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Vision Location Algorithm of Circular Hole in Distributed Clutter Background Using LVQ Network

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Abstract: In view of the traditional way of transportation of oil where loading process is to apply manpower to guide the large crane tube for perfusion, it is possibility of accidents occurred caused by inaccurate opening locating and low work efficiency. It can be a good way to solve these problems to use vision position. However, due to the interference of background clutter, the circular opening of the oil tank is immersed in the distributed clutter background. In order to accurately locate the opening of the oil tank, this study presented a vision location algorithm of the circular hole based on LVQ (Learning Vector Quantization) neural network. In this algorithm, the eccentricity, compactness and other characteristic values of closed curves, witch from the image of opening of the oil tank after image pretreatment process, was extracted and these values as the input for the target recognition system based on LVQ neural network that has been trained. Finally the circular hole is distinguished from the clutter background. Through the study of feature of the opening of oil tank to establish target recognition model, some physical quantities are extracted as input character of the LVQ neural network. And then some input characteristic values are selected to train the LVQ neural network to achieve the learning and prediction purpose. The simulation results show that, the proposed method can be used for the opening of oil tank locating.

Key words: LVQ neural Network, vision location of circular hole, image pretreatment processing, input characteristic value

INTRODUCTION

Visual locating in the distributed clutter background is an effective method for robotic arm to achieve automatic loading and unloading. In the process of oil transportation, oil loading and unloading is the key point. The traditional way is to use manpower guide the large crane tube to perfusion for oil transportation. (Sheng and Qi-Cong, 2009; Wu *et al*., 2009; Tsarouhas and Nazlis, 2006). However, the operation of the workers is labor-intensive and easily leads low accuracy.

In recent years, the visual locating has been achieved in the system of automatic loading and unloading, but the common system demands higher illumination and other field environment and is easily interfered by the distributed background clutter witch is caused by tanker vibration. Therefore, the recognition rate and the effect of system are not satisfactory.

In view of the LVQ neural network can classify the input mode which according to the different properties and learn to achieve the logical reasoning and forecast purpose, effectively control of the object that lack of an accurate model can be achieved (Gao *et al*., 2011). Therefore, the LVQ neural network can be used for target recognition in the visual positioning system. In the recognition process of LVQ neural network, some characteristic values of closed curves are extracted as the training values and the closed curves are from the similar target image after image process. The LVQ neural network obtains the ability of determine the target after training. When actual target appears in the image, it can be determined correctly and then located accurately (Dawei and Zhengbin, 2011; Yong and Yan, 2006).

In this study, it uses visual locating method based on LVQ neural network. Some images of oil tank's opening were accessed timely. The eccentricity, compactness and other physical quantities, witch were extracted from the

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target image that after image pretreatment process, as the input values of the LVQ neural network and then the opening of the oil tank can de determined. This method can accurately achieve the position of the oil tank's opening and facilitating automation operations for fuel loading and unloading.

PROCESS

The specific image pretreatment process: First, the collected RGB images were processed by the color factor to highlight the target image in the clutter background; Second, the threshold segmentation method was adopted to do image binarization processing, the processed target image and background contrast markedly; Third, the image is smoothed and denoised by using the median filtering, the consecutive pixels were removed when they are smaller than the human setting values; Fourth, The Sobel operator was used to detect the edge and the outline of target image was obtained; Finally, the characteristic values were extracted from the outline of target image and the extracted values as the input of the LVQ neural network. The flow chart of LVQ neural network target recognition is shown as Fig. 1.

Structural analysis of LVQ neural network: LVQ neural network belongs to the feed-forward neural network type, which has a wide range of applications in patter recognition and optimization field (Al-Daoud, 2009; Punitha and Santhanam, 2007). LVQ net work is suggested in the foundation of network competition and combining with the competed learning and supervised learning's rules (Chalabi *et al*., 2008; Bayir, 2008).

