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Obstacle Avoidance for AGV with Kinect Sensor

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Abstract

This paper aims the development of autonomous obstacle avoidance algorithm for automated guided vehicle with a Kinect sensor. To do this task, the followings are executed. Firstly, depth data is obtained from the Kinect sensor, and the mean filter approach is developed to filter out noises. Secondly, Otsu and U-V parallax based method is designed to identify background and obstacles. Finally, According to barrier information, corresponding fuzzy control rules is generated for the path planning. Our experiments show that the proposed method is fast, and gives promising results.

Keywords*: obstacle avoidance, neural networks, AGV*

1. Introduction

AGV (Automated Guided Vehicle) is increasingly being used to introduce large-scale enterprises and abroad. Comparing with other climbing robots, AGV can move goods to a specific location without the help of rail more quickly and more conveniently. AGV is one kind of transportation tool which is suit to working in the complex environment, such as automatic enterprise, and it is of highly automatic programming, organizing and adapting ability. Therefore, AGV has a great demand in society and has a board market space and commercial value. Path planning is the key part of AGV. The vehicle goes ahead in the fixed track by laying ceremony, which is one of the earliest navigation. Then along came electromagnetism which is used to realize the automatic guidance of AGV through laying underground cable onto the course. According to source [1], the car can travel freely and position accurately with laser guidance. Article [2] uses inertial navigation to design control system implementing path identification. The Kinect sensor provides a fairly accurate estimation of the distance of different kinds of obstacles detected in front of AGV, which is widely adopted across most of the intelligent robots field in recent year. It not only obtains optical image of environment and object position simultaneously, but also costs low. In short, Kinect sensor plays an important role in path planning for AGV. Real-time remora avoidance has been the most activity research hotspot in the area of vehicle navigation. Many scholars all over the world have explored extensively research on obstacle recognition and avoidance. The dissertation [3] uses the Kinect sensor to obtain depth data and according to mobile robot and relative positions with respect to the obstacle, avoidance obstacle path planning is given. The method described in article [4] gets a more accurate localization by using a kind of local map updating method based on statistical theory. It is studied in this article [5] that the artificial potential field method applied to path planning problem for unmanned vehicles. In source [6] a kind of path planning method based on genetic algorithm for mobile robot with the consideration of the barriers in the environment is analyzed. Although a lot of achievements have been made in topology optimization by some researchers, there are still some problems need further discussion, such as robust and productivity.

To meet the demands of efficient AGV transportation in manufacturing industry, This paper presents a Kinect sensor based path planning system for the automatic guided vehicle. To do this task, the followings are executed. Firstly, depth data is obtained from

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the Kinect sensor, and the mean filter approach is used to filter out noises. Secondly, Otsu[9] and U-V parallax is used to identify background, roads and obstacles. Finally, According to barrier information, corresponding fuzzy control rules is generated for the path planning. Our experiments show that the proposed method is fast, and gives promising results.

2. Obstacle Recognition

Firstly, the Kinect sensor adopts light binary code to generate depth image at 30 frames a second by infrared camera. In addition, optimal thresholds are determined for segmenting the depth image into background and target. As to the methods based on threshold, Otsu has good performance of stability and utilization. Thus, Otsu is used to identify background. Due to nonlinear and impulsion noises and disturbances caused by illumination condition, mean filtering algorithm is applied on depth image. When depth image is divided into background and objects by Otsu, ground is considered to be a part of targets. Therefore, in this thesis, the image without background needs to transfer U-V disparity map, and then road id extracted by Otsu. At last, Otsu is also employed to split U-V disparity map in order to obtain obstacle information. As shown in the following steps.

2.1. Image Filtering

In this paper, the method adopts mean filtering algorithm to process original depth image to eliminate noise effect. The basic idea is to average gray of several domain pixels instead of each pixel. It has simple and fast speed feature. Original image $f(x,y)$ turns into a smoothed image $g(x,y)$ through using equation 1.

$$\mathrm{g}(x,y)=\frac{1}{M}\sum\nolimits_{(x,y)\in S} f(x,y) \tag{1}$$

where S denotes point (x,y) domain; M is the total points of domain.

