Integer Wavelet Image Denoising Method Based on Principle Component Analysis

Jing Peng
College of Computer and Information Science, Chongqing Normal University, Chongqing, China
Email: jsjxy_pj@163.com

Yan Ma
College of Computer and Information Science, Chongqing Normal University, Chongqing, China
Email: csmayan@126.com

***Abstract*—Over the years a variety of methods have been introduced to remove noise from digital images, such as Gaussian filtering, anisotropic filtering, and Total Variation minimization. However, many of these algorithms remove the fine details and structure of the image in addition to the noise because of assumptions made about the frequency content of the image. It is analyzed in the way that the noise is decomposed into low and high frequency sub-band under the wavelet transformation, and subconsequently extracts the principle components feature with the method of Principle Component Analysis(PCA). This can keep the the picture as detailed as possible, while at the same time getting rid of the noise. This exeperiment proves that this method can get rid of the noise of the picture not only effectively, but also keeps the detail of the picture to the maximum.**

***Index Terms*—image denoising, integer wavelet, Principle Component Analysi**

I. Introduction

With the prevalence of digital cameras and scanners, digital images can be easily acquired nowadays. Unfortunately, digital images are often degraded by noise during acquisition or transmission process. Various image-related applications, such as medical image analysis, image segmentation, and object detection, etc., generally require effective noise suppression method to further produce reliable results. Therefore, image denoising has been one of the most important and widely studied problems in image processing and computer vision. So far, image denoising methods can be basically divided into two categories: spatial filtering methods [1-3] and transform domain filtering methods [4-5]

In spatial domain, for every pixel of noisy image, many existing noise reduction methods employ the information of its nearby local region to estimate its denoised version. Examples include Gaussian filter, median filter, bilateral filter and so on. We call these kind of denoising algorithms local-based spatial methods. Whereas, generally speaking, the information encoded in a natural image is redundant to some extent, that is to say, there may exist some repeat patterns in natural images, particularly in textured or periodic case. Based on this observation, Buadest [6] developed a non-local image denoising algorithm which takes full advantage of image redundancy. Like many noise reduction algorithm, the method is also based on weighted average. The essence of the method is: to estimate a certain pixel, the method uses the similarities between it and all the other pixels in image to act as weight, and the similarities are not computed from pixels themselves but from their neighboring window (compare window). The algorithm has demonstrated strong superiority over local-based spatial methods such as Gaussian filter, bilateral filter in terms of both PSNR and visual quality. However, certain critical issues need further investigation. Firstly, the computational cost is high for its pixel-by-pixel window matching, and it limits the method to be widely used in application. Secondly, the quality and computation cost of the algorithm is closely related to the size of compare window which represents geometrical configuration of pixel's neighboring region. For small conpare window, the algorithm is restricted to suppressing the high-frequency noise and cannot remove the low-frequency noise (1arge-scale). For large compare window, the algorithm removes the low-frequency noise effectively, but becomes less sensitive to small details and the additional burden on the computational resources becomes unacceptable.

Since the essential goal of denoising is to preserve the image features while reducing noise effectively, a logical extension of spatial denoising is to transform images into a representation that distinctive features such as edges can be extracted from image and perform noise reduction algorithms in this domain. As for denoising in frequency domain, we are more familiar with wavelets which fall into two classes: orthogonal wavelet and non-orthogonal wavelet. Orthogonal wavelet compositions are critically sampled (i.e., nonredundant) image descriptions. It has been successfully used in image compression and threshold-based image denoising. However, the non-

Manuscript received January 1, 2011; revised June 1, 2011; accepted July 1, 2011.

doi:10.4304/jsw.7.5.982-989

redundant property of orthogonal wavelet means they are not suitable for non-local means denoising which builds upon image redundancy.

Actually, the various methods about image, which eliminate noise, are going to trade-off between eliminating and keeping useful high-frequency information. Major denoising methods include Gaussian filtering, Wiener filtering, and wavelet thresholding. Many more methods have been developed; however, most methods make assumptions about the image that can lead to blurring.

