Study on Blurry and Smudgy Path Recognition by Fuzzy Neural Network

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Abstract

The Methods of recognizing blurry and smudgy navigation path are studied by using fuzzy neural network for JLUIV-2 vision navigation intelligent vehicle. Two fuzzy neural network models are developed, one model has 5 layers, and uses normal distribution probability function as its fuzzy function, another model has 6 layers, and uses π function as its fuzzy function. The dynamic BP algorithm is used to train the two fuzzy neural networks. Experiments of the path recognizing and practical autonomous navigation are done by using JLUIV-2 intelligent vehicle. The results show that the two fuzzy neural networks can effectively recognize the blurry and smudgy navigation path.

Key words: fuzzy neural network, Intelligent vehicle, vision navigation

1.Introduction

The intelligent vehicle (IV) is an autonomous vehicle. It can automatically track the navigation path. Because IV 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). A number of IV platforms are studied by some developed countries from 90's, such as Vormors-P of Germany [1], Navlab and DEMO-III of USA[2][3] and ARGO of Italy [4][5].

JLUIV-2 is a vision navigation IV, which has been developed by IV research group of Jilin University from 1997. It can automatically track the stripe path. The JLUIV-2 is installed some subsystems, such as CCD system, automatic steering system, automatic braking system, obstacle avoiding system and so on. The road surface image is captured by CCD, navigation path is identified by the image processing algorithm, and path tracking is controlled by automatic navigation controller.

The navigation path often becomes blurry and smudgy because of abrasion and pollution. In this case, it is difficult to recognize the path. As the result, reliability and robust of navigation are descending, which affects application of IV.

Artificial neural network (NN) has unique effect on some fuzzy and uncertain things. Artificial neural network is simple simulation for human nerve cell. A neural network with one hidden layer can map the relation between the input and output on L^2 level. Neural network has characters of parallelism and tolerance. In the paper, the fuzzy neural network (FNN) is used to recognize the blurry and smudgy navigation path.

2. First FNN of recognizing the blurry and smudgy path

2.1 Algorithm description

The parameters of brightness (H), 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 distribution of the parameters on the background and the path mark is accorded with the normal distribution. A five–layer FNN (FNN-I) is established to recognize the path. The detail process is: first make the image pixels in the ascending order based on the level of H, R, G and B. Calculate mean value and square value of H, R, G and B of the first one hundred pixels and the latest ten pixels respectively. Then take formal mean and square values for the background and later one for navigation path. For each pixel of the whole image, calculate its probability to belong to the background or the path. Take all the probability values as inputs to FNN-I. Train the FNN-I with the typical blurry and smudgy navigation images by using the methods mentioned above. Thus, the weight and threshold values of FNN-I can be obtained finally and use to recognize the path.

2.2 Structure of FNN-I

The probability parameters of H、R、G、B are used to identify the blurry and smudgy image, so the character space is:

F={ f1, f2, f3, f4 }={ H, R, G, B }

Pixels of navigation image are divided into path mark points and background points, so target space of classification of navigation image is $M=\{B_1, L_1\}$.

The target space of training sample is: $S=\{B_2, L_2\}$, sample amount of background and pathn_i . Based on static theory, we can get the below equation:

$$P_{ij}=\frac{1}{\sqrt{2\pi}\sigma_{ij}}\exp(-\frac{f_i-u_{ij}}{2\sigma_{ij}^2})$$

here , σ_{ij} is square value of background and path.

u_{ij} is mean vakue of background and path.

p_{ij} is prabality density of a pixel on background and path

f_i is character parameters of each pixel.

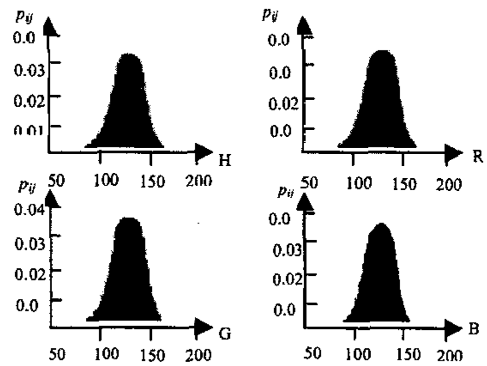
During the training, according to the width of practical navigation path, background pixels are 45000, and path pixels are 4500. A typical blurry and smudgy navigation image is shown on Figure 1, and mean value θ_{ij} and square value σ_{ij} of character space are shown on table 1.

