International Journal of Smart Home
Vol. 10, No. 8 (2016), pp. 271-280
http://dx.doi.org/10.14257/ijsh.2016.10.8.26

Carbon Emission Early Warning System Modeling and Simulation Study of Urban Regional Transportation

Hao Wu and Xianglian Zhao

College of Economics and Management, Nanjing University of Aeronautics and Astronautics
mlwhwh@sina.com

Abstract

Accurate assessment of carbon emission of urban regional transportation is the core of urban low-carbon traffic construction. Traditional carbon emission evaluation methods need a large number of samples and sample data of carbon emission of urban regional transportation is smaller, so the precision will be lower if traditional methods are adopted. This paper proposes particle swarm optimization to optimize support vector machine carbon emission early warning system of urban regional transportation (PSO − SVM) and takes the advantage of small sample data modeling of support vector machine to improve the carbon emission evaluation accuracy of urban regional transportation. Furthermore, this paper takes carbon emission evaluation accuracy of urban regional transportation as modeling target, selects reasonable evaluation index, confirms carbon emission evaluation model structure of urban regional transportation and then optimizes support vector machine (SVM) by adopting particle swarm optimization (PSO) to establish evaluation model and conduct system simulation. Results show that PSO-SVM actually increases the assessment accuracy, having practical application value in urban traffic carbon emission management.

Keywords*: urban regional transportation; carbon emission early warning; evaluation model and simulation study*

1. Introduction

In the 21st century, city scale expands unceasingly, road construction multiplies, civil cars develop fast and travel structure and status of common people have changed dramatically. With ever-increasing urban traffic demands, even if per capita energy consumption of urban traffic is still far lower than developed countries at present, overall energy consumption is increasing in rather fast speed and large range, thus resultant carbon emission also grows rapidly. High-speed growth of urban traffic carbon emission has produced great pollution to environment, affecting the life and living environment of urban residents and hindering the survival and development of cities. Therefore, carbon emission evaluation of urban traffic is a problem demanding prompt solution in domestic and foreign research[1].

Scholars have conducted a large number of researches on the problem of carbon emission evaluation of urban regional transportation and summed up lots of methods in relevant to this problem, obtaining certain achievements[2]. The earliest evaluation method is expert scoring which mainly relies on relevant experts' experience to evaluate carbon emission of urban regional transportation, hence its results have strong subjectivity and lower objectivity on carbon emission level evaluation[3]. As artificial intelligence technology become mature and neural network has self-organizing and self-learning processing capacity, it has been introduced into carbon emission evaluation of urban regional transportation by scholars[4]. However, neural network is prone to produce over-fitting, fall into local minimum and have other defects, thus having weak nonlinear

ISSN: 1975-4094 IJSH

modeling ability[5]. While it is a complex nonlinear variation relationship between carbon emission of urban regional transportation and evaluation index and requirements for nonlinear modeling ability are high, so neural network is difficult to meet the requirements of carbon emission assessment of urban regional transportation[6] [7]. Therefore, this study introduces support vector machine (SVM) which has fast learning speed and strong generalization ability compared to other two evaluation methods, meeting above higher requirements on nonlinear modeling ability and opening up a new research perspective[8] [9].

Aiming at the problem of lower carbon emission evaluation accuracy of urban regional transportation, this research proposes carbon emission warning system of urban regional transportation (PSO-SVM) that can optimize SVM parameters based on particle swarm optimization and tests the validity of this algorithm through system simulation, the result of which suggest that PSO-SVM has strong generalization ability and its modeling speed is superior to traditional artificial neural network evaluation method, being more suitable for constructing carbon emission evaluation model of nonlinear urban regional transportation.

2. Carbon Emission Evaluation Theory of Urban Regional Transportation

In terms of carbon emission evaluation of urban regional transportation, first of all, the carbon emission level should be identified, then adopt certain methods to assess and finally get evaluation results. Working principles of carbon emission early warning system of urban regional transportation based on SVM has been shown in Figure 1.