PCA(Principle Component Analysis)[6-7] technology on the basis of the neural network method, because the altitudinal parallelism and adaptability, it can extract the main characteristic component of the image, thus eliminate the noise signal of the main characteristic component. However, if we extract the main character of image space domain with PCA directly, it will lose the intrinsic existing detail of the image while suppressing the noise probably. So, this papper propose to change the image from space domain to the frequency domain through frequency transformation, low frequency and high-frequency signal are gained after resolving firstly. The noise signal concentrate on the high-frequency signal more at this moment, and extract the main characteristic to low frequency and high-frequency signal separately. Then inversed transformation goes back to the space domain, it can realize that getting rid of the noise, and will keep the detail part of more images. While going on to the image - the method to vary frequently can select the wavelet of integer transformation, and it is harmless that it can enable resolving.

II. Integer Wavelet Transform

It is all the varying of real number fields that the traditional wavelete is varied, even the digital signal is an integer array, the corresponding wavelete varies coefficient is a real number too. People hope that the wavelete transformation of the matrix of the image is the integer matrix, namely the wavelete transformation of an integer of integer, which array integer is mapping into integer wavelet coefficient, and reversible, known as " integer wavelete vary " (IWT) usually[7-9].

A. Lifting Scheme

Sweldens [7-9] put forward the new construct of wavelete, which not depend on Fourier transformation - - lifting scheme, this method can not only keeps intrinsic existing of wavelete, but also overcome the limitation from inflexibility of translation and flexion. The second generation of wavelete transformation which based on advanced method, has the fast algorithm with wavelete, it can realize transformation from integer to the integer, and carrying on the entropy code to the data after varying can realize the harmless compression of the picture. On the basis of lifting integer wavelet method is including 3 steps, viz. split, predict and update.

To figure axis labels, use words rather than symbols. Do not label axes only with units. Do not label axes with a ratio of quantities and units. Figure labels should be legible, about 9-point type.

Color figures will be appearing only in online publication. All figures will be black and white graphs in print publication.

1) Split

The primitive signal split into two sub-sets that not each other crossing in this course: Even sample and odd sample $S_{j,2l}$ $S_{j,2l+1}$

$$S_{j,2l} = \text{even}(S_j) \tag{1}$$

$$S_{j,2l+1} = \text{odd}(S_j) \tag{2}$$

2) Predict

During the processing of predicting, in order to keep the even sample $S_{j,2l}$ fixedness, we can aim at the dependence among initial data, and adopt a prediction operator which having nothing to do with datum structure P , making use of even sample $S_{j,2l}$ to predict the odd sample $S_{j,2l+1}$, and substitute the odd number sample with the odd sample $S_{j,2l+1}$ minus predicted value (called detail coefficient), predict that the expression formula of the course is as follows:

$$d_{j-1} = S_{j,2l+1} - \text{P}(S_{j,2l}) \tag{3}$$

3) Update

Because the 1st step of even signals produced is not the same as initial data on some whole qualities, so need to adopt newer course. Newer starting point to find one good sub datum set S_{j-1} , and make it keep some characteristics which initial data S_j collected, for instance energy, mean value, disappearance square, etc., namely Q (S_{j-1})=Q (S_j). So introduce upgrade operator U, act on detail coefficient and superpose on the even sample , receive the signal similarly,

$$S_{j-1} = S_{j,2l} + \text{U}(d_{j-1}) \tag{4}$$

Here predict wave filter P($S_{j,2l}$)= $\sum_l p_{j,l} s_{j,2l}$, update filter U(d_{j-1}) $= \sum_l u_{j-1,l} d_{j-1,2l+1}$, int [x] is fetched whole to the thing that x rounds up. Lifting algorithms that can be apt to realize from integer to integer mapping of wavelete transformation. And the course is all reversible.

This processing is called a lifting scheme of wavelete transformation, and the lowpass component S_{j-1} and highpass d_{j-1} are exported, the sub-band result after often some wavelete transformation still need to carry on deeper resolving further. Can be according to the request of state of the network and user (resolution ratio of users' display device, computing capability, etc.) come to adjust wavelete yardstick j in order to the resolution ratio of adjusting the image. It is to upgrade algorithms and predict algorithms that the integer lifting the core that the small wave varies, through predict algorithms may receive high-frequency message, and can receive correct low frequency information through update operator.

