A SERVICE ROBOT'S ROAD DETECTION SYSTEM INTEGRATED WITH BP-NN

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ABSTRACT: *In the field of mechanical engineering, more and more attention has been paid to the design of service-oriented robots. Because of the complexity of traffic environmental information,it's a problem to improve road's auto-detection efficiency and accuracy of the vision method.In this paper, the road detection method integrated with BP-NN(back propagation neural network) is proposed.Firstly,the recent advances of the road detection method based on machine vision are reviewed. Secondly, analyses the principle of BP neural network of the road detection system. Finally, experimental result shows that the proposed method has an important significance to detect the road ahead; the prediction accuracy (%) is about 90, which also has the practical significance to improve the road early-warning performance of the walk-aided service robot and the autonomous navigation design of driverless vehicle.*

KEYWORDS: *road detection; machine vision; back propagation neural network; service robot*

1 INTRODUCTION

As a key robotic technology, automatic road detection system has become a very important research subject, which is integrated with machine vision technology, pattern recognition and sensor technology. The world's first mobile robot SHAKEY was designed by the Artificial Intelligence Center of the Standford Research Institute (SRI) in 1972. The robot was equipped with a camera, which can help to finish the simple task of road detection. The mobile robot RAVON was developed by Germany Institute of Industrial University in Kaiserslautern and Belgium Royal Military, a set of stereo vision system was also equipped at the top of the robot, shown in Fig. 1. In China, a mobile robot CASIA-I with autonomous road detection system was designed by Chinese Academy of Science Institute of Automation. An intelligent mobile service robot developed by Harbin Institute of Technology was also equipped with a stereo vision system, ultrasonic sensors and pyroelectric infrared sensors, shown in Fig. 2. (Gao, 2014).

As to the theoretical research, the road detection system has become a concerning focus in the research on robotics, such as a stair climbing mobile robot method using an autonomous cross floor navigation system with wireless and vision sensors (Lai& Lin, 2013), a design scheme of walking robot aided with machine vision and tactile perception (Ni et al., 2015). The current road detection system has solved many problems of road detection, but still exists some shortness. The research on the road detection technology with adaptive and self-learning ability is still a difficult and necessary task for the road detection technology. Up to now, a common road detection system does not exist.

Fig. 1. RAVON

Fig. 2. Service robot designed by Harbin Institute of Technology

In order to afford the impaired people an early alert of the road condition ahead and help them to avoid the obstacles on the road in advance, the road detection system integrated with BP-NN is studied in this paper.

2 THE PRINCIPLE OF ROAD DETECTION SYSTEM INTEGRATED WITH BP-NN

2.1 Image matching algorithm of road detection

It is generally known that vision detection method is an effective way to observe the road conditions with high precision and low cost. The flow chart of the basic road detection process is shown in Fig. 3. In the road detection process, image matching algorithm is basically applied. According to the characteristics of algorithm; image matching method can be divided into two categories (Steger et al., 2008).

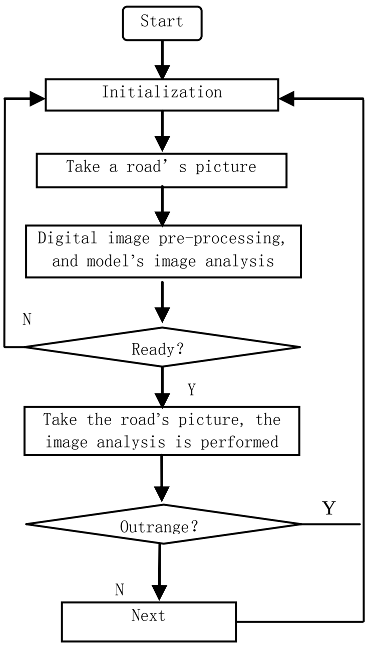


Fig. 3. The flow chart of the basic road detection method

1) NGC (Normalized Grayscale Correlation). With this matching method, the similarity between the template image and the real image is calculated to search the real road pose's parameters, which is characterized by high accuracy, good robustness and computational stability, but this matching method sometimes has more calculation which slows down the processing speed of the road detection system.

2) GPM (Geometric-based Pattern Matching). With this matching method, the constant feature factors of a road image is calculated to measure the similarity between the road's template image and the real road's image, such as the key points, the closing center of the region, the contour shape. This matching method has smaller amount of calculation, which has good ability to resist geometric or intensity distortion, but sometimes is sensitive to the image noise.