In evaluation process of SVM carbon emission of urban regional transportation, grid searching method is usually adopted to select parameters of support vector machine (SVM), but its evaluation precision is low and computation time is long. Hence, particle swarm optimization algorithm is utilized in this research to choose SVM parameters to obtain optimal SVM carbon emission assessment model of urban regional transportation which has higher evaluation precision.

In this research, carbon emission assessment precision of urban regional transportation is regarded as the objective function of particle swarm through which particle superiority can be measured. In addition, dynamically adjust flight direction of particles by using flight experience of particles and their companions and then constantly adjust and seek for optimal solution through their flight direction. Finally global optimal support vector parameter values can be easily obtained through this method.

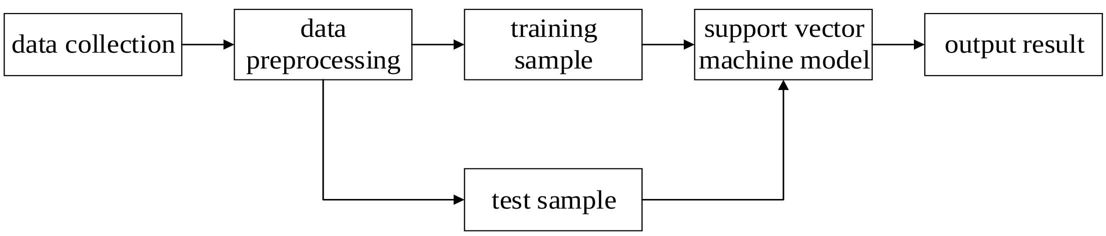

Figure 1. Working Principles of Carbon Emission Early Warning System of Urban Regional Transportation

3. Carbon Emission Evaluation Model of Urban Regional Transportation

3.1. Evaluation Index Selection

Carbon emission evaluation of urban regional transportation is an integral system, so its index system design is a critical factor to the success of research. As a result, all factors possibly affecting urban traffic carbon emission have to be analyzed and then select and establish a set of complete index system. Later, a carbon emission evaluation index system of urban regional transportation (as shown in Table 1) has been constructed on the basis of dynamism, objectivity, systematicness, scientificity and operability principles and combining experts' experience of relevant fields.

Table 1. Carbon Emission Evaluation Index System of Urban Regional Transportation

Carbon Emission Evaluation of Urban Regional Transportation	Media of Communication	Public Transportation Proportion (C_{11}) Slow Traffic Proportion (C_{12}) Proportion of New Fuel-efficient Vehicles (C_{13}) Vehicle Holding Volume (C_{14}) Bicycle Proportion (C_{15})
	Infrastructure	Infrastructure Investment (C_{21}) Slow Lane Proportion (C_{22}) Bus Lane Proportion (C_{23}) Bicycle Lane Proportion (C_{24})
	Policy Management	Energy Conservation and Emission Reduction Measure (C_{31}) Low-carbon Transportation Management Policy (C_{32}) Driver's Low-carbon Awareness (C_{33}) Vehicle Carbon Emission Detection Mechanism (C_{34})
	Traffic Environment	Tail Gas Clean-up Facility (C_{41}) Regional Ventilation Level (C_{42}) Road Network Density (C_{43}) Road Greening Degree (C_{44} Intelligent Traffic Technique (C_{45})

In the index system in Figure 1, some are qualitative indicators, such as drivers' low-carbon awareness which is difficult to gather concrete numerical values directly. Thus they need to be converted into quantitative indexes for calculation and will be divided into low, medium and high levels according to the results from expert scoring method. The minimum is 1 score and the maximum is up to 5 score. Value range of various indexes has been shown in Table 2.

