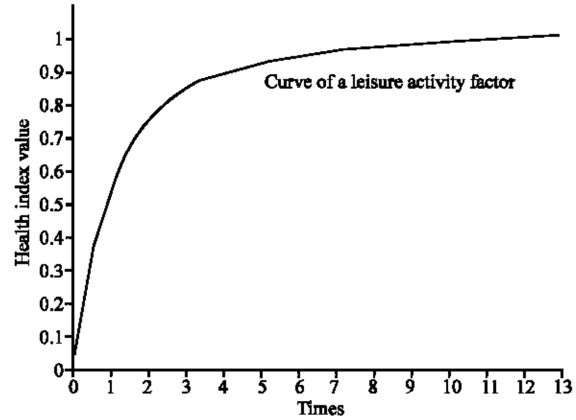

Fig. 3. Health index curve of a leisure activity

Table 3: Reflection between the health states and the range of the health index

Health index	0~0.55	0.55~0.7	0.7~0.8	0.8~0.9	0.9~1.0
Health states	Severely ill	Diseased	Weak	Sub-health	Healthy

If an old person can play leisure activities which shows his health status is very good, so the health index is set close to 1. The leisure activities usually can take place 1-3 times each type a day for an old people which are appropriate for the elderly. So, the health index rule curve for a type of the leisure activities is as shown in Fig. 3.

For a single type of the leisure activities, the health function is defined as follows to describe its influence:

$$f(x_i) = \frac{2}{\pi} \arctan x_i \tag{3}$$

If the principal factors are numbered by 1-3, the records for the secondary factors tracked expediently by RFID are numbered by 4-8, the function of part 1 can be actually designed as follows:

$$F(x) = \sum_{i=1}^{3} w_i \frac{-\alpha_i (x_i - \delta_i)^2 + \beta_i}{\beta_i} + \sum_{j=4}^{8} w_j \frac{2 \arctan x_j}{\pi} + \varepsilon' \tag{4}$$

Secondly, considering the mutual effects on these activities each other, it is too complicated to be quantified and the effects have the positive and the negative, so the total effect will be very small, it can be combined in the function err. Thus let:

$$\varepsilon' = \sum_{i=1, j=1}^{n} \rho_{ij} g(x_i, x_j) + \varepsilon \tag{5}$$

Finally, the model of the health index function is defined as follows:

Table 4: Part of sample data and preprocessing data

Date	Sample index	Preprocessing data	Date	Sample data	Preprocessing data	Date	Sample data	Preprocessing data
1	0.9707	0.9131	11	0.9173	0.7790	21	0.8903	0.7112
2	0.9185	0.7820	12	0.9424	0.8420	22	0.9388	0.8330
3	0.9472	0.8541	13	0.9599	0.8860	23	0.9306	0.8124
4	0.8305	0.5610	14	0.9692	0.9093	24	0.9529	0.8684
5	0.7633	0.3923	15	0.9854	0.9500	25	0.9080	0.7556
6	0.7254	0.2971	16	0.8709	0.6625	26	0.9302	0.8114
7	0.7525	0.3652	17	0.7536	0.3679	27	0.9307	0.8126
8	0.8592	0.6331	18	0.6270	0.0500	28	0.9255	0.7996
9	0.9109	0.76230	19	0.7863	0.4500	29	0.9438	0.8455
10	0.9284	0.8069	20	0.8634	0.6436	30	0.9643	0.8970

$$F(x)=\sum_{i=1}^{3} w_i \frac{-\alpha_i (x_i-\delta_i)^2+\beta_i}{\beta_i}+\sum_{j=4}^{8} w_j \frac{2\arctan x_j}{\pi}+\varepsilon' \quad (6)$$

The value of F(x) still ranges between the interval [0, 1]. The interval [0.9, 1] stands for healthy state of the elderly, [0.8, 0.9] stands for sub-health state, [0.65, 0.8] stands for weak state, [0.45, 0.65] stands for diseased state and [0, 0.45] stands for severely ill state. Usually it takes $\varepsilon = 0$ in the Eq. 6. The health states corresponding to the range of the health index is shown as Table 3 in detail.

HEALTH INDEX FORECASTING WITH BP NETWORK

BP network topology and parameters: A three-layer BP neural network is designed for this model which includes an input layer, an output layer and only one hidden layer. There is one node in the output layer and fifteen nodes in the input layer for the network which is corresponding to the health index sequence of former ten days.