B. Inverse Lifting Scheme

The inverse lifting scheme can be established

1) Undo Update

Given d_{j-1} and S_{j-1}, and by the following formula, we can even get updated information value of the even sampling points:

$$\text{even}(S_j)=S_{j-1}\text{-U}(d_{j-1}) \tag{5}$$

2) Undo Predict

Given d_{j-1} and S_{j-1}, and by the following formula, we can even get updated information value of the odd sampling points:

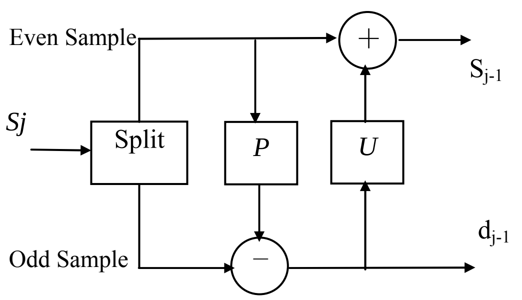
$$\text{odd}(S_j)=d_{j-1}\text{+P}(\text{even}(S_j)) \tag{6}$$

3) Merge

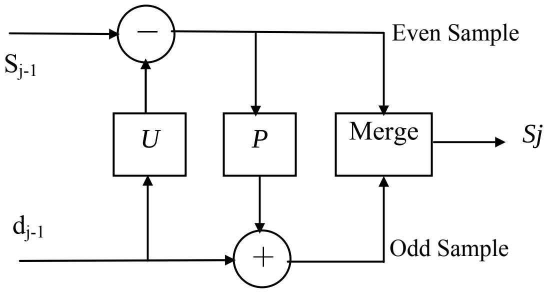
The original data will be restored from even samples and odd samples which are getted from equation (5) and equation (6), by the following formula:

$$S_j=\text{Merge}(\text{even}(S_j),\text{odd}(S_j)) \tag{7}$$

Sweldens [9] have proved that it may do integer to integer wavelet transforms based on the lifting scheme. And can be completed in the current location of the wavelet transform, saving memory and computing speed fast. This digital image compression coding to bring benefits. While the second generation of integer wavelet also has a multi-resolution features, the image can be broken down tower, respectively, transform and column transform for the line, you can remove the correlation. For the first generation wavelet watermarking method can also be used in second generation wavelet transform basis, and get better results.



(a) Decomposition



(b) Reconstruction

Figure1. Integer Wavelet Transform

III. PCA BASED ON NN

A. Network compress algorithm

The wavelet transform has achieved reallocation of energy, most of the energy concentrate on low frequency sub-band LL[10-11]. The compression degree and info retain state of the LL will influence directly upon the conceptual compression ratio of image and the fidelity of resuming image. If make quantification of the low frequency sub-band coefficient, quality of the image will be lowered, so this part is often very difficult to compress. Between lowest frequency sub-band coefficient and horizontal coefficient, vertical coefficient and diagonally coefficient there have dependence all. At the same time among the corresponding horizontal coefficient, vertical coefficient and diagonally coefficient there also exist great dependence. This dependence is a kind of information redundancy in fact. If get rid of this kind of redundancy degree farthest, so only need to save the lowest frequency coefficient, it will reduce the bits of the corresponding code. Therefore it can raise the data compression ratio at the case of minimum loss quality of image.

Artificial neuron network, such as BP network (forward neural network based BackPropagation)[12-13] has just achieve a non-linear and non-quadrature mathematic mapping from input spatial to output spatial. And it has proved that the non-linear mapping achieved by three-level feedforward artificial neural network can consistently approach the uninterrupted function on upon close aggregation, shown as Figure2. It generally including the input layer, latent layer of the middle and the output layer, every layer among them has one or more neurons that are fully connect to neurons of adjacent layer. Every connection has a weight $w_{i,j}$, represents their connection degree.

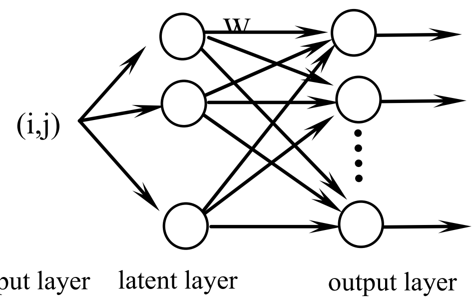


Figure.2. Structure of neural network

Through the input/output specimen aggregation train the BP neural network, namely adjust the weight value and the threshold value of each neuron. In every subsequent recursion process, adjust it according to delta learning rule, and then stop training after meeting a certain ending condition, thereby a neural network model upon functional relation between input and output has been set up. Their operation characteristic is shown as the expressions below:

