Image Classification using a Module RBF Neural Network

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Abstract

Image classification is an interesting topic in multimedia processing. Recently, there were many researchers proposed radial basis function-based (RBF) methods to deal with image classification. However, the traditional RBF neural networks were sensitive to center initialization. To obtain appropriate centers, it needs to find the significant features for further RBF clustering. In addition, the training procedure of the traditional RBF is time-consuming. In order to cope with these problems, a self-organizing map (SOM) neural network is proposed to select more appropriate centers for RBF network, and a modular RBF (MRBF) neural network is proposed to improve the classification rate and speed up the training time. The experimental results show that the proposed MRBF network has better performance than DWT-based method, traditional RBF neural network and the Tree Structured Wavelet (TWS) in image classification. The experimental results also show that the training time of proposed MRBF neural network is much faster than the traditional RBF neural network.

1. Introduction

Image classification is an interesting topic in multimedia processing. Recently, the texture-based features had been widely used in image segmentation and classification [1]. These methods could be roughly classed as structural method, statistical method and spectral method. In the structural method, the primitive textile patterns are used to analyze images and characterize texture features. The statistical method calculates the texture features to measure the distribution of the pair of pixel on image. For Spectral method, it is based on the properties of the Fourier transformation, where a texture image may be identified by an analysis of various frequencies and their orientation.

The RBF neural network [3] with simplicity of single-hidden layer structure is a good alternation to multiplayer perceptron (MLP) neural network especially in applications requiring local tunable property [4]. However, the traditional RBF neural networks were sensitive to center initialization. In addition, the training procedure of the traditional RBF is time-consuming. Thus, we propose a MRBF neural network to cope with these problems in image classification. In the proposed method, we first split each texture image into 64 non-overlapping sub-images and then decompose these sub-images through wavelet transformation to obtain sub-band images. These sub-bands images are further used to extract statistical textures features. Since the initial centers of RBF affected the efficiency of RBF significantly. A self-organizing map (SOM) neural network is applied to obtain prototypes in the form of local data clustering. The resulting prototypes are then incorporated into MRBF neural network for image classification. The experimental results show that the proposed MRBF neural network has good performance than DWT-based method [8], traditional RBF neural network [3] and the Tree Structured Wavelet (TWS) [8].

This paper is organized as follows. In section 2, we briefly introduce the applied techniques: the wavelet transformation (DWT), texture analysis and self-organizing map (SOM). The proposed method is presented in section 3. Experimental results and discussions are shown in section 4. Finally, the conclusions are given in section 5.

2. Related works

2.1. Wavelet transformation

The wavelet transformation is a mathematical tool that can transform the original image into different sub-band images by wavelet and scaling function. This process is recursively applied to the low-frequency sub-band image to generate the next level of sub-band images. Therefore, for an image, it can generate a sub-

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bands set which consist of three detail images $D_{j,k}$ and a approximate image L_j where k=1,2,3 and j representing the level of the transformation.

2.2. Texture Analysis

After wavelet transformation, the j-level wavelet transformation of an image can be represented as $\{L_j, D_{j,k}\}_{j=1,2,\ldots,J;k=1,2,3}$. We consider all sub-band images for the purpose to extract texture features from the image efficiently.

In order to obtain different texture features. Five common gray-level statistical features are presented in Eq. (1)-(5).

$$\text{Contrast} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} (i-j)^2 P_\delta(i,j) \tag{1}$$

$$\text{Energy} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_\delta(i,j)^2 \tag{2}$$

$$\text{Entropy} = -\sum_{i=0}^{N-1} \sum_{j=0}^{N-1} P_\delta(i,j) \log(P_\delta(i,j)) \tag{3}$$

$$\text{Homogeneity} = \sum_{i=0}^{N-1} \sum_{j=0}^{N-1} \frac{P_\delta(i,j)}{1+(i-j)^2} \tag{4}$$

$$\text{Max probability} = Max[P_\delta(i,j)] \tag{5}$$

where $P_\delta(i,j)$ is the co-occurrence matrix under a specific conditions $\delta(r,\theta)$, in which r denotes the distance and θ is the orientation between two adjacent intensity (i, j). Theoretically, $P_\delta(i,j)$ represents the conditional-joint probabilities of all pair combination of gray levels of an image.

