Study on Navigating Path Identification by Fuzzy Neural Network

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Abstract

The Method of recognizing navigating path in shadow is studied by using fuzzy neural network for autonomous vehicle. the fuzzy neural network model has 6 layers, and uses π function as its fuzzy function. The dynamic BP algorithm is used to train the fuzzy neural network. Experiments of practical path identification are done. The results show that the method can effectively identify the path in shadow environment.

1. Introduction

The autonomous vehicle (AV) can automatically track the navigation path and autonomously drive. Because AV can efficiently lighten the driver's burden and reduce the traffic accident, the research of it is regarded as important area of intelligent transport system (ITS) and logistics. A number of AV platforms are developed, such as Vormors-P of Germany [1], Navlab and DEMO-III of USA[2] and THMR of China [3]. Vision navigation is one of the most important navigation methods. The algorithm for identifying the navigation path is the core area of vision navigation research. Some studied algorithms are reported in last five year [4] [5] [6] [7].

Drive separating line on the road is usually used as the navigation path. The separating line often becomes blurry under the tree shadows background in the varying sun light. In this case, the accurate rate of path identifying is descending. As the result, reliability and robust of navigation are descending.

Fuzzy artificial neural network (FNN) has unique effect on some uncertain things for its characters of parallelism and tolerance. In the paper, the FNN is used to identify the blurry and smudgy navigation path ①.

2. FNN of recognizing the blurry and smudgy path

2.1 General description

The parameters of red part (R), green part (G) and blue part (B) of a image pixel are used to identify whether the pixel point is background or navigation mark.

The fuzzy neural network for path identifying is made up of input layer, pre-fuzzy layer, post-fuzzy layer, BP hidden layer, BP output layer and clearing layer. The input parameters of FNN are R, G and B of a pixel of navigation image. The output of FNN is 0 and 1. 0 represents background point, 1 represents the path point.

2.2 Structure of FNN

The structure of FNN is shown on Figure 1.

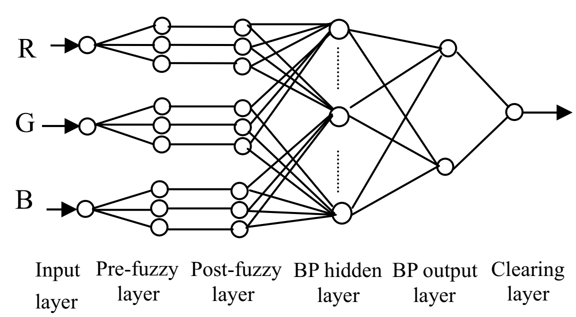

Figure 1. Structure of FNN

2.2.1 Input layer. The input layer has 3 nodes and its vector is:

$X=\{x_1, x_2, x_3\}=\{R, G, B\}$.

2.2.2 Pre-fuzzy layer. The input parameters are converted into three levels of membership degree which are low (m_{li}), medium (m_{mi}) and high(m_{hi}). The output vector of the layer is:

$M=(m_{l1},m_{m1},m_{h1},m_{l2},m_{m2},m_{h2},m_{l3},m_{m3},m_{h3})$. The π function is used as the membership function. It can convert any parameters into three levels which are low,

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medium and high.

$$\pi(r,c,\lambda)=\begin{cases} 2\left[1-\frac{\|r-c\|}{\lambda}\right]^2 & \frac{\lambda}{2}\le\|r-c\|\le\lambda \\ 0 & \|r-c\|>\lambda \qquad \|r-c\|<0 \\ 1-2\left[\frac{\|r-c\|}{\lambda}\right]^2 & 0\le\|r-c\|\le\frac{\lambda}{2} \end{cases}$$

Here, λ is radius of π function.,

c is center point,

r is to be fuzzied parameters.

λ and c are chosen by :

$$\begin{cases} \lambda_m(x_i)=\frac{1}{2}(x_{i\max}-x_{i\min}) \\ c_m(x_i)=x_{i\min}+\lambda_m(x_i) \end{cases}$$

$$\begin{cases} \lambda_l(x_i)=\frac{1}{\alpha}(c_m(x_i)-x_{i\min}) \\ c_l(x_i)=c_m(x_i)-0.5\lambda_l(x_i) \end{cases}$$

$$\begin{cases} \lambda_h(x_i)=\frac{1}{\alpha}(x_{i\max}-c_m(x_i)) \\ c_h(x_i)=c_m(x_i)+0.5\lambda_h(x_i) \end{cases}$$

Here, α is the parameter which control the overlap degree of adjacent fuzzy aggregation. It is 0.3 in the case. The λ and c based on above formulas can ensure that at least one of x_l、x_m、x_h is bigger than 0.5. The x_{imax} and x_{imin} are shown on table 1.

Table 1 Maximum and minimum of *X*

	R	G	B
x_{imax}	210	210	210
x_{imin}	90	90	90

2.2.3 Post-fuzzy layer. The parameters of *M* are modified according to their importance in the layer. Because the correlation different among the parameters of *M*, and classified results are often different, the contributions of the different parameters of *M* to classified results are also different.