2.2. Background Extraction

This article uses adaptive threshold algorithm – Otsu, to divide the image into background and object. Otsu is able to obtain an effective threshold for the binarization of the defect image. Meanwhile, with this method, image binarization is easy, fast and self-adaptive [7]. Suppose $f(x,y)$ denotes the gray value at point(x,y) of the depth image size of M*N and it has L grey levels. That is to say, $f(x,y)\in[1,L]$. f_{i} is corresponded to the number of pixels about grayscale i, $(i=1,2,\ldots L)$. The probability of gray level i:

$$p(i)=\frac{f_i}{M*N} \tag{2}$$

The segmentation threshold between background and object is t, background C_0 is pixels which gray level $[1,t]$ and object C_1 is pixels which gray level $[t+1,L]$. The probability of C_0 and C_1:

$$\omega_0=P(C_0)=\sum\nolimits_{i=1}^{t} p(i) \tag{3}$$

$$\omega_1=P(C_1)=\sum\nolimits_{i=t+1}^{L} \mathrm{p}(i)=1-\omega_0 \tag{4}$$

The average of gray C_0 and C_1 respectively and the average of gray of depth image:

$$\mu_0=\sum\nolimits_{i=1}^{t} iP(i\,|\,C_0)=\sum\nolimits_{i=1}^{t} i\frac{p(i)}{\omega_0} \tag{5}$$

$$\mu_1 = \sum_{i=t+1}^{L} \mathrm{i}P(\mathrm{i}\,|\,C_1) = \sum_{i=t+1}^{L} i\frac{p(i)}{\omega_1} \tag{6}$$

$$\mu = \omega_0\mu_0 + \omega_1\mu_1 = \sum_{i=1}^{L} ip(i) \tag{7}$$

optimal threshold of Otsu is given by:

$$T = \underset{0\leqslant t\leqslant L}{\arg\max}\,\{\sigma^2(\mathrm{t})\} \tag{8}$$

$$\sigma^2(t) = \omega_0(\mu_0-\mu)^2 + \omega_1(\mu_1-\mu)^2 \tag{9}$$

where the range of values for t is 1 to L. The maximum $\sigma^2(t)$ will be found after walking through each value t, so T is optimal threshold at the moment. In a word, Otsu can select thresholds automatically which are most or least different among different classes when it segment depth image.

2.3. Ground Extraction

Firstly, depth image is transferred to disparity map by calculating and then the projective histogram along both horizontal and vertical directions are obtained from disparity map in order to obtain U-V disparity map. As illustrated in Figure 1, the depth data of the Kinect sensor is calculated by disparity between infrared emitter and infrared camera.

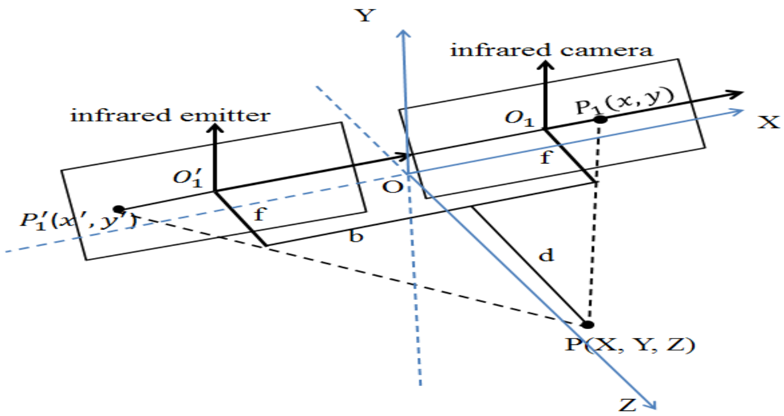

Figure 1. Kinect Imaging Model

where f is focal length of camera; b is baseline, d is distance between point P and camera imaging plane, which is depth distance. Based on the principle of binocular stereovision, disparity is given as follow:

$$disparity = \frac{f*b}{d} \tag{10}$$

Thus, depth image is turned into disparity map with this formula and then the projective histogram along horizontal direction is obtained from disparity map in order to obtain V disparity map. What is more, the point denoting road in the depth image are transformed to the world coordinate (X,Y,Z) and its coordinate is plugged into the plane equation $aX + bY + cZ + d=0$ in order to get parameters. If the points satisfy $-0.05<AX+BY+CZ-1<0.05$, they represent the ground and should be removed.

2.4. Obstacles Localization

This paper uses Otsu in the U-V disparity map to detect obstacle information again. According to parallax, obstacle localization is found in disparity map so that its location is determined in the world coordinate. At first, ground information is extracted in the U disparity map with Otsu. Furthermore, by using Otsu and Hough transform in combination, roadblock data is located.