3.2 Evaluation Index Standardization

Each evaluation index dimension will not lead to great index value difference. In order to eliminate adverse effect of dimension, the original data must be scaled up into [0, 1,] section when evaluating carbon emission of urban regional transportation with SVM. The standardized formula is shown specifically as follows:

$$x_{ij}^{'} = \frac{x_{ij} - \min(x_i)}{\max(x_i) - \min(x_i)} \tag{1}$$

here, x_{ij} is the j th value of i th index, $x_{ij}^{'}$ is the value of x_{ij} after standardization and max and min stand for selecting the functions with maximum and minimum values.

Table 2. Value Range of Various Evaluation Indexes

Type of indexes	Specific index	Value range of indexes	Type of indexes	Specific index	Value range of indexes
Media of Communication	C_{11}	[0,100%]	Policy Management	C_{31}	[1,5]
	C_{12}	[0,100%]		C_{32}	[1,5]
	C_{13}	[0,100%]		C_{33}	[1,5]
	C_{14}	[0,100]		C_{34}	[1,5]
	C_{15}	[0,100%]	Traffic Environment	C_{41}	[0,100]
Infrastructure	C_{21}	[0,100]		C_{42}	[1,5]
	C_{22}	[0,100%]		C_{43}	[0,100]
	C_{23}	[0,100%]		C_{44}	[1,5]
	C_{24}	[0,100%]		C_{45}	[1,5]

3.3 SVM Algorithm

SVM is a new machine learning method which is proposed directing at pattern recognition problems, used for solving classification problems at first and later for prediction problem solving by introducing the most sensitive loss function. As carbon emission evaluation of urban regional transportation belongs to prediction problem, thus support vector regression algorithm is mainly introduced here.

Suppose that there are in total n learning samples expressing as $\{x_i, x_j\}$ and i=1,2,…,N, among which x_i represents sample input and y_i stands for expected value of model output, then SVM estimate function is:

$$f(x) = w \cdot \varphi(x) + b \tag{2}$$

Among them, w and b shows weight vector and offset vector respectively.

After adopting optimization function to optimize target value, there is:

$$\min J = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i^* + \xi_i) \tag{3}$$

Constraint condition as following:

$$\begin{cases} y_i - w \cdot \varphi(x) - b \le \varepsilon + \xi_i & (4) \\ w \cdot \varphi(x) + b - y_i \le \varepsilon + \xi_i^* & (5) \\ \xi_i, \xi_i^* \ge 0, \quad i = 1,2,\ldots,n & (6) \end{cases}$$

ξ_i , ξ_i^* indicate as relaxing factor and C stands for penalty factor.

By introducing Lagrange's multipliers, the optimization problem above can be changed into typical convex quadratic optimization as following:

$$L(w,b,\xi,\xi_i^*,\alpha,\alpha^*,\gamma,\gamma^*) = \frac{1}{2}\|w\|^2 + C\sum_{i=1}^{n}(\xi_i^* + \xi_i) - \sum_{i=1}^{n}\alpha_i[\xi_i + \varepsilon - y_i + f(x)] - \sum_{i=1}^{n}\alpha_i^*[\xi_i^* + \varepsilon - y_i + f(x)] - \sum_{i=1}^{n}(\xi_i\gamma_i - \xi_i^*\gamma_i^*) \tag{7}$$

α_i and α^* representing as Lagrange's multipliers.

In order to accelerate solving speed, (4), (5) and (6) are changed into dual form as following:

$$W(\alpha,\alpha^*) = -\frac{1}{2}\sum_{i,j=1}^{n}(\alpha_i-\alpha_i^*)(\alpha_j-\alpha_j^*)[\varphi(x_i),\varphi(x_j)] + \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)y_i - \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)\varepsilon \tag{8}$$

As for linear regression problem, the SVM function is:

$$f(x) = \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)[\varphi(x_i),\varphi(x_j)] + b \tag{9}$$

