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A novel approach of ship wakes target classification based on the LBP-IBPANN algorithm

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Abstract. The detection of ship wakes image can demonstrate substantial information regarding on a ship, such as its tonnage, type, direction, and speed of movement. Consequently, the wake target recognition is a favorable way for ship identification. This paper proposes a Local Binary Pattern (LBP) approach to extract image features (wakes) for training an Improved Back Propagation Artificial Neural Network (IBPANN) to identify ship speed. This method is applied to sort and recognize the ship wakes of five different speeds images, the result shows that the detection accuracy is satisfied as expected, the average correctness rates of wakes target recognition at the five speeds may be achieved over 80%. Specifically, the lower ship's speed, the better accurate rate, sometimes it's accuracy could be close to 100%. In addition, one significant feature of this method is that it can receive a higher recognition rate than the nearest neighbor classification method.

Keywords: ship wake; target classification; Local Binary Patterns; BP artificial neural network model

1. Introduction

The ship wakes detection technique is of significant industrial relevance, and it has received quite a lot attention. In general, owing to the cavitations of the ship's propeller and wave breaking, a moving ship generates a belt of air curtain that contains a mass of bubbles, which is generally considered as ship wake. This wake forms a wedge-shaped pattern in synthetic aperture radar (SAR) images, as shown in the Fig. 1. In Fig. 1, for ease of next processing, the ship can be excluded from the image because the hull itself can produce a high radar reflector relative to the wakes. SAR images of sea surface often reveal ship wakes; therefore, many of research methods relevant to the ship wakes of SAR image come forth in recent decades (Eldhuset 1996, Jin and Chen 2003, Courmontagne 2005, Zilman *et al*. 2005). In this paper, we are unconcerned about the ship wakes of SAR image; on the contrary, we just handle ordinary ship wakes of image (as shown in the Fig. 2) with a novel wake analytical method. As far as the ship wakes analytical approach is concerned, there are two methods: one is numerical simulation (Pham *et al*. 2010), and the other is image analysis method, this paper will adopt the latter to unfold in the next few sections.

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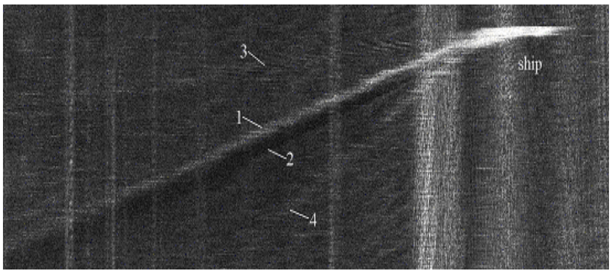


Fig. 1 Ship wakes of SAR image

Fig. 2 Ship wakes image

There is a lot of surface texture in the ship wakes image, the Local Binary Patterns (LBP) algorithm is just an effective method of texture analysis, so LBP suits to analyze the ship wakes image. In recent years, the LBP algorithm is mainly used for the area of face recognition (Ahonen *et al*. 2006, Zhao and Pietikäinen 2007, Song *et al*. 2009), lots of literatures results show that this method can efficiently increase the face recognition accuracy and consistently illustrate satisfactory performance even in severe illumination conditions. In this paper the texture feature of the ship wakes image is extracted by employing the LBP method, and the wakes targets are distinguished by the improved back propagation (IBP) artificial neural network (ANN) model, this means of features extraction and recognition of ship wakes image that is called LBP-IBPANN method. An artificial neural network (ANN), usually called neural network (NN), which is a mathematical model or computational model, and is inspired by the structure or functional aspects of biological neural networks. The utility of ANN mainly lies in the fact that it can be used to infer a function from observations. In the field of machine vision, ANN is chiefly applied to perform target recognition, edge detecting and so forth (Srinivasan *et al*. 1994, Ha *et al*. 2004, Xiao 2005). There are many network models available, the BP artificial neural network is probably the most commonly practical artificial neural net, according to the statistics, about 90% ANN is using the standard BP algorithm. Therefore, this paper is also based on the BP artificial neural network, and a LBP-IBPANN method is creatively put forward for classifying ship wakes images.

The paper is organized as follows. First of all, a brief introduction is provided to present the fundamental concepts of the LBP algorithm in Section 2; in this section, the gray histogram of a ship wake image is acquired by the LBP method for constructing the BP artificial neural network training set. Then, the text presents, in Section 3, the proposed improved BP artificial neural network model for target characteristic recognition of ship wakes images; in this section, firstly the BP artificial neural network method is recalled, next an advanced artificial neural network method is put forward through the parameter modification of the multilayer BP artificial neural network. Experimental results are presented in Section 4. Finally, Section 5 concludes this paper.