3. Obstacle Avoidance

The method of barrier avoidance for AGV based on the fuzzy neural network was presented after sensing obstructions. Fuzzy control creates mathematical model and then applies fuzzy logical reasoning according to actual human experience and decision in order to simplify real situation. In the meantime, the whole control process is described by fuzzy language. However, relying merely on fuzzy control has its shortcomings, such as low accuracy and adaptive ability and large fuzzy rule base. In order to overcome shortcomings of single fuzzy control, this paper process fuzzy neural network which incorporate the fuzzy control and neural network. Combine with the self- learning of the neural networks, the whole intelligence degree of the system is improved. The process of obstacle avoidance is given, as shown in Figure 2.

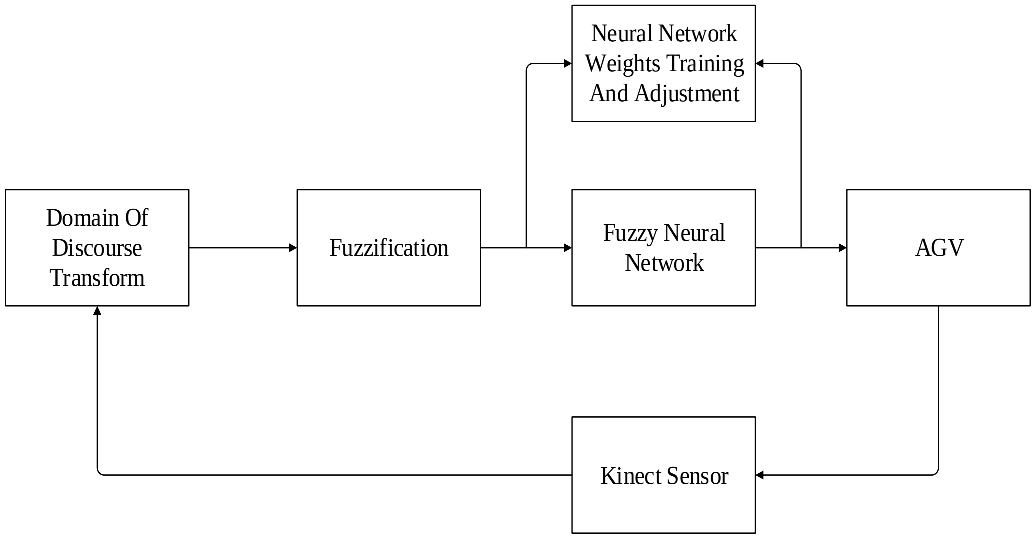

Figure 2. The Process of Obstacle Avoidance

When the Kinect sensor obtains the distance between AGV and obstacle, the data is obscured at feature level by fuzzy logic and neural network is used to handle the decision level fusion of input fuzzy logic. At last, AGV can change direction to avoid collisions.

3.1. Fuzziness of Input and Output Signal

In this paper fuzzy logical controller with three fuzzy inputs (right side, left side, in the front) and one fuzzy output (angle of steering wheel) is established. FD, LD and RD represent left, front and right distance between AGV and obstacle information respectively.

To reduce calculation load, the correlation between AGV and obstacle in the front is divided into 3 levels including {Near, Medium, Far}, which corresponds to domain that [0, 80cm), [80cm, 160cm), [160cm, 240cm]. When the minimum distance of a section is more than 240cm then it is considered that there is no obstruction in the front of AGV. The linguistic variables of left and right is the same as front. The domain of input signal should be adjusted to [0, 15] in order to realize the fuzzy controller standardization. That is to say, the universe of FD, LD and RD is [0, 15]. If real input domain is [a, b], the universe is changed through the following transformation formulas:

$$y = \frac{5}{b-a} \tag{11}$$

The linguistic variables of output are {TLB, TLS, F, TRS, TRB}, which corresponds to {“big left turn”, “small left turn”, “stop”, “small right turn”, “big right turn”}. The value of the output variable is set to match AGV’s maximum turn degree of 31 degrees and the input of the obstacle detection is set to match the Kinect sensor and the field of view that is also 31 degrees.