As for nonlinear prediction problem, replace $[\varphi(x_i),\varphi(x_j)]$ with kernel function $k(x_i, x)$ to avoid the "curse of dimensionality". Then SVM regression function is:

$$f(x) = \sum_{i=1}^{n}(\alpha_i-\alpha_i^*)k(x_i,x) + b \tag{10}$$

3.4 Particle Swarm Optimization Algorithm

Particle swarm optimization is a swarm intelligence algorithm which expresses each feasible solution of problem with particle, evaluates superior degree of each particle by objective function, dynamically adjusts flying method according to its own optimal solution (pbest) and group optimal solution (gbest) in particle flying process and then searches for optimal solution. In dynamic flight, adjust their own speed and position according to formula (11) and (12).

$$v_{id}(t+1) = w\cdot v_{id}(t) + c_1\cdot r_1\cdot[p_{gd}(t) - p_{id}(t)] + c_2\cdot r_2\cdot[p_{gd} - p_{id}(t)] \tag{11}$$

$$p_{id}(t+1) = p_{id}(t) + v_{id}(t+1) \tag{12}$$

Among them, r_1 and r_2 are random numbers; w is inertia weight; c_1 and c_2 are accelerated factors.

3.5 Carbon Emission Evaluation Model Workflow of Urban Regional Transportation

(1) Build carbon emission evaluation index system of urban regional transportation based on relevant experts' experience.

(2) Collect relevant data according to constructed carbon emission evaluation index system of urban regional transportation and conduct standardization process for related data.

(3) Set particle swarm parameters c_1 and c_2, population size m and maximum number of iteration Nmax.

(4) Randomly generate particle swarm containing m particles, each of which is composed by initial position and speed.

(5) Set objective function of particles of which the specific definition is as (13). Then work out adaptive speed of particles in accordance with objective function.

$$f = \frac{1}{m}\sum_{i=1}^{m}\left|\frac{y_i - \hat{y}_i}{y_i}\right| \tag{13}$$

Among them, y_i and $\hat{y}_i$ is respectively actual value and predicted value of carbon emission.

(6) Update each particle's position and speed according to formula (11) and (12).

(7) Compare the adaptive value of each particle with individual optimal value (pbest) in history. If the former is superior to pbest, then replace individual optimal value in history with the particle's position.

(8) Compare the adaptive value of each particle with group optimal value (gbest) in history. If the former is superior to gbest, then replace group optimal value in history with the particle's position.

(9) If terminal conditions are satisfied, then iteration is finished and output optimal particle position; Otherwise, turn to step (5).

(10) Output SVM parameter and establish carbon emission evaluation model of urban regional transportation. The entire workflow has been shown in Figure 3.
The entire workflow has been shown in Figure 2.

3.6 Carbon Emission Model Performance Evaluation Standards of Urban Regional Transportation

Evaluate the performance of carbon emission evaluation model of urban regional transportation by using relative error (ERROR) and root mean square error (MSE), of which the definitions are:

$$Error(n) = \frac{|x(n,true) - x(n,pred)|}{x(n,true)} \tag{14}$$

$$MSE = \sqrt{\frac{1}{N}\sum_{n=1}^{N}[X(n,true) - x(n,pred)]} \tag{15}$$

4 Simulation Study

4.1 Simulation Data

This research adopts Matlab to conduct system simulation and takes road traffic of certain big city area as simulation object to collect data. Collected original data has been shown in Table 3.

Table 3. Carbon Emission Evaluation Original Data of Urban Regional Transportation

Project Number	C_{11}	C_{12}	C_{13}	C_{14}	……	C_{45}	Evaluation Results
1	0.38	0.69	0.34	70	……	2	0.435
2	0.47	0.74	0.27	71	……	4	0.228
3	0.48	0.62	0.61	68	……	3	0.372
4	0.35	0.65	0.57	74	……	5	0.552
5	0.38	0.59	0.94	69	……	4	0.398
6	0.47	0.72	0.87	70	……	3	0.402
7	0.48	0.68	0.69	72	……	4	0.292
8	0.35	0.71	0.59	73	……	5	0.476
9	0.38	0.63	0.72	69	……	5	0.532
10	0.47	0.73	0.47	68	……	3	0.616
……	……	……	……	……	……	……	……
18	0.35	#VALUE!	0.35	69	……	4	0.736