2.3. Self-Organizing Map

The initial centers selection plays important role in the traditional RBF neural network. Self-Organizing Map neural networks (SOM) had proven to have capability of auto-clustering [3]. In order to avoid the difficulty of center selection, a SOM neural network is applied to obtain the appropriate centers for RBF neural network.

To perform the prototypes using SOM neural network, we are given a texture vector for each training pattern from the previous extraction operation. Therefore, we have N texture vectors denoted N training patterns for each class. We then assign the N texture vectors into SOM neural network to obtain the weight vectors $\mathbf{V} = \{v_1, v_2, \ldots, v_J\}$.

3. A module RBF neural network

Since the traditional RBF neural networks have many nice characters, such as simplicity, robustness and optimal approximation. They were successful applied to the image classification [5] and image index [4]. However, in order to obtain a better learning capacity, it needs to adjust many learning parameters manually. In addition, the traditional RBF neural networks were sensitive to training patterns resulted in interpolated these training patterns incorrectly and need more time for training.

In this paper, we applied the modular concept to construct a specific network, called modular RBF network (MRBF) to cope with the mentioned problems. The outputs of hidden neurons are then connected to different output neurons. Figure 1 shows the architecture of the proposed MRBF neural network with M hidden module and M output neuron.

To carry out learning capacity using MRBF neural network, we are given a prototypes $\mathbf{V} = \{v_1, v_2, \ldots, v_J\}$ obtained from the SOM algorithm for each class. We then assign the prototype from the i-th class as the center of the i-th module in the hidden layer of MRBF neural network. In other words, the MRBF neural network uses J dimensional Gaussian distributions to describe the training patterns for each class.

The parametric model of the proposed MRBF neural network can be given as follows

$$f_j(\mathbf{x}) = \sum_{i=1}^{N} w_{ji} \phi_{ji}(\| \mathbf{x} - \mathbf{c}_{ji} \|) \tag{6}$$

where $\mathbf{x} \in R^n$ is an input vector, ϕ_{ji} is the basis function of the MRBF neural network from R^n to R, w_{ji} is the weight vector between the j-th output neuron and the i-th hidden neuron of module j. $\mathbf{c}_{ji} = (c_{ji1}, c_{ji2}, \ldots, c_{jin})^T$ are the i-th center nodes of the j-th module, and symbol $\| \; \|$ denotes the Euclidean norm. If the basis function of the MRBF network is a Gaussian function, then

$$\begin{aligned} f_j(\mathbf{x}) &= \sum_{i=1}^{N} w_{ji} \phi_{ji}(\| \mathbf{x} - \mathbf{c}_{ji} \|) \\ &= \sum_{i=1}^{N} w_{ji} \exp([-\| \mathbf{x} - \mathbf{c}_{ji} \| / \sigma_{ji}]^2) \end{aligned} \tag{7}$$

where σ_{ji} is the i-th bandwidth of the Gaussian function of the j-th module as follows

$$\sigma_{ji} = \frac{d_{\max}}{\sqrt{k}} \tag{8}$$

where d_{max} is the maximum Euclidean distance between the selected center of the j-th module, and k is the number of the centers of the j-th module.

Therefore, the error cost function is defined as follows

$$J(n) = \frac{1}{2}\left[\sum_{j=1}^{M}\left(y_j^{desired}(n) - \sum_{i=1}^{N} w_{ji}(n)\exp(-\|\mathbf{x}(n) - \mathbf{c}_{ji}(n)\|^2 / \sigma_{ji}^2(n))\right)\right] \tag{9}$$

where $y_j^{desired}$ denotes the desired output of the j-th output neuron.