3.2. Fuzzy Neural Network Structure

This paper adopts five typical layers structure of fuzzy neural network and topological graph is shown by Figure 3. In picture, input variables are denoted by X=(x_1, x_2, x_3) and output variables are denoted by Y=(y_1, y_2, y_3, y_4, y_5). This network comprises input layer, membership function layer, inference layer, normalization layer and output layer.

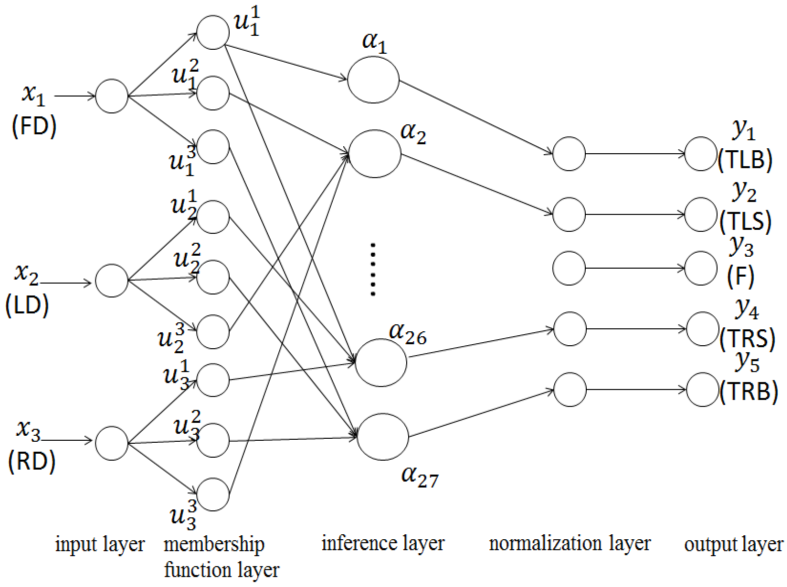

Figure 3. Five Layers Structure of Fuzzy Neural Network

The first layer consists of three input signals acting as input layer, denoting the distance between AGV and obstacle on the left, right and in the front respectively. Every node connects the components of input vector in order to transmit input to membership function layer, where x_1=FD, x_2=LD, x_3=*RD*. Thus the layer has three nodes.

The second layer is membership function layer, with the effect of determining membership u_i^j and completing the fuzziness of input. In this layer, s_i represents the fuzzy partitions of input variable x_i. Fuzzy partitions of three input is denoted by S=(s_1, s_2, s_3). What is more, $s_1 = s_2 = s_3 = 3$, because *FD* consists of three kinds of distances including near, medium and far. *LD* and *RD* is the same with *FD*. This paper adopts Gauss function as membership function to improve smoothness degree.

$$u_i^j = \exp[-\frac{(x_i - c_{ij})^2}{\delta_{ij}^2}], \text{ (i=1, 2, 3; j=1, 2…, } s_i \text{)} \tag{12}$$

Where c_{ij} is the center of the Gauss function; δ_{ij} is the width of the Gauss function. For all three inputs three membership functions to match the measures distances as fuzzy values as shown on Figure 4(a) and (b). The membership functions of output shown on Figure C.

