

Fault Diagnosis for Industrial Images Using a Min-Max Modular Neural Network

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Abstract. This paper presents a new fault diagnosis method for industrial images based on a Min-Max Modular (M^3) neural network and a Gaussian Zero-Crossing (GZC) function. The most important advantage of the proposed method over existing approaches such as radial-basis function network and support vector machines is that our classifier has locally tuned response characteristics and the misclassification rate of faulty product images can be controlled as small as needed by turning two parameters of the GZC function while the correct rate can be influenced to some extent. The experimental results on a real-world fault diagnosis problem of industrial images indicate that the effectiveness of the proposed method.

1 Introduction

The aim of developing a fault diagnosis system for industrial images described in this paper is to exactly classify all the CCD sensing images acquired from a product line into two categories: qualified product and faulty product. A strict requirement for the classifier used in fault diagnosis systems is that the classifier is not allowed to mistakenly classify images of faulty products into the category of qualified products. Although various image classification methods have been developed in the last few years [3], many of these methods, however, are not suitable to fault diagnosis for industrial images because they lack locally tuned response characteristics and the misclassification rate on faulty product images can not be controlled by a user.

In our previous work we have proposed a min-max modular (M^3) neural network [1] for dealing with large-scale pattern classification problem. As a kind of divide-and-conquer technique, the main idea of M^3 network is to divide a complex multi-class problem into a series of smaller and simpler two-class subproblems and combine the individual solutions of all the subproblems into a solution to the original problem. An attractive feature of the M^3 networks is that any multi-class problem can be decomposed into a number of linearly separable subproblems.

For linearly separable problems, we have proposed a Gaussian Zero-Crossing (GZC) function. The combination of the M^3 network and the GZC function has two important advantages over existing classifiers. One is that fast learning

without error can be achieved to any complex pattern classification problems; the other is that the locally tuned response features of the GZC function are maintained in the entire M^3 network. In this paper, we apply the M^3 network with the GZC function to a fault diagnosis problem of industrial images.

2 Feature Extraction with Wavelet Transform

2.1 Image Processing

A real-world image set used in this paper consists of CCD sensing images acquired from a product line at a leading manufacturing company. In this paper, all the images are in the form of 256 gray-scales bitmap and are classified into two classes: *correct image* and *faulty image*. The size of the images is 128*128 in pixels. Two kinds of enlarged images are illustrated in Fig. 1, in which (a), (b) belong to *correct image* and (c) is classified into *faulty image*.

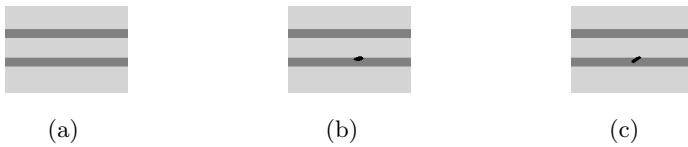


Fig. 1. Industrial CCD sensing images for qualified products (a) and (b), and defective product (c)

2.2 Feature Extraction Using Wavelet Transform

We used wavelet transform techniques to extract the features of images. The image data were convolved by using the Daubechies wavelets [6], which is orthogonal and with compact support. In the experiments below, the order N was set to 2 with the encoding level 1. After wavelet transforming, the dimension of the feature vector representing an image is 4225.

3 M^3 Network and GZC Function

3.1 M^3 Network

The proposed method is based on a min-max modular neural network model [1]. With the task decomposition method, a K -class problem can be uniquely partitioned into a number of linearly separable problems, each of which includes only two different training data that belong to two classes. The number of linearly separable problems is given by

$$\sum_{i=1}^{K-1} \sum_{j=i+1}^K L_i \cdot L_j \tag{1}$$

where L_i denotes the number of training data belonging to class C_i .

After training individual component modules assigned to learn associated two-class sub-problems, all the trained component modules are integrated into a min-max modular neural network with the MAX, MIN, or/and INV units according to two module combination laws [1].

3.2 Gaussian Zero-Crossing Discriminant Function

A fatal weakness of linear discriminant functions is that they lack locally tuned response characteristics [2]. This deficiency may lead classifiers to mistakenly produce proper output even when an unknown input is presented.

To overcome the deficiency of linear discriminant functions, we have proposed a Gaussian Zero-Crossing (GZC) function for solving linearly separable problems in our previous work [2]. The definition of the Gaussian zero-crossing discriminant function is given by:

$$f_{ij}(x) = \exp \left[- \left(\frac{\|x - c_i\|}{\sigma} \right)^2 \right] - \exp \left[- \left(\frac{\|x - c_j\|}{\sigma} \right)^2 \right] \quad (2)$$

where $x \in \mathbf{R}^n$ is the input vector, $c_i \in \mathbf{R}^n$ and $c_j \in \mathbf{R}^n$ are the given training inputs belonging to class \mathcal{C}_i and class \mathcal{C}_j ($i \neq j$), respectively, and are used as two different receptive field centers, $\sigma = \lambda \|c_j - c_i\|$ is the receptive field width, λ is a user-defined constant ($0 < \lambda$), and the norm $\|z\|$ is the Euclidean norm of vector z [2]. An important advantage of the GZC discriminant function over existing linear discriminant functions is its locally tuned response characteristics.

The output for the M^3 network with GZC discriminant function is defined by

$$g(x) = \begin{cases} 1 & \text{if } y_i(x) > \theta^+ \\ \text{Unknown} & \text{if } \theta^- \leq y_i(x) \leq \theta^+ \\ -1 & \text{if } y_i(x) < \theta^- \end{cases} \quad (3)$$

where θ^+ and θ^- are the upper and lower threshold limits of the M^3 network, respectively; and $y_i(x)$ denotes the transfer function of the M^3 network for class \mathcal{C}_i .