The update equations for the MRBF neural network parameters are given by

$$\begin{aligned} w_{ji}(n+1) &= w_{ji}(n) - \mu_w \frac{\partial}{\partial w_{ji}} J(n)\,|_{w_{ji}=w_{ji}(n)} \\ &= w_{ji}(n) + \mu_w e(n)\psi(n) \end{aligned} \tag{10}$$

$$\begin{aligned} \mathbf{c}_{ji}(n+1) &= \mathbf{c}_{ji}(n) - \mu_c \frac{\partial}{\partial \mathbf{c}_{ji}} J(n)\,|_{\mathbf{c}_{ji}=\mathbf{c}_{ji}(n)} \\ &= \mathbf{c}_{ji}(n) + \mu_c \frac{e(n)w_{ji}(n)}{\sigma_{ji}^2(n)} \\ &\cdot \exp([-\|\mathbf{x}(n) - \mathbf{c}_{ji}(n)\| / \sigma_{ji}(n)]^2)[\mathbf{x}(n) - \mathbf{c}_{ji}(n)] \end{aligned} \tag{11}$$

$$\begin{aligned} \sigma_{ji}(n+1) &= \sigma_{ji}(n) - \mu_\sigma \frac{\partial}{\partial \sigma_{ji}} J(n)\,|_{\sigma_{ji}=\sigma_{ji}(n)} \\ &= \sigma_{ji}(n) + \mu_\sigma \frac{e(n)w_{ji}(n)}{\sigma_{ji}^2(n)} \\ &\cdot \exp([-\|\mathbf{x}(n) - \mathbf{c}_{ji}(n)\| / \sigma_{ji}(n)]^2)\,\|\mathbf{x}(n) - \mathbf{c}_{ji}(n)\|^2 \end{aligned} \tag{12}$$

where

$$\psi(n) = [\phi_{j1}(\|\mathbf{x}(n) - \mathbf{c}_{j1}(n)\|),\ldots,\phi_{jN}(\|\mathbf{x}(n) - \mathbf{c}_{jN}(n)\|)]^T \tag{13}$$

$$e(n) = y_j^{desired}(n) - y_j(n) \tag{14}$$

In addition, μ_w, μ_c, and μ_σ are appropriate learning rate parameters.

The training processes of the proposed MRBF neural network are summarized as follows.

Step 1. Choose the centers for the MRBF neural network using SOM neural network.

Step 2. Calculate the initial value of the spread parameter for the MRBF neural network according to Eq. (8).

Step 3. Initialize the weights in the output layer of the MRBF neural network randomly.

Step 4. Present the input vector of the j-th class and compute the network output according to (7).

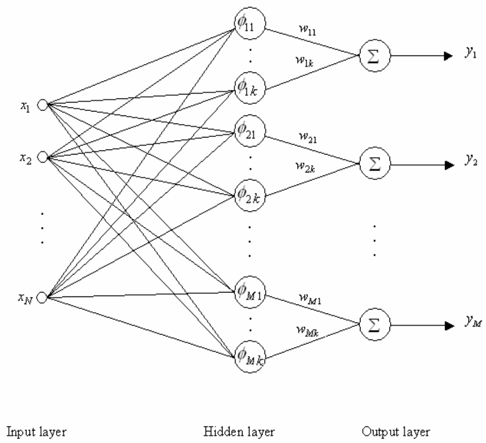

Fig. 1: The architecture of the MRBF neural network.

Step 5. Update the network parameters according to Eq. (10), (11), and (12).

Step 6. Stop if the network has converged; else, go back to step 4.

4. Experimental results and discussions

To show that the proposed MRBF method has good classification capability, the proposed method was compared with the DWT-based method [8], traditional RBF neural network [3] and the Tree Structured Wavelet (TWS) [8]. Nine texture images selected form Brodatz albums [7] shown in Fig. 2 are used to conduct the experiments. The image size of each texture image is 512 × 512, with 256 gray levels.