$$net_{pj} = \sum_i w_{ji} o_{pj}$$

$$o_{pj} = f_j(net_{pj})$$

$$f_j(x) = 1/(1 + e^{-x})$$

Concept of compress static image data by BP neural network: image after n-level wavelet decompose, with lowest-frequency sub-band coefficient LL_n as the input of BP neural network, separately with the corresponding coefficients of three high-frequency sub-band HL_n, LH_n and HH_n of the highest level, then HL_{n-1}, LH_{n-1} and HH_{n-1} of the secondary high-level, until the HL_1, LH_1 and HH_1 of first layer as output, to set up each three level BP neural network model. And then process the network training. For example, when the data of output layers is the coefficient of HL_n then set up BP network with one input neuron and one output neuron. If data of output layers is the coefficient of HL_{n-1} then set up BP network with one input neuron and four output neuron, the rest may be deduced by analogy. If the image size is N*N, then network model of layer n is:
Input aggregation:

$$X = \{(i, j) \mid i < l_n, j < l_n\};$$

Output aggregation:

$$Y_1^n = \{(i, j + l_n)\},$$
$$Y_2^n = (i + l_n, j\},$$
$$Y_3^n = (i + l_n, j + l_n$$
$$Y_1^n = \{(i, j + l_n)\},$$
$$Y_2^n = (i + l_n, j\},$$
$$Y_3^n = (i + l_n, j + l_n\}$$

And the network model of layer n-1 is:
Input aggregation:

$$X = \{(i, j) \mid i < l_n, j < l_n\};$$

Output aggregation[12-15]:

$$Y_1^{n-1} = \{(2i, 2j + l_{n-1}), (2i, 2j + l_{n-1} + 1), (2i + 1, 2j + l_{n-1}), (2i + 1, 2j + l_{n-1} + 1)\}$$

$$Y_2^{n-1} = \{(2i + l_{n-1}, 2j), (2i + l_{n-1}, 2j + 1), (2i + l_{n-1} + 1, 2j), (2i + l_{n-1} + 1, 2j + 1)\}$$

$$Y_3^{n-1} = \{(2i + l_{n-1}, 2j + l_{n-1}), (2i + l_{n-1}, 2j + l_{n-1} + 1), (2i + l_{n-1} + 1, 2j + l_{n-1}), (2i + l_{n-1} + 1, 2j + l_{n-1} + 1)\}$$

While preserving the data, only need to process bit-level encode on lowest-frequency sub-band coefficient, in this way it can reduce the data quantity. When decompress image, the data of other sub-bands can gained by emulate compute in each corresponding BP network with the lowest-frequency coefficient as emulation data input. Accordingly gained the wavelet coefficient matrix, then the image can be resumed by contradictorily wavelet transform.

B. Principle Component Analysis

Suppose that it is composed of k samples to observe a group of data vector quantities $X = \{X^1, \cdots, X^k\}, X^l \in R^n, l = 1, 2, \cdots, k$, extracting the main characteristic with a lot of neurons, and can calculate the characteristic value of corresponding to each neuron right one by one[16-18].

1) *Goal function*

Through the introduction of a series of sample data to a certain neuron, adjusting the vector quantity of right in usage, and making it close to the characteristic vector quantity of corresponding to biggest characteristic value as much as possible, function is to define the goal:

$$E(w_j) = -\ln(w_j^T R_x w_j) + w_j^T w_j + \int_L \frac{\sum_{i<j} e_i e_i^T R_x w_j}{w_j^T R_x w_j} dw_j \tag{8}$$

mong them R_i is the covariance matrix of the sample, restrain the condition, goal function is satisfied $E(\infty) = \infty$, and $E(0) = \infty$.