Input layer, competing layer and output layer constitute LVQ neural network, its structure as shown in Fig. 2, input layer is N neurons that accept input vector, which completely connect with competing layer; competing layer is M neurons which were divided into groups and rank in one-dimensional linear array; output layer each neuron just connects with a group neurons of competing layer and connecting weight is fixed for 1. In process of training LVQ network, connection weight between input and competing layers is gradually adjusted for clustering center. When a input sample were sent to LVQ network, competing layer's neurons get through winner-take-all competing rule to produce triumph's neuron, admit its output is 1, but the others is 0 and then the current input sample's model had been provided (Umer and Khiyal, 2007).

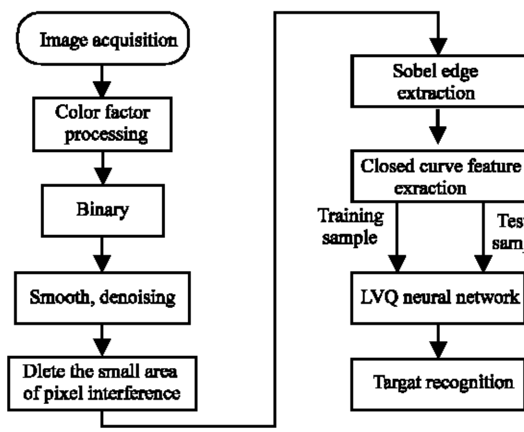

Fig. 1: Flow chart of LVQ neural network target recognition

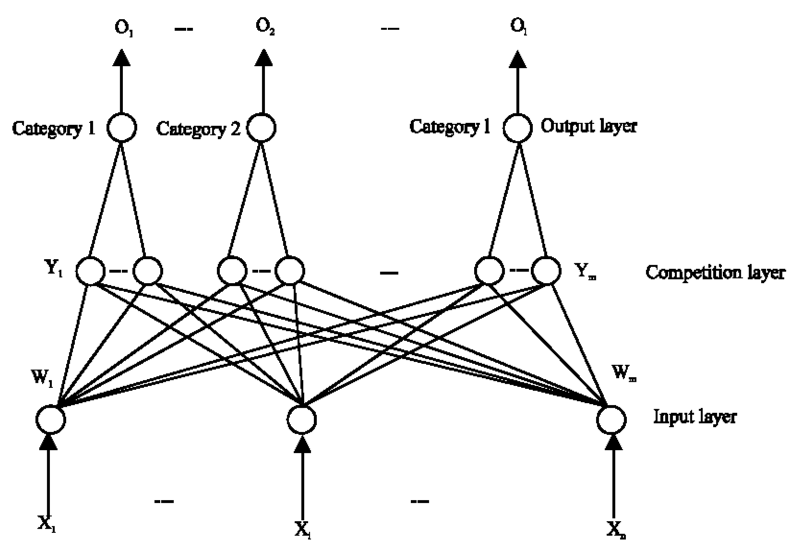

Fig. 2: LVQ (learning vector quantization) neural network structure chart

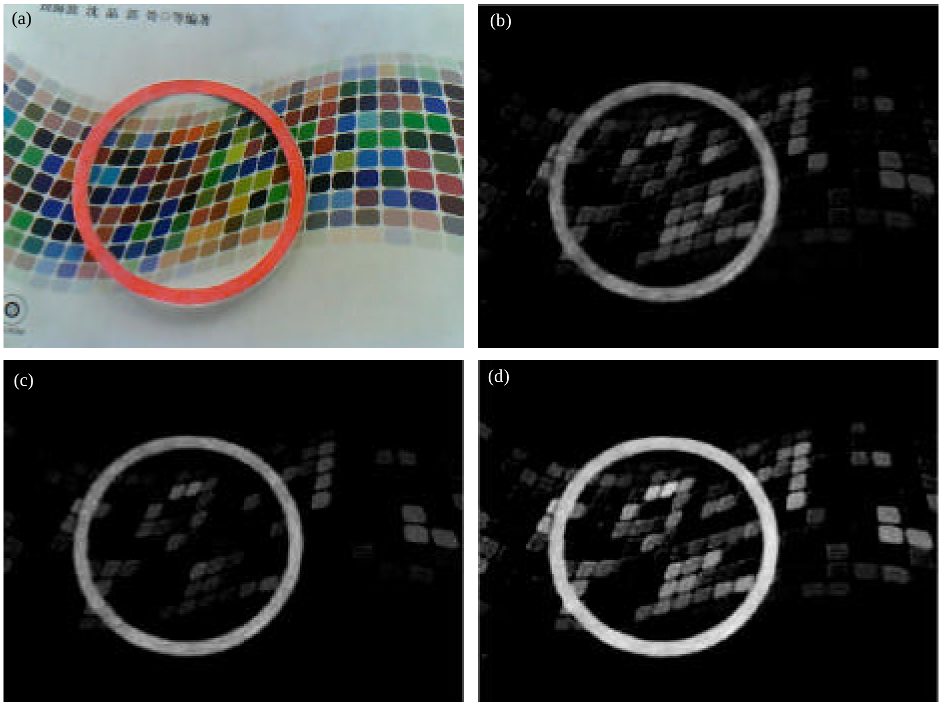

Fig. 3(a-d): Comparison of color factor (a) Original image, (b) R-B image, (c) R-G image and (d) |R-B|+|R-G| image, R: Red, B: Blue, G: Green

LVQ network each layer's math describes as follows: X represents the input vector:

$$X = (x_1, x_2,...,x_N)^T \quad (1)$$

Y represents the competition layer's output:

$$Y = (y_1, y_2, ..., y_M)^T, y_i \in \{0, 1\}, j = 1, 2 ..., M \quad (2)$$

O represents the output layer's output:

$$O = (O_1, O_2,..., O_l)^T \quad (3)$$

d represents the network's expectation output:

$$d = (d_1, d_2, ..., d_l)^T \quad (4)$$

W^1 represents the weights matrix between input layer and competition layer:

$$W^1 = (W^1_1, W^1_2, ..., W^1_j, ..., W^1_M) \quad (5)$$

One column vector W^1_j is the hidden layer's the first j neurons corresponding weights vector.

W^2 represents the competition layer to output layer's weights array:

$$W^2 = (W^2_1, W^2_2, ..., W^2_k, ..., W^2_l) \quad (6)$$

One column vector W^2_k is the hidden layer's the first k neurons corresponding weights vector (Hagan *et al.*, 2005; Kusumoputro *et al.*, 2011).