In order to improve the calculation speed and efficiency of the image matching algorithm, multi-resolution image matching algorithm has been proposed, such as the use of multi-scale operator for image edge detection (Rosenfeld & Thurston, 1971), and the different spatial resolution of an image (Hanson &Riseman, 1973). The idea of image multi-resolution, and propounded multi-resolution image pyramid has been proposed for the first time (Crowley, 1981). SIFT (Scale Invariant Transform) algorithm was proposed (David G. Lowe, 1999). It is an effective way to speed up the image detection efficiency with multi-resolution analysis (David G. Lowe, 2004).

In multi-scale image decomposition stage, the image is down sampled with vertical direction and horizontal direction, each layer of the original image is obtained, and so an image pyramid layer is formed (shown in Fig. 4). The spatial resolution at higher layer will have a smaller image pixel size, otherwise, the reverse. The typical methods of down sampling include Gauss filter, neighborhood average filter, Mallat wavelet transform, and so on (Zhu & Yu, 2011). The road image matching analysis can be carried out in each layer.

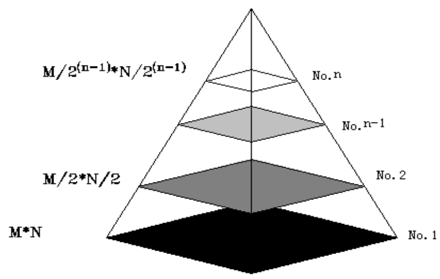
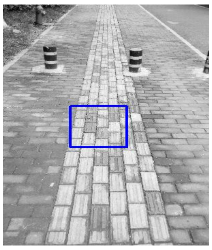
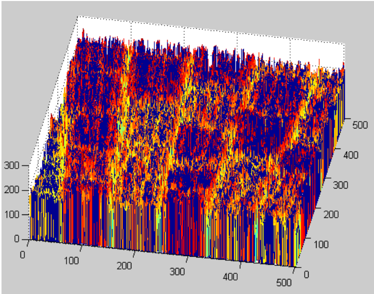


Fig. 4. Schematic diagram of the multi-resolution image pyramid

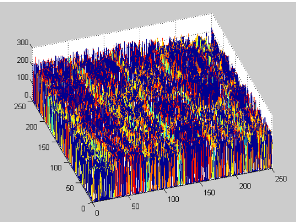
A road image's 3-D surface appearance with neighborhood average filter is shown in Fig. 5. The designated ROI in the blue frame of the detected gray road image is shown in Fig. 5(a), and the different layer's 3-D surface appearance of the ROI obtained with neighborhood average filter is shown in Fig. 5(b,~,g). From Layer No.1 to Layer No.6, the spatial resolution of the image is 480×480, 240×240, 120×120, 60×60, 30×30, 15×15 pixels respectively.



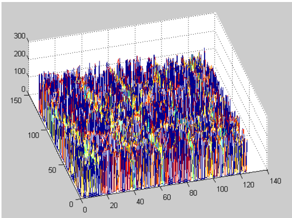
(a) Original image



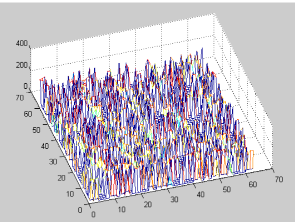
(b) Layer No.1



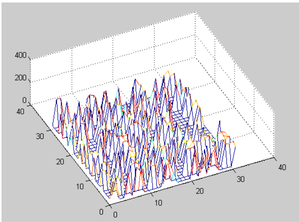
(c) Layer No.2



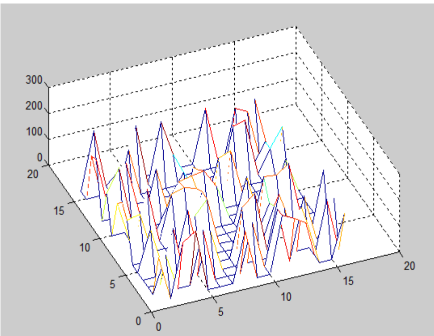
(d) Layer No.3



(e)Layer No.4



(f) Layer No.5



(g) Layer No.6

Fig. 5. 3-D surface appearance of a detected road image

With the multi-resolution image analysis method, the road matching analysis has the characteristics of higher processing speed and better computational stability, but there are some limitations with this approach, which sometimes lead to the failure of image matching method.

2.2 Road detection system integrated with BP-NN

Since several factors of the road background are often uncertain and transient, the road detection system based on the matching analysis is not always stable. Therefore, it is necessary to improve the intelligence of the road detection system and make it adapt to the changing of the external environment.