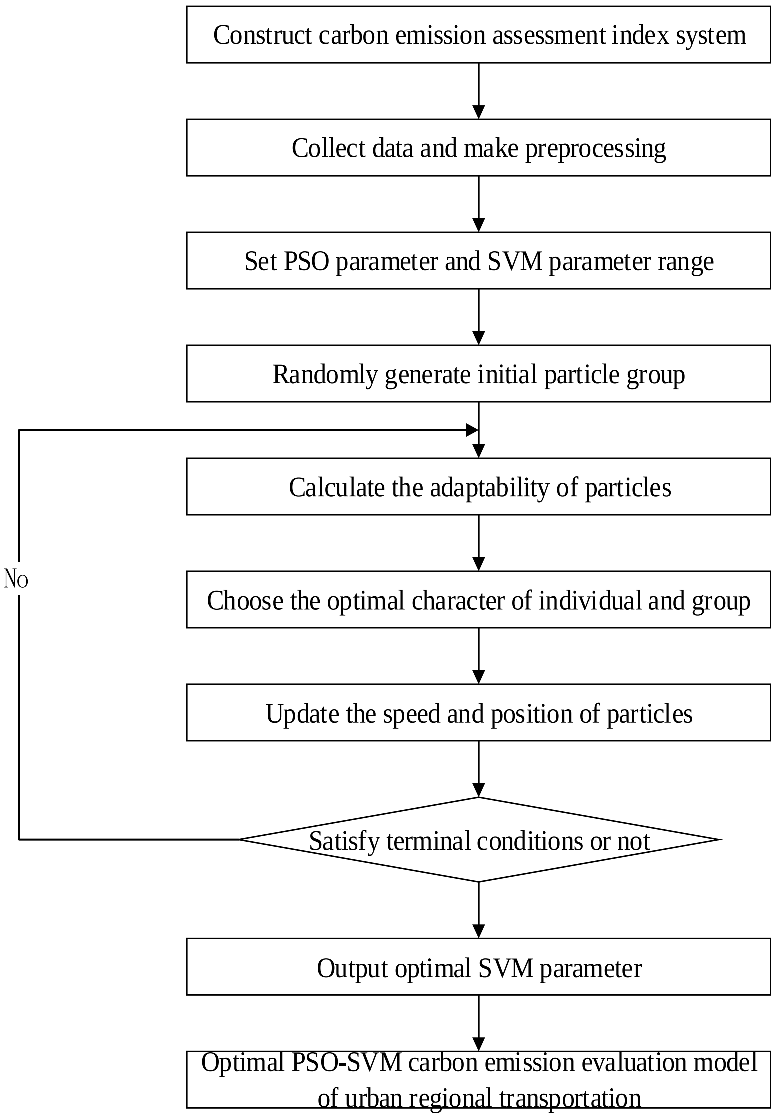

Figure 2. SVM Parameter Selection Process through Particle Swarm Optimization

4.2 Model Realization

Make standardization processing for data in Table 3 and then divide processed data into training sample and test sample sets. First of all, input training sample set in SVM for training and optimize SVM parameters by using particle swarm optimization algorithm. Parameter optimization process has been shown in Figure 3 which tells that fitness function of optimal particle is in stable status to some degree when particle swarm iterating to about 220 generations. It illustrates that algorithm's terminal conditions have been satisfied. Then decode position sets of optimal particles, obtain SVM parameters including c = 200, p = 0.0119, g = 0.156, adopt the above optimal parameters, set up carbon emission evaluation of urban regional transportation based on training sample set and have an exam on test samples.