It is crucial to confirm the number of nodes in the hidden layer. Research shows that the number of nodes in the hidden layer is not only related to the number of nodes in the input and output layer but also to the complexity of the problem needed to solve, as well as to the form of the transfer function and the feature of sample data (Liu and Li, 2012; Ouyang and Lu, 2011; Wang *et al.*, 2013; Wang and Wu, 2013). Therefore, a trial-and-error method is selected to determine the optimal number of nodes in the hidden layer according to the Eq. $1=\sqrt{n+m+\alpha_i}$ where n and m is the number of nodes of the input layer and output layer, respectively, α is a random number in the interval [1,10], L is the result which is considered as the preliminary number of the nodes for reference in the hidden layer. Through testing continually by changing the number of nodes in the hidden layer, the training times and the output accuracy, the optimal number of nodes in the hidden layer can be ultimately determined as 11 during the training process. Thus a BP network as 15-11-1 nodes is established.

The transfer function is taken as Logsig (x) $=1/(1+e^{-x})$ it can reflect the input values to the interval [0,1] nonlinearly. In order to achieve better effect of the convergence in the BP network, an initial number of node weights is set in all layers with the range of the interval [-0.25, 0.25] before training.

Sample data pretreatment and prediction data transformation inversely: In order to be more suitable for the input of the BP network, all the sample data of the health index obtaining from the function of the model should be pretreated for learning and training.

When the index sequence is distributed in the [0.05, 0.95] interval, the BP network can usually work better. So, the original data of the health index is standardized to the interval range as far as possible. The original data are pretreated with as the follow Eq. 7. It is used for the original data sequence of the health index normalizing to the interval:

$$Y_k'=\frac{Y_k-\min(Y_k)}{\max(Y_k)-\min(Y_k)}*0.9+0.05 \quad (7)$$

where, Y_k is the k-th value of the health index obtained by Eq. 6 from the activities data, Y_k' is the k-th value of the health index pretreated, Y_k is the minimum value in the original sequence of the health index and Y_k is the maximum value in the original sequence.

In order to compare with the health index of the model, the prediction value of output from the BP network will be transformed reversely. If the inverse transformation is continuous every day for an old person, all results will construct a prediction sequence of the health index. The transformation formula is as follows:

$$H=\frac{(H'-0.05)(\max(Y_k)-\min(Y_k))}{0.9}+\min(Y_k) \quad (8)$$

In the above Eq. H' is the forecast value of the health index from the BP network and H is the value of the health index normalized inversely.

According to the activities data from RFID every day, the records of 30 elderly in a month as a sample set are selected to preprocess. The health index of an old person as the part sample data sequence and pretreatment values are shown in Table 4.