Image pre-processing: The purpose of the image pre-processing is mainly to achieve the preliminary separation of target and background. Determine the threshold through the calculation of the image acquisition color factor and achieve the binarization of the gray image. Then interference and eliminate the small area of the image and do the Sobel edge detection.

In this study, the background of the experiment image is a colorized bar and a ring witch outer radius is 40 mm and inner radius is 35 mm is on.

The color space of image: The RGB (Red, Green and Blue) color model is the most basic color model which based on the trichromatic principle of the human visual. In the color model, each pixel color of the color image can be represented by a point in the first quadrant of the three-dimensional space, compare the R-G, R-B and |R-G|+|R-B| color factor respectively by math and the experimental results shown in Fig. 3.

In Fig. 3b-d is respectively the image of the color factor processed by R-G, R-B, |R-G|+|R-B|. It can be clearly seen that in the image that processed by the color factor, ring color is very different from surrounding environment, that's conducive to the further image segmentation and recognition. Figure 3b is the image which processed by the R-G color factor, the difference between the ring and the background color is not very obvious and the misjudged phenomenon will happen after the split, that cause part of the background be retained as a target. Figure 3c is the image which processed by the G-B color factor, the color of image becomes very dark, the difference is not great and it is also not conducive to the latter part of image segmentation. Compared to Fig. 3b-c, the target ring in Fig. 3d is significantly different from the surrounding color, laid the foundation for the next separate dealt. Therefore, synthetic factor |R-G|+|R-B| is adopted to process the original image.

Image segmentation: Threshold Segmentation Method is to extract the differences in gray of target special body and background and divide the image into the combinations of target area and background area with different gray level. Threshold segmentation applies to the image which has larger objects and background contrast, its calculation is relatively simple and can define the overlap region through the closed and connected boundary, it is the most effective and practical technology in the image segmentation (Quan and Ming, 2011; Yang *et al*., 2010).