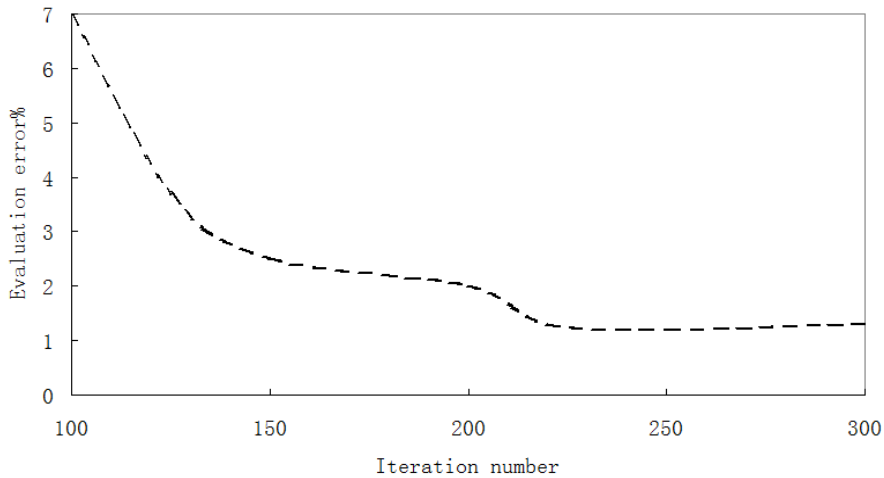

Figure 3. SVM Parameter Optimization Process by PSO

Author names and affiliations are to be centered beneath the title and printed in Times New Roman 12-point, non-boldface type. Multiple authors may be shown in a two or three-column format, with their affiliations below their respective names. Affiliations are centered below each author name, italicized, not bold. Include e-mail addresses if possible. Follow the author information by two blank lines before main text.

4.3 Simulation Results and Analysis

Adopt RBF neural network as a model and verify the superiority of PSO-SVM model through comparison and analysis. Testing results of RBF neural network model and PSO-SVM model on test sample set has been shown in Figure 4. As for evaluation error of two means, see Table 4.

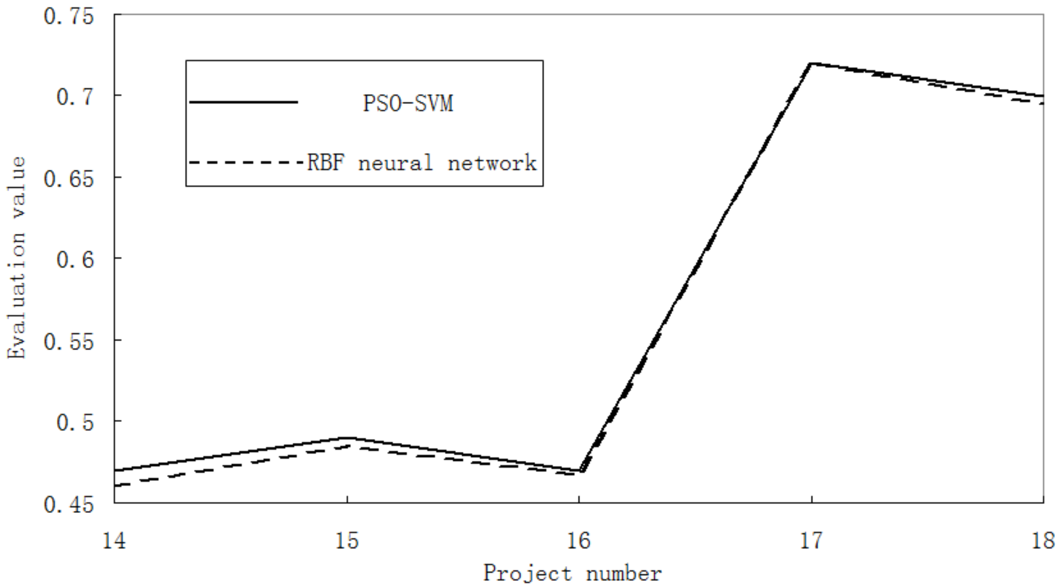

Figure 4. PSO-SVM and RBF Evaluation Results

Table 4. Evaluation Error Comparison of Two Methods

Project number	PSO-SVM Error	RBF neural network Error
14	0.018	0.082
15	0.007	0.077
16	0.007	0.072
17	0.005	0.083
18	0.003	0.025
MSE	0.0049	0.0390

After comparing the evaluation results and errors of two methods in Figure 4 and Table 4, it is clear that both evaluation effect and accuracy of carbon emission evaluation model of urban regional transportation based on SVM are better than that of RBF neural network. While the minimizing principle of PSO-SVM can help find the best compromise between learning ability and complexity of the model to acquire global optimal solution, thus having smaller evaluation error and higher precision.