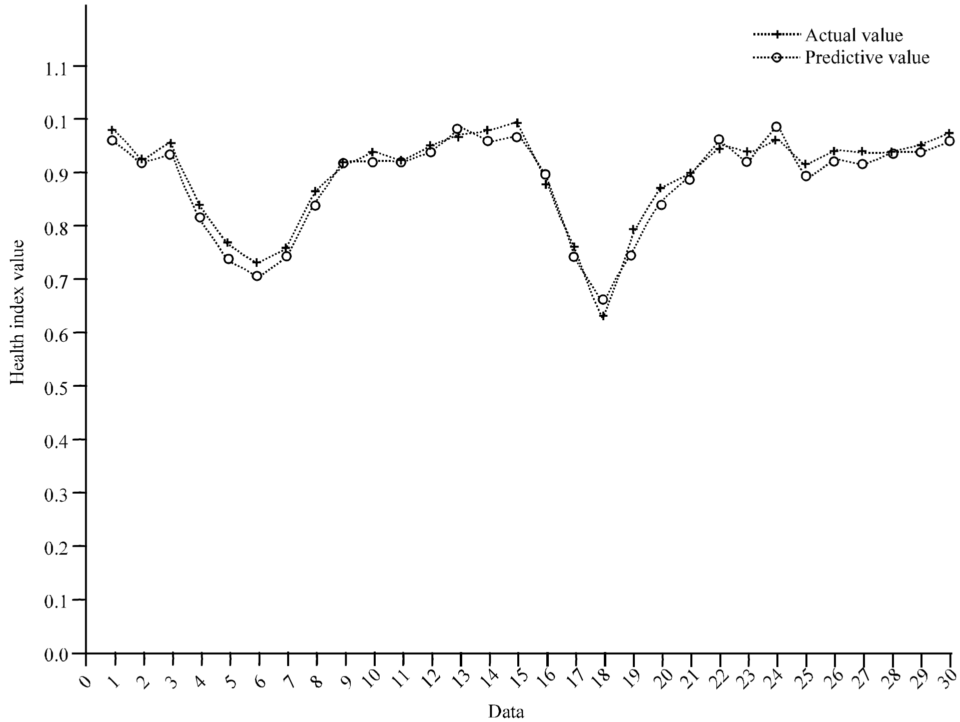

Fig. 4: In contrast with the actual index and the prediction index of the elderly health

Tab. 5: Comparison with the actual index, the predictive index and doctor's diagnosis of an old person

Date	Health index of model(*Y*)	State of health	Prediction health index(*H*)	State of health	Doctors diagnosed results	Date	Health index of model(*Y*)	State of health	Prediction health index(*H*)	State of health	Doctors diagnosed results
1	0.9707	Healthy	0.9513	Healthy	Healthy	16	0.8709	Sub-health	0.8883	Sub-health	Cold
2	0.9185	Healthy	0.9128	Healthy	Healthy	17	0.7536	Weak	0.7558	Weak	Cold
3	0.9472	Healthy	0.9237	Healthy	Healthy	18	0.6270	Diseased	0.6373	Diseased	Fever
4	0.8305	Sub-health	0.8105	Sub-health	Cold	19	0.7863	Weak	0.7212	Weak	Cold
5	0.7633	Weak	0.7309	Weak	Diarrhea	20	0.8634	Sub-health	0.8338	Sub-health	Cold
6	0.7254	Weak	0.7019	Weak	Diarrhea	21	0.8903	Sub-health	0.8816	Sub-health	Healthy
7	0.7525	Weak	0.7375	Weak	Diarrhea	22	0.9388	Healthy	0.9516	Healthy	Healthy
8	0.8592	Sub-health	0.8322	Sub-health	Cold	23	0.9306	Healthy	0.9105	Healthy	Healthy
9	0.9109	Healthy	0.9095	Healthy	Healthy	24	0.9529	Healthy	0.9801	Healthy	Healthy
10	0.9284	Healthy	0.9129	Healthy	Healthy	25	0.9080	Healthy	0.8953	Sub-health	Healthy
11	0.9173	Healthy	0.9105	Healthy	Healthy	26	0.9302	Healthy	0.9124	Healthy	Healthy
12	0.9424	Healthy	0.9298	Healthy	Healthy	27	0.9307	Healthy	0.9102	Healthy	Healthy
13	0.9599	Healthy	0.9679	Healthy	Healthy	28	0.9255	Healthy	0.9284	Healthy	Healthy
14	0.9692	Healthy	0.9501	Healthy	Healthy	29	0.9438	Healthy	0.9305	Healthy	Healthy
15	0.9854	Healthy	0.9587	Healthy	Healthy	30	0.9643	Healthy	0.9595	Healthy	Healthy

Healthy simulation experiments and discussion: Before predicting the elderly's health index with Matlab 8 as the simulation tool, the original data is divided into a training set and a test set. Per fifteen indexes of time on continuous is taken as a sequence of input to forecast the next index. The training set is the activity data of the first 19 elderly people during a month and the test set is the activity data of an old person chosen during a month. There is a comparison with the health index calculated by the health model (Y), the prediction value of the health index which are normalized inversely (H) and the real results of medical diagnosis. It is shown as in Table 5, where the diagnosed Results by Doctors are from the report of Xiangtan Red Cross for a two-month health inspection activities of the elderly in the bead-house.

Through simulation experiments, forecast data are almost fit the actual data of the health index of the elderly people and is very close to the doctor's diagnosis results. So, the prediction results basically reflect the health status of the elders. Fig. 4 is a Fig. contrasting with the actual index values and the estimated values generated by the Matlab 8.