The importance coefficients of *M* parameters are defined as:

$Q=(q_1, q_2, q_3)=(0.3, 05, 0.2)$

The output vector of the layer is:

$$I_i=(i_{li},i_{mi},i_{hi})=M_i\bullet q_i=(m_{li}q_i,m_{mi}q_i,m_{hi}q_i) \qquad i=1,2,3$$

2.2.4 BP hidden layer. The layer has 18 neural nodes. It is traditional BP neural network. The stimulative function is:

$$O=\frac{1}{1+e^{-I}}$$

2.2.5 BP output layer. The layer has two nodes. The outputs of the layer are membership degrees of a pixel which will determine the pixel belongs to background or path.

The membership degrees are defined as

$$\mu_k(X^m)=\frac{1}{1+\left[\frac{w_{mk}}{\beta}\right]^{\gamma}}$$

Here, *m* is the number of the training sample，β and γ are parameters that control the fuzzy degree of the membership aggregation. Here, set: β＝0.3,γ=0.5.

For R, G, B，w_{ik} is:

$$w_{mk}=\left\{\sum_{j=1}^{n}\left[\frac{x_j^m-M_k}{U_k}\right]^2\right\}^{1/2} \qquad k=1,2$$

Here, *n* is the amount of the training sample.

M_k is mean value

U_k is mean square.

x_j^m is H, R, G, B of the *m*th pixel of the training sample.

2.2.6 Clearing layer. The final output layer has one neural node.

$$\begin{cases} u_1(k)-u_2(k)>=0 & K=0\text{；background} \\ u_1(k)-u_2(k)<0 & K=1\text{；path} \end{cases}$$

Here, $u_1(k)$ is membership degree of background

$u_2(k)$ is membership degree of and path.

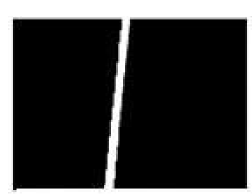
K represents the identified result.

2.3 Training of the FNN

The dynamic BP algorithm is used to train the FNN [8]. The two training images are shown on Figure 2. Each training images has 300×200 pixels. Total 3000 pixels which are in line 2, 50, 100,150, 198 of two images are used to train the FNN.

The FNN is converged after 3865 training epochs for image one and 3150 training epochs for image two. The weight matrixes and threshold matrixes of BP hidden layer and BP output layer are finally obtained.

Training images 1



Target image of image 1

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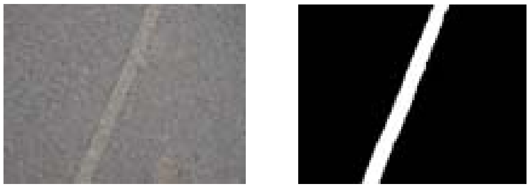


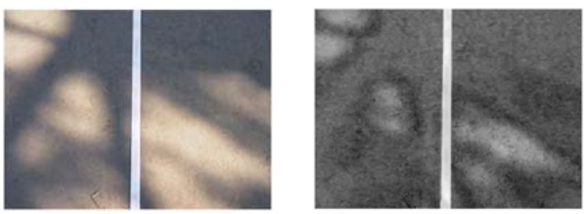
Training images 2 Training target of image 2

Figure 2. The training images of FNN

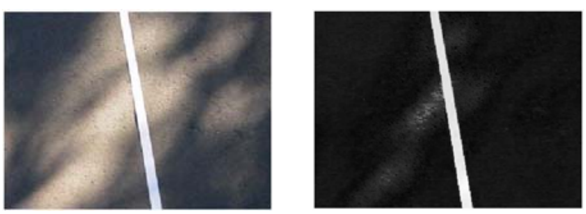
3 Experiments

3.1 Path recognizing experiment by using the FNN

The 280 navigating images with shadow are captured by the vision system in the road outside the campus. Every image has 200*300 pixels. The FNN is used to identify the path from the images. The paths in 271 images have been identified. The recognition correct rate reaches 96.7%. Some of identified results are shown on Figure 3.



(a) Original image (b) Identified path



(a) Original image (b) Identified path

Figure 3. Identified blur and smudge path by FNN

3.2 Experiments of recognizing path from the interesting area

Although the FNN can effectively identify the path from blur image, the recognizing speed can not satisfy the real time requirement of autonomous navigation. The recognizing time for an entire image is over 1000 ms. In order to improve the recognizing speed, an interesting area can be chosen. With 44 line intervals, total 5 lines of the image are chosen to be the interesting area. The FNN is used to process the only area. The method of linear regression is then used to identify the navigation path.

By this way, the times recognizing of FNN is reduced to 16.1ms, and it can satisfy the real time requirement of autonomous navigation. The experiment results of recognizing path by this method are shown on Figure 4.

(a) Original image

(b) Path regression (c) Identified path by FNN

Figure 4. Identifying path from interesting area

4 Conclusion

The fuzzy neural network is developed to identify the blurry path from shadow image. The π function is used as membership degree function of FNN. The experiments are made for identifying the blurry path. The results show that the FNN can effectively identify the path. The correct rate of recognizing the path by FNN reaches to 96.79%.

In order to reduce the recognizing time, an interesting area is chosen, path segments are identified from the area, and the regression method is used to identify the path from the segments. The times of path recognizing from the area by using FNN is reduced to 16.2 ms, and can satisfy the image process requirement of practical autonomous navigation.

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