5. Conclusion

This study presents a carbon emission evaluation model of urban regional transportation based on PSO-SVM which better solve the difficult problem of low evaluation accuracy of traditional SVM parameter optimization and traditional neural network. Take urban regional transportation of some big city as system simulation object to test the superiority of PSO-SVM. Finally, simulation results suggest that the accuracy of carbon emission evaluation of urban regional transportation based on PSO-SVM is higher than that of RBF neural network, thus possessing certain theoretical significance and application value in carbon emission management of urban regional transportation.

Acknowledgements

This research was supported by the key project of Jiangsu Social Science Research (Grant NO.2013ZDIXM015), the Nanjing University of Aeronautics & Astronautics cooperative research base of the open fund project (Grant NO.56XZA12074) and Jiangsu Innovation Program for Graduate Education (Granted NO.KYZZ_0093), all support is gratefully acknowledged.

References

[1] Jiang D, Xu Z, Chen Z, *et al*. Joint time-frequency sparse estimation of large-scale network traffic[J]. Computer Networks, 2011, 55(15): 3533-3547.Jinyu Hu, Zhiwei Gao and Weisen Pan. Multiangle Social Network Recommendation Algorithms and Similarity Network Evaluation[J]. Journal of Applied Mathematics, 2013 (2013).

[2] Jinyu Hu and Zhiwei Gao. Modules identification in gene positive networks of hepatocellular carcinoma using Pearson agglomerative method and Pearson cohesion coupling modularity[J]. Journal of Applied Mathematics, 2012 (2012).

[3] Lv Z, Tek A, Da Silva F, *et al*. Game on, science-how video game technology may help biologists tackle visualization challenges[J]. PloS one, 2013, 8(3): 57990.

[4] Su T, Wang W, Lv Z, *et al*. Rapid Delaunay triangulation for randomly distributed point cloud data using adaptive Hilbert curve[J]. Computers & Graphics, 2016, 54: 65-74.

[5] Shuang Zhou, Liang Mi, Hao Chen, Yishuang Geng, Building detection in Digital surface model, 2013 IEEE International Conference on Imaging Systems and Techniques (IST), Oct. 2012

[6] Jie He, Yishuang Geng, Kaveh Pahlavan, Toward Accurate Human Tracking: Modeling Time-of-Arrival for Wireless Wearable Sensors in Multipath Environment, IEEE Sensor Journal, 14(11), 3996-4006, Nov. 2014

[7] Lv Z, Halawani A, Fen S, *et al*. Touch-less Interactive Augmented Reality Game on Vision Based Wearable Device[J]. Personal and Ubiquitous Computing, 2015, 19(3): 551-567.

[8] Guanqun Bao, Liang Mi, Yishuang Geng, Mingda Zhou, Kaveh Pahlavan, A video-based speed estimation technique for localizing the wireless capsule endoscope inside gastrointestinal tract, 2014