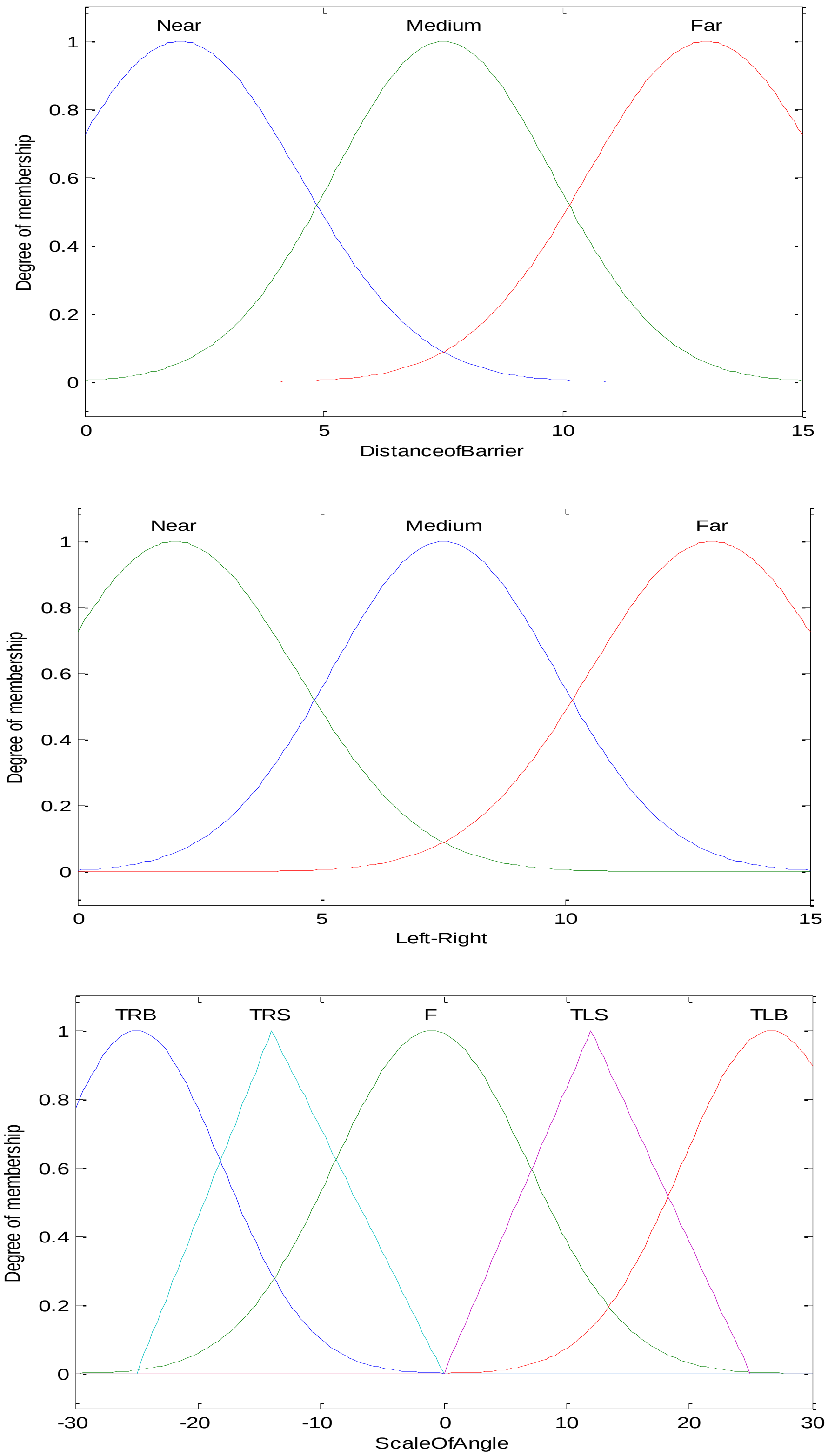

Figure 4. Input and Output Membership Functions

The third layer is inference layer, which every node represents a fuzzy rule set. What is does is match the premises of fuzzy rules while produce a matching factor as output for each rules [8]. The fitness value is the following:

$$\alpha_{\mathrm{j}} = u_1^{i_1} u_2^{i_2} u_3^{i_3} \quad (j=1,2,...,27) \tag{13}$$

Where $i_1, i_2, i_3 \in \{1,2,3\}$.

The forth layer matches the consequence of fuzzy rules acting as normalization layer by the following equation:

$$\overline{\alpha}_{\mathrm{j}} = \frac{\alpha_j}{\sum_{i=2}^{27} \alpha_i} (j=1,2,...,27) \tag{14}$$

The fifth layer is output layer and its function is removing fuzziness. The output is rotation direction of AGV.

3.3. Fuzzy Control Rules

According to Fuzzy Set theory, the inference rules of If-Then are established. At the same time, according to environment types and expertise, the number of the rules of the fuzzy control should be lessened so that control rule becomes simply. For example, when the minimum distance of a section is more than 240cm then it is considered that there is no obstruction in the front of AGV. Thus, AGV can travel forward without considering the distances both on the sides. If the obstacles are the same distance away on both sides, then the left turn is preferred.