2) *Learning with muti-neuron*

Study of a lot of neuron networks. It is goal function (8) type, or in order gain other characteristic vector one by one, adjustment formula of right is as follows:

$$\Delta w_j = -\eta \nabla E(w_j) \tag{9}$$

Also, by this goal function, it can try to get the characteristic vector of corresponding to biggest characteristic value, k a sample of inputting, if the adjustment formula of its right shows formally:

$$w_j(t+1) = w_j(t) + \eta' \sum_{l=1}^{k} \left(y_j X^l - y_j^l \sum_{i \le j} w_i(t) y_i^l \right) \tag{10}$$

Among them, can be asked out to the biggest m characteristic vector of a characteristic value of fixing the datum association's variance matrix learnt to collect with an feed-forward type artificial neural network. Study the step as follows[19-25]:

a) Imputing data were arranged a column vector, if two-dimensional picture data, with it is make up one dimension arrange vector to meet end to end among being competent to arrange. is express l pieces of data to take, l =1,2, …,k.

b) Ask the observation mean value of a series of samples:. $\overline{X}=\frac{1}{k}\sum_{l=1}^{k}X^{l}$

c) Composition new sample collection, l=1,2,⋯,k.

d) Import the new sample to the first neuron network, use (**10**) the type , through many times iterations, ask out the right of the network, solve vectorially for the greatest characteristic .

e) Ask it after appearing, the value of the ones that regard it as (**10**) item three of the right of the type , start the second neuron network, use (**10**) the type, study the characteristic vector of the second largest of the characteristic value.

Continue step e), can according to size of characteristic of value, it is come out to learn from quantity corresponding characteristic one by one. The characteristic vector that the artificial neuron network will represent the backbone is studied one by one, principal components analysis with step b) counting amount, its base is totally handed in.

C. Integer Wavelet Image Denoising Method Based on PCA

We propose to change the image from space domain to the frequency domain through frequency transformation, low frequency and high-frequency signal are gained after resolving firstly. The noise signal concentrate on the high-frequency signal more at this moment, and extract the main characteristic to low frequency and high-frequency signal separately. Then inversed transformation goes back to the space domain, it can realize that getting rid of the noise, and will keep the detail part of more images. While going on to the image -the method to vary frequently can select the wavelet of integer transformation, and it is harmless that it can enable resolving. The algorithm is as follows:

a) Using integer wavelet transform to the original image, to get high frequency coefficients and low frequency coefficients respectively;

b) And using the method of our PCA based on neural network to those high frequency coefficients and low frequency coefficients, then get these characteristics's value;

c) Then, according the inverse lifting scheme, the original data will restored from those characteristics's value , and this is the images to remove noise.

D. PSNR(Peak signal to noise ratio)

PSNR is "Peak Signal to Noise Ratio", if is generally used for the maximum value of signal and background noise between a project. Usually after image compression, image output will usually have to some degree with the original image is not the same. In order to measure the processed image quality, we usually refer to PSNR as a treatment method is not satisfactory.

PSNR calculation formula is as follows:

$$MSE=\frac{\sum_{n=1}^{Framesize}\left(I^{2}-P^{2}\right)}{Framesize}$$

$$PSNR=10\times\log\left(\frac{255^{2}}{MSE}\right) \tag{11}$$

MSE is Mean Square Error (mean square error, the difference between the value of n power and average), *I* refers to the original image N pixel values, *P* refers to the image after processing the first N pixel values. The PSNR unit is dB. So the value of PSNR is increasingly big, on behalf of the distortion is less, the smaller the PSNR, then the distortion degree bigger.

PSNR is the most common, the most widely used evaluation objective image measurement, but many experimental results show, PSNR scores and the human eye cannot be completely consistent visual quality, there may have a high PSNR looks rather than PSNR lower deviation. This is because the human eye vision for the error sensitivity is not absolute, its perception results will be affected by many factors such as: the human eye to change (a lower spatial frequency differences between higher sensitivity, eye on the luminance contrast of relatively high chroma, eye for a regional perception results will be affected by the surrounding regional effects).

IV. SIMULATION RESULT

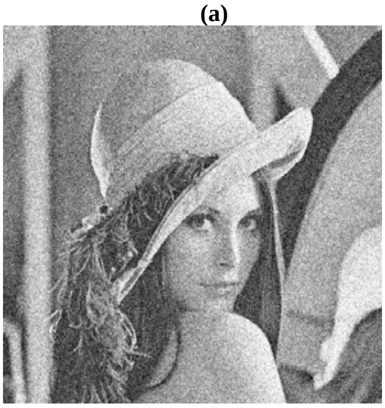
Use the standard 512*512 gray-level image Lena as experiment image, and add Gaussian noise into it (as Figure3(a)), which PSNR is 15.09. Then through calculating and simulating with the proposed method, when the number of neuron is 30, the denoised image can be got as Figure3(b). It is conscious obviously that edge information is substantially retained. Changing the number of neuron, difference results are got, as Figure3(c). There are two curves, which one is the result of our method and another is the old method with PCA. It shows that PSRN of Our method is better than the other from Figure4.