Machine learning algorithm can be applied in road detection system, including the genetic algorithm, BP-NN, and PSO algorithm (LI, 2016). Many scholars have conducted much experimental research on road's machine learning algorithm (Pacurar et al., 2008), such as a multi-direction texture histogram Gabor to better characterize the texture information (Ye et al., 2011), a detection algorithm for the road intersection, through unsupervised learning characteristics to achieve robust classification of the image, classification the manual marking sample road area method (Yang & Liu, 2014), a method to learn discriminative features from training data in an unsupervised manner (Slavkovikj et al., 2014), an effective method for classifying terrain cover based on color and texture features of an image, and discrete wavelet transform coefficients were used to extract those features (Sung et al., 2010), an adaptive unstructured road detection method for fast adaptive outdoor autonomous mobile robot (Du et al., 2014).

As an important artificial intelligence algorithm, BP-NN is a generalization of the Widrow-Hoff learning rule to multiple-layer networks and nonlinear differentiable transfer functions. A typical multilayer perceptron (shown in Fig. 6) consists of an input layer, one or more hidden layers, and one output layer. What's more, the neurons of the same layer should not be linked together, and each output will only affect the input of the next layer. BP-NN can be regarded as excellent nonlinear function mapping from input to the output. The network's learning consists of two procedures: In the positive spread process, the neuron input is disposed orderly from the input layer to the hidden layers, then transmits to the output layer. If the output is not expected, their discrepancy will return back and the weight matrixes are modified, which in turn make the output closer to the expected. (Zhang& He, 2016)

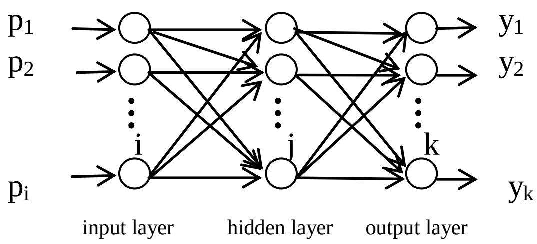


Fig. 6. Structure of BP-NN

The input variable i of the input layer is p_i.The input variable j of the hidden layer x_j is

$$x_j = \sum_{j=0}^{m-1} w_{ji} p_i - b_j \tag{1}$$

Where w is the weight factors, b_j is the threshold of the hidden layer.

The output variable j of the hidden layer O_j is

$$O_j = f(x_j) = \frac{1}{1 + e^{-x_j}} \tag{2}$$

Where f is an activation function neuron between the hidden layer and the output layer, which may be a linear or nonlinear function of x_j.

The input variable k of the output layer u_k is

$$u_k = \sum_{j=0}^{m-1} v_{kj} o_j - c_k \tag{3}$$

Where c_k is the threshold of the output layer.

The output variable k of the output layer y_k is

$$y_k = f(u_k) = \frac{1}{1 + e^{-u_k}} \tag{4}$$

The BP algorithm for multiplayer networks is a gradient descent optimization procedure where an error function E performance index is minimized, which can be calculated from function.

$$E = \frac{1}{2} \sum_k (t_k - y_k)^2 \tag{5}$$

Where k is the number of the training or testing samples, tk is the corresponding expected output value of the prediction categories, yk denotes the actual output of a neural network.

The network learns to infer the relationship between the layers by adjusting the network's weights and thresholds so as to minimize the error in its predictions on the training set.The adjustment of the weight w is in converse direction, in other words, it is in the direction from the output layer to the hidden layer, and the offset Δw_{kj} is calculated by Eq.(6).

$$\Delta w_{kj} = -\eta \frac{\partial E_p}{\partial w_{kj}} \tag{6}$$

Where η is a learning rate, $\eta \in [0,1]$.

As to the output layer neurons,

$$\Delta v_{kj} = -\eta \delta_k a_j \tag{7}$$

Where

$$\delta_k = y_k (1 - y_k)(t_k - y_k) \tag{8}$$

As to the hidden layer neurons,

$$\Delta w_{ji} = \eta \delta_j O_i \tag{9}$$

Where

$$\delta_j = a_j (1 - a_j) \sum_k \delta_k v_{kj} \tag{10}$$

For many years, some scholars have done some research on how to accelerate the convergence speed of BP-NN. In 1994; Hagan et al firstly applied the numerical optimization Levenberg Marquardt algorithm (LMA) into the BP-NN. (Martin,T. Hagan & Mohammad, B. Mcnhaj,1994) Levenberg Marquardt algorithm, an iterative procedure, provides a numerical solution to the problem of minimizing a nonlinear function.

The modification of the BP-NN weight is aimed to search and minimize the error function $E(w)$.If the current weight is $w(t)$, the next weight will be: $w(t+1) = w(t) + \Delta w(t)$,which can be obtained by the following equation.

$$\hat{H}(w(k)) = \hat{H}(w(k)) + \beta_k \hat{Q}) \tag{11}$$

Where $\hat{Q}$ is a given positive definite matrix.