Assume that (x, y) is the plane coordinates of the two-dimensional digital image, the range of the image gray level is G = {0, 1, 2, ..., L-1}, Where 0 is the darkest gray level, L-1 indicates the brightest grayscale, the pixel gray value in the coordinates (x, y) is expressed by f (x, y). Assume that τ is threshold value and b0, b1 both represent a binary grayscale, then the results of the image {f(x, y)} on the threshold τ can be expressed as:

$$f_\tau(x,y) = \begin{cases} b_0, & f(x,y) < \tau \\ b_1, & f(x,y) \geq \tau \end{cases} \tag{7}$$

Threshold image segmentation is the process of seeking the optimal threshold according to a criterion function and the optimal threshold is not limited to a single one. Assume there are M pixels in the image and there are mi pixels which gray-scale is i, then the probability pi of gray level i as follows:

$$p_i = \frac{m_i}{M} = \frac{m_i}{\sum_{i=0}^{L-1} m_i} \tag{8}$$

Therefore, the result of threshold segmentation method depends on the choice of thresholds to a large extent. The segmented image is shown as Fig. 4.

Image edge detection: Edge is the mutation of the gray-scale or structure in the image, image edge detection is to extract the characteristics of the contours of the target image (Zhou *et al*., 2010). Therefore, the edge needs to be accurate and smooth in the image detection process. It can be seen in Fig. 4, due to the randomness of the natural conditions, there will be some interference information in the image acquisition and processing. Therefore, further smoothing and denoising is necessary and some empty or small area of pixels interference can be artificially removed. In this study, the experimental image after threshold segmentation processing was treated by median filtering and denoising, the inanition and small area of continuous pixels less than the setting value 500 were removed. Edge detection results after being filtered shown in Fig. 5.

The extraction of target features: The main purpose of feature extraction method is to make the characteristic value very close from different sample of the same category and make the characteristic value a great difference from samples of different types. The common methods of image recognition characteristics have edge, shape, the image of the matrix decomposition, constant torque, etc. Shape characteristics mainly have area, perimeter, spindle, ratio and area and perimeter can be gotten through satiating the statistical target pixel count and boundary pixels count by image processing; Spindle and ratio value can be acquired by calculating the biggest length and width of the minimal circumscribed rectangle cut rectangular. As a neural network's input need to meet the principle, that similar objects have similar features, the

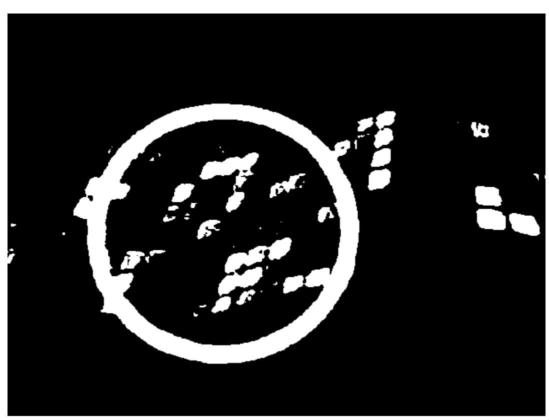

Fig. 4: Threshold segmented image

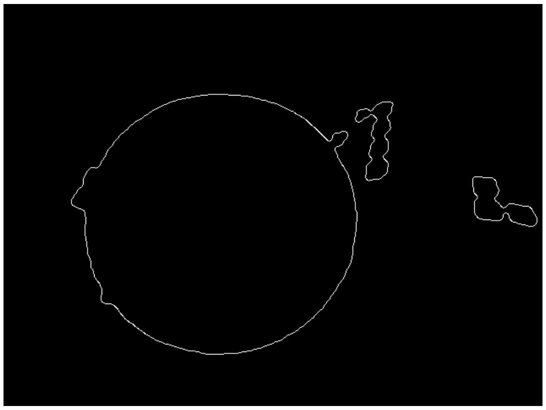

Fig. 5: Sobel edge detection after being filtered

difference objects have a bigger difference of characteristics, so five characteristics and normalized as LVQ neural network's input are chosen.