First, each texture image was split into 64 non-overlapping sub-images, in which a half of sub-images

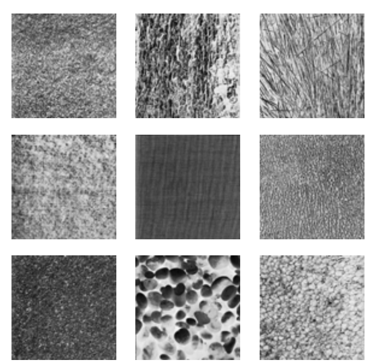

Fig. 2: The texture images from the Brodatz album used in classification experiments, from left-right and top-bottom: D9, D12, D15, D19, D21, D24, D29, D30, D112.

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are used for training and the others are used for testing. Then, a 2-level wavelet transformation is applied to all the sub-images. Accordingly, each sub-image can be represented as seven sub-band images. Each sub-band image is then used to extract texture features according to Eq. (1-5) for four orientations (0, 45, 90, and 135 degree). Therefore, each sub-image is described by 140-dimensional textures vector.

The proposed MRBF neural network consist of 9 RBF modules and each module unit contains 32 hidden neurons. In order to evaluate the efficiency of our method, the compared traditional RBF neural network also consists of 288 hidden neurons.

The quantitative measurement of the classification result is measured by the average classification rate (ACR) of the 32 × 9 sub-images,

$$ACR = \left[\sum_{i=1}^{9} R_i\right] / 9, \quad (15)$$

where the accuracy rate of the *i*-th class R_i is defined as follows.

$$R_i = \frac{\text{\# of relevant subimages for image i}}{32} \times 100\% \quad (16)$$

The average classification rate is shown in Table I. The RBF neural network receives the lowest ACR of 86.8%, especially in D112 and D29. The ACR of DWT and TSW is 89.6% and 94.1%, respectively. While the DWT method presented low classification rate under D9 and D15. On the contrary, the average classification rate of MRBF neural network is 100%. The MRBF neural network demonstrated significant improvement in texture classification. Based on the experimental results, we can conclude that the proposed MRBF neural network has better ACR than DWT, TSW and traditional RBF neural network.

Table I
The ACR of the 32 × 9 sub-images.

Texture Images	DWT (%)	TSW (%)	RBF (%)	MRBF (%)
Bark(D12)	93.8	84.4	96.9	100.0
Bubble(D112)	90.6	96.9	65.6	100.0
Canvas(D21)	100.0	100.0	100.0	100.0
Grass(D9)	75.0	84.4	96.9	100.0
Leather(D24)	96.9	96.9	100.0	100.0
Sand(D29)	100.0	100.0	56.3	100.0
Stone(D30)	100.0	100.0	84.4	100.0
Straw(D15)	59.4	87.5	93.8	100.0
Woolen(D19)	90.6	96.5	87.5	100.0
ACR	89.6	94.1	86.8	100.0

Table II
The learning time for training the 32 × 9 sub-images.

	RBF	MRBF
Learning time (minute)	1953	34

In order to evaluate the learning speed for training 32×9 images, the proposed MRBF neural network are compared with the traditional RBF neural network. Table II shows that the MRBF neural network needs 34 minutes for training 32 × 9 images, while the traditional RBF neural network has to spend 1953 minutes to do this. Therefore, the proposed MRBF neural network provides faster learning speed than the traditional RBF neural network.

5. Conclusions

The traditional RBF networks were the most popular architecture and used in variety applications. However, it was sensitive to the center initialization. In the proposed MRBF network, we adopted a SOM network to obtain better initial centers, and applied the modular concept to the hidden layer to construct a specific network for texture image classification. The experimental results shown that the proposed method can achieve the highest classification rate compared with the other methods in texture classification.

6. References

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