Select the search direction as

$$d(k) = -\hat{H}^{-1}(w(k))^{-1} g(w(k)) \tag{12}$$

Where $g(t)$ is the gradient vector of $E(w)$,$\hat{H}$ is the positive definite matrix Hessian.

$$w(k+1) = w(k) + \eta_k d(k) \tag{13}$$

With the global convergence of the gradient method, training a BP-NN with LMA can greatly improve the convergence speed, which is faster than other method. The flow chart of the road detection method integrated with BP-NN is shown in Fig. 7.

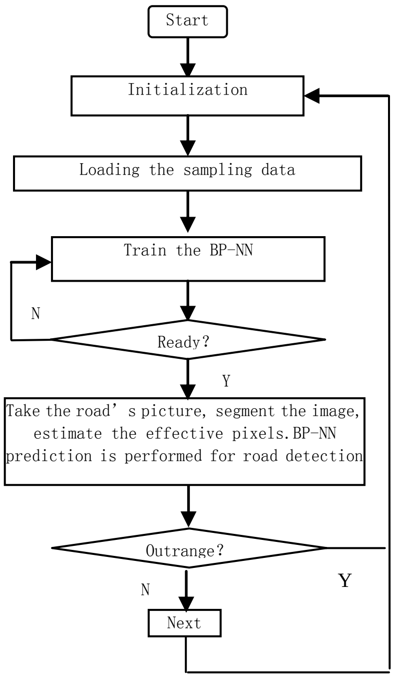


Fig. 7. The flow chart of the road detection method integrated with BP-NN

3 EXPERIMENTS

In order to verify the feasibility of the road detection method integrated with BP-NN, the following experiment is conducted.

(1) Experiment on the blind road line detection with matching method

Taking the blind road as an example, the road line is analyzed by matching method to minimize the key points' distance between the template road's image and the real road's image. As the environmental information changes, the computational or the time cost of the road detection will inevitably increase, too. It is no doubt that the understanding of the road image features is of great significance to the road detection problem, including the color or the texture of the road scene, and the analysis of these road features can help us to detect the passable road easily.

The result of the blind road line's matching experiment is shown in Fig. 8. In Fig. 8(b), five matching instances are obtained, and the feasible path (or direction) of the robot is obtained, but there is a failed instance, which leads to the necessity of road detection technology integrated with BP-NN.

(2) Experiment on the road detection system integrated with BP-NN

Select a set of key regions from the road image, which are taken as the local viewfinders for road detection, shown in Fig. 9. The number of each ROI's effective pixels is taken as the input pi of the BP-NN to predict the road direction.

In this experiment, 8 nodes of the input layer are considered to be the characteristic road parameters, which is defined as

p_i = [ROI11,ROI12,ROI13,ROI4,ROI21,ROI22,ROI23,RO24]

The output layer is set to be 3 nodes. The possible directions in this experiment can be divided into three types, which are put as the target output of the blind road BP-NN. Since out of range of the output parameters will lead to reduce the convergence speed, the output parameter of the blind road BP-NN is defined between 0 and 1000.

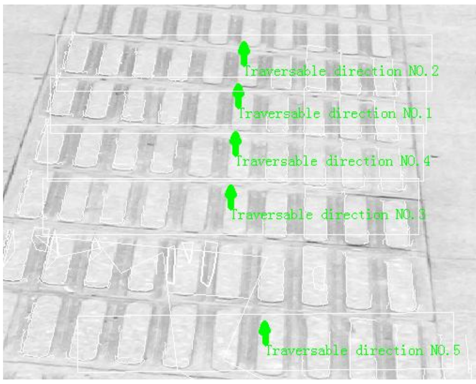
The input sampling data are normalized, and limit their distribution between 0 and 1 with the following formula

$$y = \frac{x - \text{MinValue}}{\text{MaxValue} - \text{MinValue}} \qquad (14)$$

Where x and y are the values before and after normalization, Max Value and Min Value are the minimum and maximum values for each row accordingly.

The blind road BP-NN is trained with Levenberg Marquardt algorithm.The activation function between the input layer and the hidden layer is a sigmoid function.The transfer function between the hidden layer and the output layer is a pure line function.