Table1. Mean and square of character space

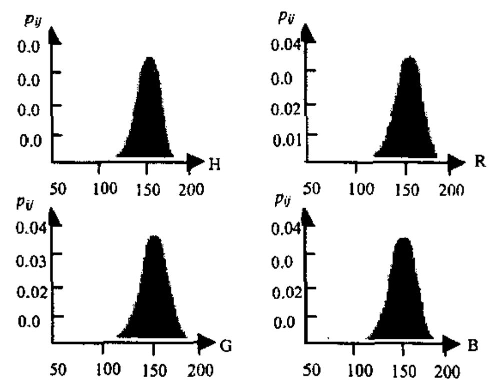
character		H	R	G	B
background	mean θ_{ij}	123.66	126.02	123.03	120.74
	square σ_{ij}	13.16	13.30	13.21	13.32
	Probability density P_{ij}	0.018, …, 0.021	0.023, …, 0.026	0.012, …, 0.015	0.022, …, 0.023
path	mean θ_{ij}	152.28	154.45	152.9	150.48
	square σ_{ij}	13.1	13.01	13.17	13.37
	Probability density P_{ij}	0.002, …, 0.004	0.005, …, 0.003	0.003, …, 0.004	0.002, …, 0.001

Obviously, if a pixel is the background point, the probability of its character parameters for the background will be large, otherwise it will be small. For the path pixel, the situation is just reverse. So probability density function can be used as the fuzzy function.

(a) A typical blurry and smudgy navigation image



(b) Probability distribution of background pixels



(c) Probability distribution of path pixels

Figure1. Distribution of character space

The structure of FNN-1 is shown on Figure 2. Amount of nodes in the input layer are 4. Fuzzy layer is made up of 4 node groups of nodes. Each group has 2 nodes. In fact, original input character parameters are changed into probability density P_{ij}.

The hidden layer has 20 nodes, and output layer has one node. The nodes among output layer, hidden layer and fuzzy layer are fully connected.

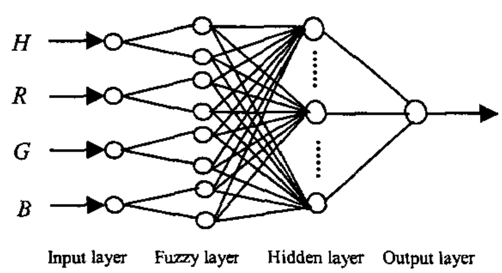


Figure2. Structure of FNN-I

2.3 The training of FNN-1

The output layer, hidden layer and fuzzy layer form a standard front-feedback neural network. The dynamic BP algorithm is used to train the FNN-1. The two training images are shown on Figure 3. FNN-1 is converged after 4650 training epochs for image1 and 5275 training epochs for image 2. After that, the weight matrixes and threshold matrixes of hidden layer and output layer are obtained.

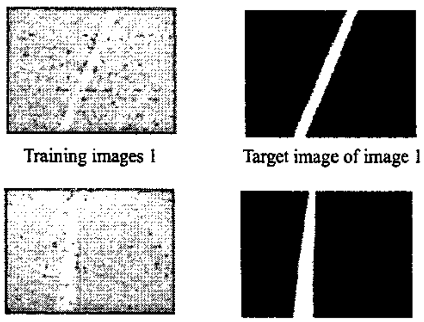


Figure3. The training images of FNN-1

3. Second FNN of recognizing blurry and smudgy path

3.1 General description

The second fuzzy neural network (FNN-II) 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-II are H, R, G and B of a pixel of navigation image. The output of FNN-II is 0 and 1. 0 represents background point, 1 represents the path point.

3.2 Structure of FNN-II

The structure of FNN-II is shown on Figure 4.

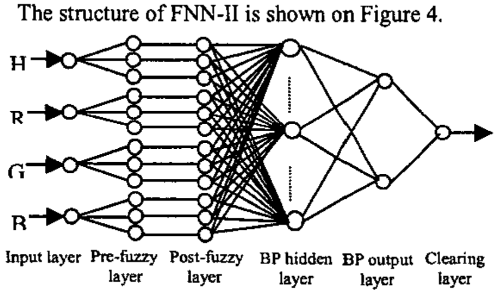


Figure 4. Structure of FNN-II

3.2.1.Input layer. The input layer has 4 nodes and its vector is:

$$X=\{x_1, x_2, x_3, x_4\}=\{H, R, G, B\}.$$

3.2.2.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_{bi}). The output vector of the layer is:

$$M=(m_{l1},m_{m1},m_{b1},m_{l2},m_{m2},m_{b2},m_{l3},m_{m3},m_{b3},m_{l4},m_{m4},m_{b4})$$

The π function is used as the membership function. Tt can convert any parameters into three levels which are low, medium and high.