If (*FD* = Far) then *F*;
If (*FD* = Medium && *LD* = Near && *RD* = Near) then *F*;
If (*FD* = Medium && *LD* = Near && *RD* = Far) then *TRS*;时
If (*FD* = Medium && *LD* = Far && *RD* = Near) then *TLS*;
If (*FD* = Medium && *LD* = Far && *RD* = Far) then *TLS*;
If (*FD* = Medium && *LD* = Medium) then *TRS*;
If (*FD* = Medium && *RD* = Medium) then *TLS*;
If (*FD* = Near && *LD* = Near && *RD* = Near) then *TLB*;
If (*FD* = Near && *LD* = Near && *RD* = Medium) then *TRB*;
If (*FD* = Near && *LD* = Near && *RD* = Far) then *TRB*;
If (*FD* = Near && *LD* = Medium && *RD* = Near) then *TLB*;
If (*FD* = Near && *LD* = Medium && *RD* = Medium) then *TLB*;
If (FD = Near && LD = Medium && RD = Far) then TRB;
If (FD = Near && LD = Far && RD = Near) then TLB;
If (FD = Near && LD = Far && RD = Medium) then TLB;
If (FD = Near && LD = Far && RD = Far) then TLB;

3.4. A Learning Algorithm of Neural Network

At first, control rules should be stored in the database and then all input elements in fuzzy domain should be grouped in accordance with fuzzy control rules. The sample data used for the networking training and subsequently for classifying are provided by the depth map forthe Kinect sensor. Train parameters include every node’s center value of membership function in premise network which is c_{ij}, width is δ_{ij} and output weighting. During online learning, the system which has network trained offline should be run and weighting should be adjusted by network online according to objective function which is defined

4. Experiments and Results

4.1. Simulation Study

This paper presents a simulation of fraise avoidance control using fuzzy neural network at Matlab environment. The experimental result is shown in Figure 5. In this Figure, obstacles are shown as red empty circles while the movements of vehicle are shown as black dots. From a starting point of (0,0), the car makes the judgment and avoid collisions in the movement when it detect unknown obstacles. For example, AGV can judge the barrier in the front left and then turn away when it approaches the second barrier. This thesis verifies the reliability and effectiveness of the obstacle-avoidance algorithm by MATLAB simulation tests and AGV can avoid collisions safely.

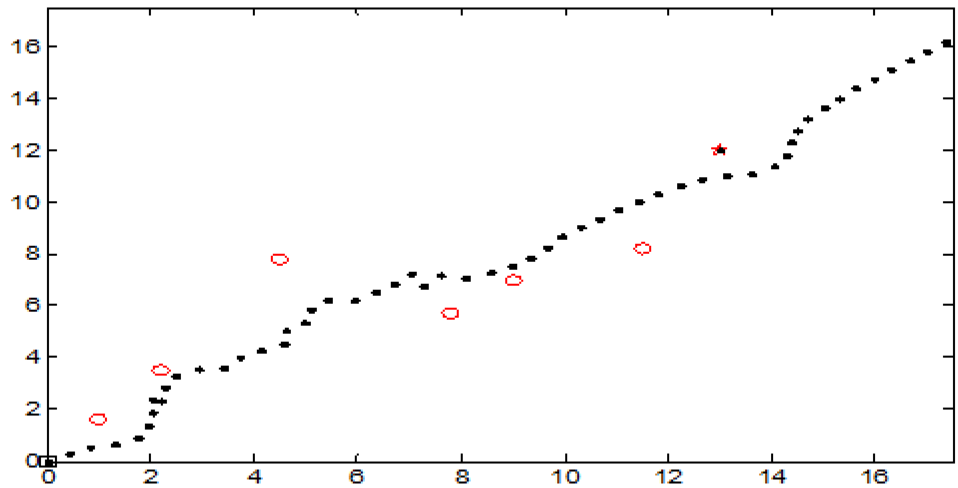

Figure 5. Simulation Result

4.2. Obstacle Avoidance Experiment

The Kinect sensor is linked with Raspberry Pi(RPi) arranged on a handcart and is tested in the corridor outside the science lab. At the same time, reasonably locating obstacles can enhance the accuracy, reliability and comparability of the laboratory testing results. The experiment verifies the reliability and effectiveness of obstacle avoidance algorithm so that the car can travel without collision.

5. Conclusion

This paper does research in fuzzy neural network algorithm and its application in path planning in static AGV environments. At first, the Kinect sensor obtains depth data of obstacles and mean filtering algorithm is processed original depth image to eliminate noise effect. Meanwhile, the usage of Otsu and U-V disparity recognizes background, ground and barrier. In addition, fuzzy neural network algorithm is adopted to avoid collisions and the fuzzy system is optimized by the training of neural network algorithm. Hence, AGV can avoid barriers quickly and accurately.

Acknowledgments

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