(a) Original image



(b) Detected blind road

Fig. 8. The blind road line's matching result

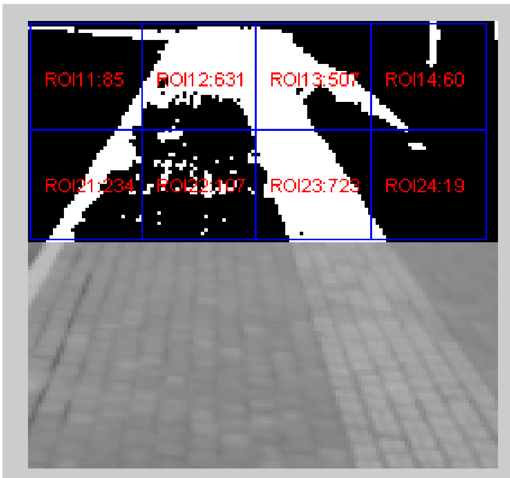


Fig. 9. A set of key regions selected from the road image

The parameters of the blind road BP-NN are shown in Table 1.

Table 1 Prameters of the blind road BP-NN

Neural network type	BP
Layers	3
Number of neurons in each layer	8-18-3
Transfer function	Sigmold Purelin
Learning rate	0.095
Performance objective function	MSE
Maximum training times	2000
Maximum iterative error	0.0001

The neural network is trained so that the net weight changes to adapt the relationship between the input and the output.

Through the experiment, effective sample data of 90 groups on the number of each ROI's effective pixels and the corresponding road direction are obtained, shown in Table 2. Select the last 10 groups as the test samples, and test the validity of the BP-NN model.

Table 2. Sample data for the road direction system integrated with BP-NN [pixels]

No.	ROI11	ROI12	ROI13	ROI14	ROI21	ROI22	ROI23	ROI24	Direction
1	936	833	576	792	903	899	733	732	↑
2	98	811	177	24	383	607	1	3	↖
3	929	835	587	810	910	919	808	788	↑
4	235	93	735	27	123	31	535	443	↗
	…	…	…	…	…	…	…	…	…
89	361	644	7	3	280	261	0	0	↖
90	228	114	707	17	150	24	572	368	↗

The simulation result of the road direction system integrated with BP-NN is shown in Fig. 10, the prediction accuracy (%) is about 90, and the performance of BP neural network training is shown in Fig.11.

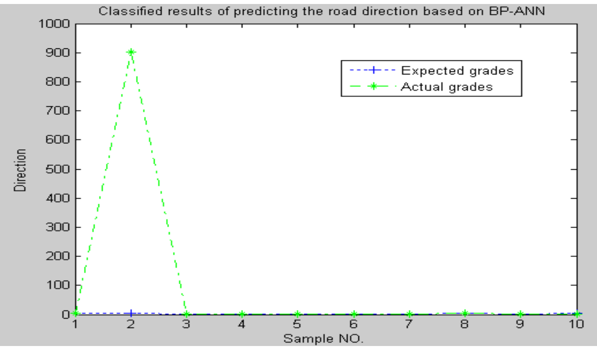


Fig.10. Simulation result of the road direction system integrated with BP-NN

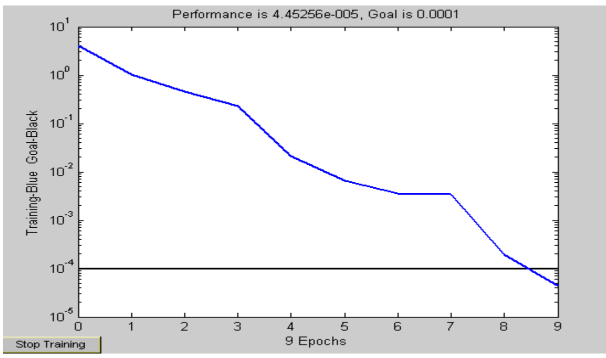


Fig.11. Performance of the road BP-NN training

The experiment shows that the road detection system integrated with BP-NN is effective to predict the road directions, which also has more road detection adaptability and intelligence than the matching method.

Continued works will be made to design the enhanced input parameters of the neural networks which affect the road detection result more directly, so as to improve the accuracy of the road detection system integrated with BP-NN for a higher degree. The detailed experiment of this idea will be the focus of our future research.

4 CONCLUSIONS

In the field of mechanical engineering, more and more attention has been paid to the design of service-oriented robots. Road detection technology can be used to improve the road early-warning performance of the walk-aided service robot. The road detection technology with adaptive and self-learning ability is also an important but difficult task for our walk-aided service robot research. Aiming to the current existing problem of the road detection system based on machine vision technology; this paper does an analysis on the principle of the service robot's road detection system integrated with BP-NN. The experiment proves its efficiency and accuracy. Further research on this method will undoubtedly have a positive significance for the improvement of the robotic research.

5 ACKNOWLEDGMENT

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