36th Annual International Conference of the IEEE Engineering in Medicine and Biology Society (EMBC), Aug. 2014
[9] Degui Zeng, Yishuang Geng, Content distribution mechanism in mobile P2P network, Journal of Networks, 9(5), 1229-1236, Jan. 2014
[10] Gu W, Lv Z, Hao M. Change detection method for remote sensing images based on an improved Markov random field[J]. Multimedia Tools and Applications, 2015: 1-16.
[11] Chen Z, Huang W, Lv Z. Towards a face recognition method based on uncorrelated discriminant sparse preserving projection[J]. Multimedia Tools and Applications, 2015: 1-15.
[12] Gan Yan, Yuxiang Lv, Qiyin Wang, Yishuang Geng, Routing algorithm based on delay rate in wireless cognitive radio network, Journal of Networks, 9(4), 948-955, Jan. 2014
[13] Lin Y, Yang J, Lv Z, *et al*. A Self-Assessment Stereo Capture Model Applicable to the Internet of Things[J]. Sensors, 2015, 15(8): 20925-20944.
[14] Wang K, Zhou X, Li T, *et al*. Optimizing load balancing and data-locality with data-aware scheduling[C]. Big Data (Big Data), 2014 IEEE International Conference on. IEEE, 2014: 119-128.
[15] Zhang L, He B, Sun J, *et al*. Double Image Multi-Encryption Algorithm Based on Fractional Chaotic Time Series[J]. Journal of Computational and Theoretical Nanoscience, 2015, 12: 1-7.
[16] Su T, Lv Z, Gao S, *et al*. 3d seabed: 3d modeling and visualization platform for the seabed[C]. Multimedia and Expo Workshops (ICMEW), 2014 IEEE International Conference on. IEEE, 2014: 1-6.
[17] Yishuang Geng, Jin Chen, Ruijun Fu, Guanqun Bao, Kaveh Pahlavan, Enlighten wearable physiological monitoring systems: On-body rf characteristics based human motion classification using a support vector machine, IEEE transactions on mobile computing, 1(1), 1-15, Apr. 2015
[18] ADAZEH A, GHADERI S F, IZADBAKHSH H, 'Integration of DEA and AHP with computer simulation for railway system improvement and optimization', Applied Mathematics and Computation(2007), Vol.195, No.8, pp.775-785.
[19] AMEKUDZI A A, KHISTY C, MELECKIDZEDECK K, 'Using the sustainability footprint model to assess development impacts of transportation systems', Transportation Research Part A: Policy and Practice(2009), Vol.43, No.5, pp. 339-348.
[20] JACCO F, FLOORTJE A, 'Analysis of barriers in the transition toward sustainable mobility in the netherland', Technological Forecasting and Social Change(2010), Vol.77, No.2, pp. 1260-1269.
[21] Zhao Hui, Jiang Heng, Wu Nan, 'evaluation of low carbon Transportation Strategy Study on method of traffic information ', Traffic simulation(2012), Vol.53, No.2, pp. 71-82.
[22] Guo Jie, Chen Jianying, Ouyang Bin, 'Study on the evaluation index system of regional comprehensive transportation', Lowcarbon traffic Chinese(2012), Vol.19, No.6, pp. 38-42.
[23] Wang Jianwei, Zhang Xiaoming, Song Qingliang, Gao Jie, 'Research on low-carbon transportation development evaluation PSR model', Traffic university journal(2013), Vol.49, No.10, pp. 24-27.
[24] Guo Lijun, Huang Yan, 'The long line of establishment and application of Tan city cluster of low carbon traffic DPSIR evaluation model of traffic science and technology in Hunan' , Lowcarbon traffic Chinese(2014), Vol.28, No.12, pp. 144-148.
[25] Cheng Dongxiang, Chen Jing, Zhu Dajian, Yan Dawei, Wu Xiuling, 'Research on evaluation model of regional low carbon traffic' , Environmental pollution and control(2014), Vol.21, No.6, pp. 91-95.
[26] Wang Lijun, Li Yingjie, Chen Jiang, 'Regional green cycle low carbon transportation development' , Management of transportation(2014), Vol.14, No.6, pp. 39-41.

Authors

Hao Wu, He received his master degree in Enterprise Management from Jiangsu university in Zhenjiang, China. He is currently a Ph.D Candidates in the College of Economics and Management at Nanjing University of Aeronautics and Astronautics. Her research interest is mainly in the area of low carbon transportation simulation. He has published several research papers in scholarly journals in the above research areas and has participated in several books.