Where:

$$\text{Elongation} = \frac{\text{Max}_{\text{length}} - \text{Min}_{\text{length}}}{\text{Max}_{\text{length}} + \text{Min}_{\text{length}}} \tag{9}$$

$$\text{Compactness} = \frac{\text{Area}}{\text{Perimeter}^2} \tag{10}$$

$$\text{Bspect ration} = \lg\frac{\text{Height}}{\text{Width}} \tag{11}$$

$$\text{Excentricity} = \frac{\text{Max}_{\text{length}}}{\text{Min}_{\text{length}}} \tag{12}$$

This study used the above five characteristics, which are value compactness, aspect ratio, spindle-circumference ratio, elongation and eccentricity, as the neural network's input variables to input. It is not clearly defined for the quantity of training samples. Now the common method that confirms the number of training samples is the rule of thumb and it is said that the number of training samples is about 10 times the total number of neural network weights. So, it must have at least 100 training samples in this experiment. This experiment used 300 different samples (200 training sample, 100 test sample) to test and extracted the characteristic value as the LVQ network input. This not only effectively reduced the input of the network LVQ but also is made preparations for building an efficient, stable neural network. In order to accurately obtain the position of centroid, using the least squares method to fit the contours and the center is the centroid of the target seeking.

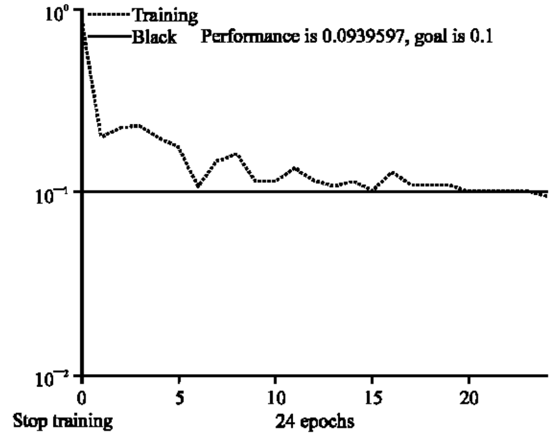

Fig. 6: Simulation of the LVQ network's training process

Table 1: Some eigenvalues of the sample

Elongation	Spindle-circumference ratio	Compactness	Aspect ratio	Eccentricity
0.0611	0.2901	0.0319	0.0531	0.4659
0.4618	0.3667	0.0135	0.4339	0.9297
0.1701	0.3138	0.0333	0.1492	0.7050
0.0356	0.2219	0.0252	0.0310	0.3646
0.7088	0.5239	0.0873	0.7684	0.9854
0.2193	0.3874	0.0732	0.1936	0.7681
0.1238	0.3983	0.0806	0.1081	0.6261
0.0447	0.2961	0.0323	0.0389	0.4048
0.3639	0.3023	0.0120	0.3312	0.8846
0.2676	0.3300	0.0376	0.2382	0.8161
0.0261	0.2221	0.0260	0.0227	0.3149
0.6836	0.5339	0.0913	0.7260	0.9822

The characteristic feature was selection after the image through Sobel operator edge detection and by MATLAB program calculation (Kaihong and Yaohong, 2005). It can obtain characteristic value in turn, as is shown in Table 1.

As shown in Fig. 6, is the training process of simulation LVQ network diagram. It can be seen that, in the case of set goals error 0.1, when the iteration number of training LVQ network for 24 times, learning curve and experimental goal intersection, complete the learning process.