One attractive feature of the GZC discriminant function is that the proper generalization performance of the M^3 network can be easily controlled by tuning θ^+ and θ^- . From (2), we see that the receptive field width of the GZC function is determined by two factors: the constant λ defined by a user and the distance between two different receptive field centers.

4 Experiment Results

To evaluate the effectiveness of the proposed method and compare it with support vector machines, we carry out simulations on a real-world fault diagnosis problem of industrial images. The training data set consists of 500 images and the test data set contains 83 images. Table 1 shows the distributions of the training and test data.

Table 1. Distributions of The Training and Test Data

Class	No. Data	
	Training	Test
Images for qualified products	400	100
Images for faulty products	6	23

Table 2. Performance Comparison of M³-GZC with SVMs

Methods	SVs	Success Rate(%)		Error No. in Testing	
		Training	Test	Correct→Fault ^a	Fault→Correct ^b
M ³ -GZC	N/A	100.00	96.75	0	4
SVMs($\sigma=2.0$)	137	100.00	96.75	0	4
SVMs($\sigma=1.4$)	206	100.00	96.75	0	4
SVMs($\sigma=1.0$)	328	100.00	92.69	0	9
SVMs($\sigma=0.7$)	438	100.00	83.74	0	20
SVMs($\sigma=0.5$)	460	100.00	81.30	0	23

^a The number that the Correct are misclassified to the Fault.

^b The number that the Fault are misclassified to the Correct.

4.1 Experiment 1

In this experiment, we compare our method with standard SVMs. Both θ^+ and θ^- were set to 0.01 for the M³ network with the GZC function and C for SVMs [4] was selected as 4, 8, 16, 32. The experimental results are shown in Table 2.

From Table 2, we see that our method has the same recognition rate on the whole test data as the standard SVMs. The results demonstrate that the M³ neural network with the GZC function has a well-performed structure for classification problems. When the radius (σ) of the kernel function¹ in SVMs is narrowed, however, the corresponding recognition rate become worse, especially, more number of images for defective products are mistakenly classified as the category of qualified products. From this result, we can point out that it is difficult for SVMs to reduce the misclassification rate on faulty images by shrinking the radius of the kernel function.

4.2 Experiment 2

In this experiment, we demonstrate that the rate of misclassifying the images of faulty products to the category of qualified products can be reduced to 0 with the use of the GZC discriminant function, while the correct recognition rate can be maintained in certain level. The results of the experiment is illustrated in Fig. 2. Here, $\theta^- = -\theta^+$. The unknown recognition rate means the percentage of the M³ network producing ‘I don’t know’ outputs. From Fig.2 (a) and (b), we can see that when $|\theta|$ is greater than or equal to 0.6147, the error recognition

¹ $\exp(\frac{\|X-X_i\|^2}{-2\sigma^2})$.

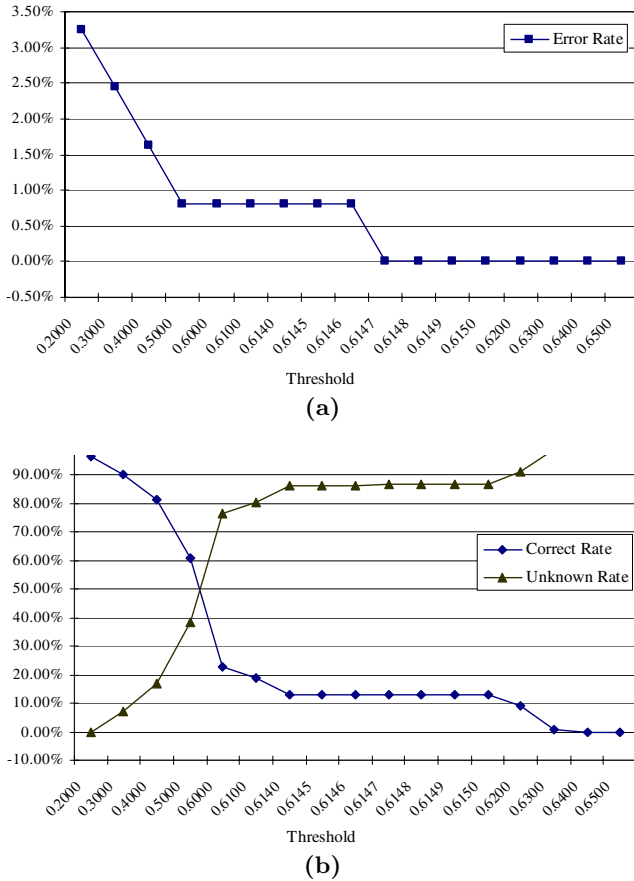


Fig. 2. Correct recognition rate and unknown recognition rate (a), and error recognition rate (b), as a function of the value of threshold of the M^3 network

rate is reduced to 0%. Meanwhile, the correct recognition rate is kept at 13.01%. Although this correct recognition rate is highly unsatisfactory for practical applications, the proposed method provides us with a promising approach to dealing with fault diagnosis problems of industrial images.

5 Conclusions

We have presented a fault diagnosis method based on the combination of the M^3 neural network and the Gaussian Zero-Crossing discriminant function. The experiment results indicate that the proposed method has the advantage to reduce the misclassification rate on faulty products that SVMs are lacking in our experiments. As to future work, we will refine the internal classification structure for improving correct recognition rate while reducing the rate of misclassifying faulty product images.

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