Table 6: Rates of error and accuracy in this model

	accuracy	False positives	False negatives	Total
Times	6491	349	285	7125
Ratio	91.1%	4.9%	4.0%	100%

There are 7125 sets of valid data of the elderly's activities during the past 12 months from the RFID system and the health index sequence is correspondingly obtained with the data sets by the predictive model. After the sequence data pretreated, the forecast results of the health index in BP neural network are close to the model's value. Compared with the diagnosis results and the predictive ones, the rates of and accuracy and the errors of false positives and negatives are as showed in Table 6. It shows the higher accuracy and the lower error.

Compared with the remote system of the people's health diagnosis based on intelligent sensors, the accuracy of result is a little low. It should be noted that this study has examined only in small number of the elderly people and the sample data are the average values based on the statistics. Perhaps there was seriously some difference with the sex. Moreover, the BP neural network might be optimized for the more reasonable results, for example, increasing the input data of the sequence.

Notwithstanding its limitation, this study does suggest a novel method to forecast the states of the elderly health based on RFID by lower cost and try to describe the relationship between the physical activities of the life and the health of the elderly.

CONCLUSION

The model of forecasting the elderly health index based on RFID makes use of the BP neural network to predict and reflect the elderly people's health states through the physical activities of the life. It presents an approach for the elderly people's health care of their families and managers and provides a warning and reference for nursing by lower cost. It also extends the application for the monitoring system based on RFID. The experiments show that the model is basically described the relationship between the physical activities of the life and the health of the elderly and it have relative accuracy for forecasting the elderly health index. In the future work, we will consider the difference with the sex or more other factors to our model for study, such as the time during the activities, etc.

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REFERENCES

An, Y.Q., Y.J. Wang and W.W. Gao, 2013. Forecasting of Vehicle Capacity Based on BP Neural Network. In: Proceedings of the 19th International Conference on Industrial Engineering and Engineering Management, Qi, E., J. Shen and R. Dou (Eds.). Springer, Berlin, Germany, pp: 369-375.

Anderson, D.T., M. Ros, J.M. Keller, M.P. Cuellar, M. Popescu, M. Delgado and A. Vila, 2012. Similarity measure for anomaly detection and comparing human behaviors. Int. J. Intell. Syst., 27: 733-756.

Cen, R.F. and J. Liu, 2011. Design of muti-parameters optimization CMAC controller based on GA. Manuf. Autom., 33: 37-40.

Li, C. and X.S. Xing, 2012. Research and application of BP neural network prediction based on adaptive genetic algorithm. Shanxi Normal University, Shanxi, China.

Lin, Z.H. and C.X. Xie, 2008. Research on a video-based community intelligent tele-healthcare system. Data Acquisit. Monitor., 24: 77-79.

Liu, X.M. and M.C. Li, 2012. Prediction system of stock index based on BP neural network. Dalian University of Technology, Liaoning, China.

Ouyang, J.L. and L.M. Lu, 2011. Application of the improved BP neural network in commodity export. Shanghai Normal University, Shanghai, China.

Ren, C.X. and C.B. Wang, 2013. The Prediction of Short-Term Traffic Flow Based on the Niche Genetic Algorithm and BP Neural Network. In: Proceedings of the 2012 International Conference on Information Technology and Software, Lu, W., G. Cai, W. Liu and W. Xing (Eds.). Vol. 211, Springer, New York, pp: 775-781.

Wang, X.H. and J.H. Wu, 2013. Forecasting Incidence Age of Coal Workers Pneumoconiosis Based on BP Neural Networks. In: Proceedings of the 2nd International Conference on Green Communications and Networks, Yang, Y. and M. Ma (Eds.). Vol. 223, Springer, New York, pp: 657-664.

Wang, Y., D. Zheng, S.M. Luo, D.M. Zhan and P. Nie, 2013. The research of railway passenger flow prediction model based on bp neural network. Adv. Mater. Res., 605-607: 2366-2369.

Xuan, Y.D. and Z. Zhao, 2011. A wireless body sensor network for the elderly health monitoring system. J. Comput. Res. Dev., 48: 355-359.

Zhang, Z.T., 2011. Development of wireless and wearable multiple physiological parameter monitoring system. Changchun Industry University, Jilin, China.

Zhong, X.Y. and Z.B. Li, 2013. The design and implementation of the tracking and monitoring system for gerocomium based on semi-active RFID technology. Proceedings of the 2nd International Conference on Computer Science and Electronics Engineering, March 22-23, 2013, Hangzhou, China, pp: 2718-2721.