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

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 taken as 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 2.

Table 2 Maximum and minimum of X

	H	R	G	B
x_{imax}	198	200	200	200
x_{imin}	97	100	100	100

3.2.3.Post-fuzzy layer. The parameters of M are modified according to their importance in the layer. Because the correlation among the different 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:

$Q = (q_1, q_2, q_3, q_4) = (0.4, 0.2, 0.2, 0.2)$

The output vector of the layer is:

$$I_i = (i_{li}, i_{mi}, i_{ni}) = M_i \bullet q_i = (m_{li} q_i, m_{mi} q_i, m_{ni} q_i) \quad i = 1,2,3,4$$

3.2.4.BP hidden layer. The layer has 20 neural nodes. It are traditional BP neural network. The stimulative function is:

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

3.2.5.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: $\beta = 0.3$, $\gamma = 0.5$.

For H, R, G, B, w_{ik} is:

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

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 mth pixel of the training sample.

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

$$\begin{cases} u_1(k) - u_2(k) >= 0 \\ u_1(k) - u_2(k) < 0 \end{cases}$$

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

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

K represents the recognized result.

3.3 Training of FNN-II

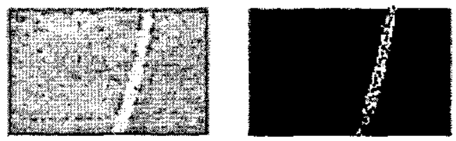
The dynamic BP algorithm is used to train the FNN-II. The figure 3 is also use to train the FNN-II. The FNN-II is converged after 5650 training epochs for image one and 4800 training epochs for image two. The weight matrixes and threshold matrixes of BP hidden layer and BP output layer are finally obtained.

4. Experiments

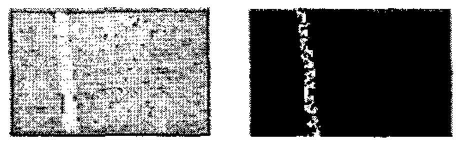
The 285 blurry and smudgy images, which are 222*300 resolution, are captured by the vision system of JLUIV-2 in the campus and the street outside the campus. The FNN-I and FNN-II are used to recognize the path from the images respectively.

4.1 Path recognizing experiment by using FNN-1

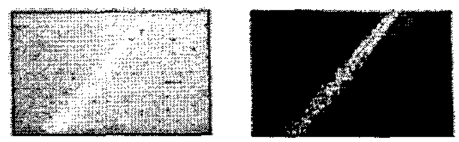
The FNNI-I is used to recognize the path from the 280 images, which have different intensities of illumination and different blurry and smudgy degrees. 255 images have been recognized. Correct recognizing rate reaches to 91.1%. Some of recognized results are shown on Figure 5.



(a) Original image (b) Recognized path



(a) Original image (b) Recognized path

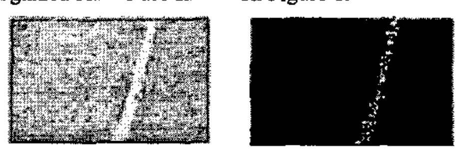


(a) Original image (b) Recognized path

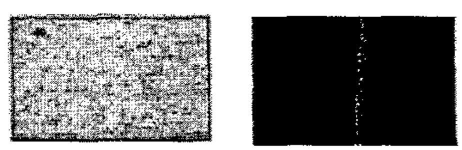
Figure5. Recognized blurry and smudgy path by FNN-I

4.2 Path recognizing experiment by using FNN-II

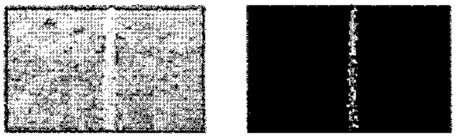
The FNN-II is used to recognize the path for the 280 images. The paths in 260 images have been recognized. The recognition correct rate reaches 92.9%. Some of recognized results are shown on Figure 6.