Then we use the standard 512*512 gray-level image Barbara as experiment image(as Figure5(a)), and add Gaussian noise(σ = 0.001) into it (as Figure5(b)). When using different coefficients of the Gauss noise is added in the Barbara image, and with old denoised methods to compare the results in TABLE II. Figure 6 is composed of the values in Table 1 are the comparison chart.

TABLE I
SHOW THE EXPERIMENT RESULT USING DIFFERENT NUMBER OF NEURON.

NO._neuron	Wavelet_PCA	PCA
10	13.96	7.82
20	14.64	9.68
30	15.11	8.91
40	15.09	9.01

(a)



(b)

(c)

Figure 3. (a) original Lena ; (b) Lena noise image; **(c)** Lena denoised

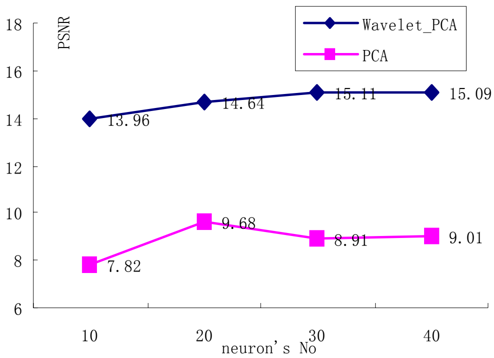


Figure4. Test with difference number of neuron

(a)

(b)

(c)

Figure 5. (a) originalc ; (b) noise image; (c) image denoised

TABLE II
SHOW THE EXPERIMENT RESULT USING VARIOUS VARIANCES OF GAUSSIAN NOISE WITH ZERO-MEAN.

σ	Proposed method	Old method
0.001	19.86	12.31
0.002	18.55	10.68
0.005	16.07	9.22
0.01	15.13	8.64
0.02	14.22	7.51

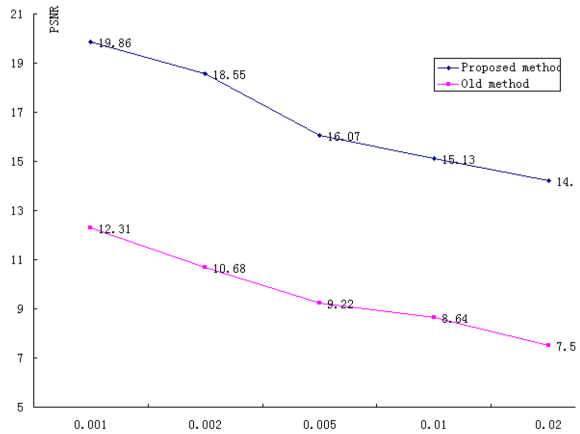


Figure 6. Test with difference values of σ

From the experimental results, for any intensity image Gauss noise, the results getted by using our denoising method based on PCA and integer wavelet Image Method are much better than the old method.

V. SUMMARY

In the image transfer process, because of the used device and limitation in the transmission passway, and has been joined a large number of noises, the visual effect of the picture has been influenced and even hindered people's normal discernment seriously. So for a long time, the noise dispelled and reducing in the picture has been one of an important subjects for research of the pattern process field all the time .

In this papper, the eliminating noise method of image always was puzzled by eliminating noise and reservation of useful high-frequency. Edge feature is the most useful high-frequency information of image, it can reserve image's edge feature as you can while eliminating noise. The noise is decomposed into low frequency and high-frequency sub-band under the wavelet transformation, and then extracts principle components feature with PCA method separately, it can keep the detail part of the picture as much as possible while getting rid of the noise.

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Jing Peng received her M.E. degree in software engineering from University of Electronic Science and Technology of China, Sichuan chengdu in 2006.

Her research interests include digital image processing and information hiding.

Yan Ma, 1982 graduated from the yunnan university physics electronics profession and got a bachelor's degree, after graduation in zhaotong city, normal colleges teaching; Sept. 1990 was admitted to huazhong normal university and information technology is a master's degree, June 1993 graduate and obtained a master degree, received a doctor's degree in 2008. His research interests include artificial intelligence, semantic meshes and education grid.