The simulation results: The experiment was collected 200 training samples under different conditions to carry out LVQ neural network training. Finally, the LVQ neural network, which has 5 neurons in competitive layer and the learning rate is 0.01, is used in the opening recognition test system. 100 samples under different conditions were selected as the network testing samples, through the

Table 2: Some analysis results of the test sample

Elongation	Spindle-circumference ratio	Compactness	Aspect ratio	Eccentricity	Whether the target	Simulation results
0.0186	0.4257	0.0470	0.0161	0.2676	1	1
0.3222	0.4826	0.1103	0.2902	0.8586	2	2
0.6507	0.4610	0.0441	0.6745	0.9774	2	2
0.4521	0.4225	0.0217	0.4233	0.9261	2	2
0.3952	0.5171	0.0396	0.3631	0.9012	2	2
0.2229	0.2321	0.0169	0.1969	0.7722	2	2
0.0366	0.4365	0.0438	0.0318	0.3692	1	1
0.1625	0.2309	0.0230	0.1425	0.6936	2	2
0.1412	0.2871	0.0238	0.1235	0.6586	2	2
0.6743	0.4933	0.0477	0.7110	0.9809	2	2

1: Yes, 2: No

Table 3: Influence of the different number of training samples

The number of training samples	50	100	200	300	400	500
The correct rate of identify (%)	85	92	98	99	98	96
The recognition time (msec)	48.31	50.69	50.91	54.56	61.35	70.23

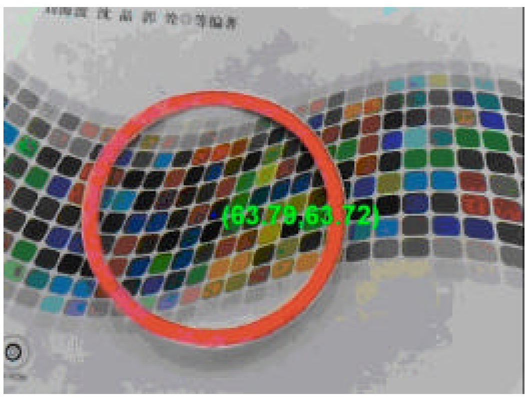

Fig. 7: The results of recognition

trained network LVQ validation test. Test experimental result of part of the training sample was randomly selected is as shown in Table 2.

Through calculating and analyzing all of the testing samples, it is concluded that the recognition correct rate reached 98%. But because of the neural network in some degree of stability, in order to prevent individual error recognition of a large sample of test samples, it can be compensated in the actual application. Because image collection has a high frequency and target recognition is independent, even if one image has a target judge mistake, the following image recognition was not affected. The final recognition result is as shown in Fig. 7.

From the Fig. 7, it is intuitive that the coordinates of the center of the ring is (63.79, 63.72). If the centroid of the tanker's opening is the center of the circular ring in actual oil loading and unloading process, it is easy to positioning the tanker's opening and make automatic perfusion becomes possible when the Specific coordinates of the tanker's opening is given.

In order to determine the influence of the number of training samples for the performance of LVQ neural network system, different number of training samples had been simulated. The simulation results as shown in Table 3.

From the Table 3, it is able to find that the correct rate of identify is the highest when the rate is between 200 and 400. Because of the sample size is too small and can not contain the entire sample space when the number of training sample is 50, the correct rate is not high. When the number of training samples is between 400 and 500, too much samples lead to more redundant information, not only increase the difficulty of network training, but also lead to over-fitting and weaken network performance. For the recognition time of the LVQ neural network, with the increase of the number of training samples, it takes longer to identify. Therefore, it is must be considered that the balance between the correct rate of identify and the recognition time of the LVQ neural network when choice the training samples.

CONCLUSIONS

In this study, 300 different samples were selected in MATLAB 7.0 environment (200 training samples and 100 test samples). The LVQ neural network was trained by training samples and the number of competitive layer of neural network is 5, the learning rate is 0.01. Through analysis of all the test results, obtained the correct rate of identify is 98% and the recognition time of LVQ neural network is only 50.91 msec. But the recognition time of the vision location system of circular hole is 1.2604 sec. And it can be more efficient when the balance between the correct rate of identify and the recognition time of the LVQ neural network is considered. The experimental data shows that the algorithm based on LVQ neural network can realize the positioning of the circular ring in the clutter background. And if the image pretreatment process is optimized, it has a higher precision and faster speed. It is possible to use the algorithm in the oil automatic loading and unloading process.

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