(a) Original image (b) Recognized path



(a) Original image (b) Recognized path

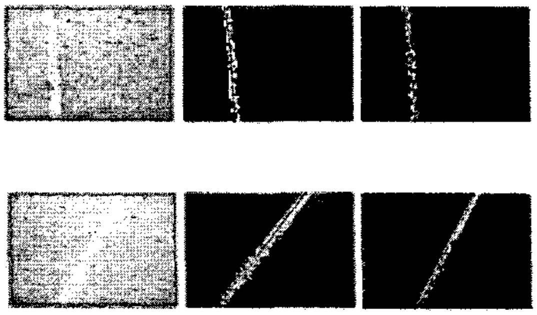


(a) Original image (b) Recognized path

Figure6. Recognized blurry and smudge path by FNN-II

4.3 Comparison of FNN-I and FNN-II

The correct rate of path recognition of FNN-II is higher than that of FNN-II, but FNN-I needs a lightly less time. The general effect of FNN-I is almost same as that of FNN-II. The recognized paths by FNN-I in some extreme blurry and smudgy images have much noise. The paths recognized by FNN-I and FNN-II for the same images are shown on Figure 7.



(a) Original image (b) Recognized path of FNN-I (c) Recognized path of FNN-II

Figure7. Compare of recognized results of FNN-I and FNN-II

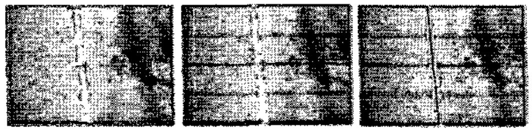
4.4 Experiments of recognizing path from the interesting area

Although the FNN-I and FNN-II can effectively recognized the blurry and smudgy path, the recognizing speed can not satisfy the real time requirement of autonomous navigation. In fact, their 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-I or FNN-II 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-I and FNN-II are reduced to 32.1ms and 37.9 ms. Obviously it can satisfy the real time requirement of autonomous navigation.

The experiment results of recognizing path by this method are shown on Figure 8.

(a) Original image (b) Result by FNN-I (c) Path regression



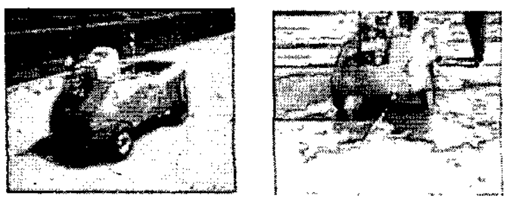
(a) Original image (b) Result by FNN-I (c) Path regression

Figure8. Recognizing path from interesting area

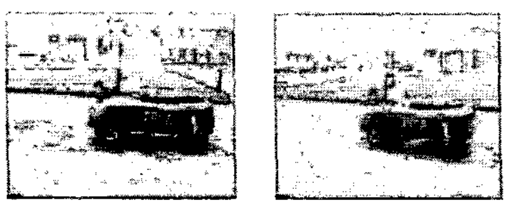
4.5 Experiments of practical path recognition of autonomous navigation

The practical autonomous navigation experiments of tracking the blurry and smudgy path were done by using JLUIV-2 in October of 2001 on the road in the campus. The tracked paths include straight and arc paths.

In addition, illumination intensities are also different. The speed of tracking the straight blurry and smudgy path is 7km/h, and that of tracking the arc blurry and smudgy path is 6 km/h. The experiment results show that FNN-I and FNN-II can reliably recognize the blurry and smudgy path. Therefore, JLUIV-2 can stably track the path. Figure 9 shows the experimental scene.



(a) JLUIV-2 intelligent vehicle (b) Tracking the blur and smudgy path in strong illumination



(c) Tracking the blur and smudgy path in weak illumination

Fig.9. Autonomous navigation of tracking blurry and smudgy path

5.Conclusion

Two fuzzy neural networks, FNN-1 and FNN-II, are developed to recognize the blurry and smudgy path.

The normal distribution probability density function is used as membership degree function of FNN-I, and the π function is used as membership degree function of FNN-II.

The experiments are made for recognizing the blurry and smudgy path. The results show that the FNN-I and FNN-II can effectively recognize the path. The correct rate of recognizing the path by FNN-I reaches to 91.1%. The correct rate of recognizing the path by FNN-II reaches to 92.9%.

In order to reduce the recognizing time, an interesting area is chosen, path segments are recognized 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-I and FNN-II are reduced to 32.1ms and 37.9 ms.

The practical autonomous navigation experiments of tracking the blurry and smudgy path are made. The results show the proposed the fuzzy neural network modes are correct and can be used for practical application.

6.Acknowledgement

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