2. Short state of the LBP

The LBP was first described in 1994 (Ojala *et al*. 1994). It is a type of feature used for classification in machine vision, and has since been found to be a powerful feature for texture classification. The basic LBP operator is an image pixel block with the 3×3 neighborhood, which corresponds to nine gray values. For each pixel block, comparing the center pixel value to each of its eight neighbors, if the center pixel's value is greater than the neighbor, mark "1", otherwise, mark "0". Thus it gives an 8-digit binary number, and then these numbers are read according to a given sequence (clockwise or counter-clockwise manner) as the characteristic value of the 3×3 rectangular element. The LBP operator's formula (Timo *et al*. 2009) and block diagram are shown as the following

$$LBP = \sum_{k=0}^{7} S\left(g_k - g_c\right) \times 2^k \tag{1}$$

where: $S(Z) = \begin{cases} 1, & Z \geq 0 \\ 0, & Z < 0 \end{cases}$.

Due to the LBP algorithm with discriminative power and computational simplicity, this methodology has led to significant progress in texture analysis. Many researchers also found ways to improve and expand this algorithm, and proposed some advanced operator, such as the expanded LBP ($LBP_{P,R}$) operator, the uniform LBP ($LBP_{P,R}^{u2}$) operator (Ojala *et al*. 2002) and so on. In the $LBP_{P,R}^{u2}$, the subscript represents using the operator in a (P, R) neighborhood (P denotes a circular neighborhood, R is its radius), superscript u2 stands for using only uniform patterns and labeling all remaining patterns with a single label.

In this section, a net train set data is constructed by the LBP algorithm. The used images are the ship wakes patterns at different speeds, the representative pictures of the five speeds now appear as shown in Fig. 4.

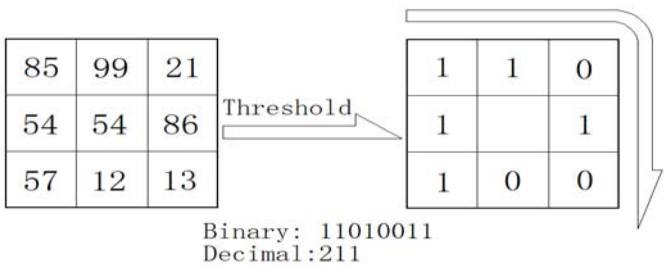


Fig. 3 Basic LBP operator

Fig. 4 Ship wake patterns at different speeds

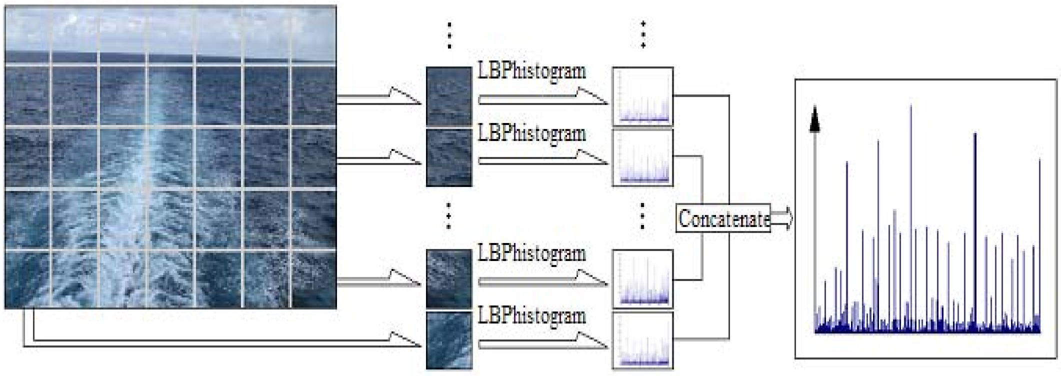


Fig. 5 Ship wake description with sub-area LBP histograms features

The gray histogram of each ship wakes image is acquired by the LBP method, but we also should be clearly aware that the histogram is only a relatively weak distinguishing feature. That is because the histogram just is the first-order statistical characteristics of image, and can not describe the image structural information. If only one LBP histogram is built for a whole image, then the local region wakes information will be lost. Consequently, the sub-area LBP feature will be an effective solution to this problem. The specific approach is that an image is appropriately partitioned into the M×N regions, and then the LBP texture descriptors are extracted from each region, and the histogram feature of each partition is calculated, finally these sub-regions' histograms are concatenated to form a global histogram of the image, as shown in Fig. 5.

3. The improved BP artificial neural network

3.1 The standard BP artificial neural network

The standard BP artificial neural network was designed by Rumelhart and McCelland, *et al.* in 1986. As shown in the Fig. 6, the BP artificial neural network consists of an input layer, an output layer and several hidden layers. The Fig. 6 illustrates a three-layer BP artificial neural network, the first layer consists of n input nodes; each of the n input nodes is connect to each of the h nodes in the hidden layer; the h output nodes of the hidden layer are all connected to each of the m nodes in the output layer (Li and Xu 2010).

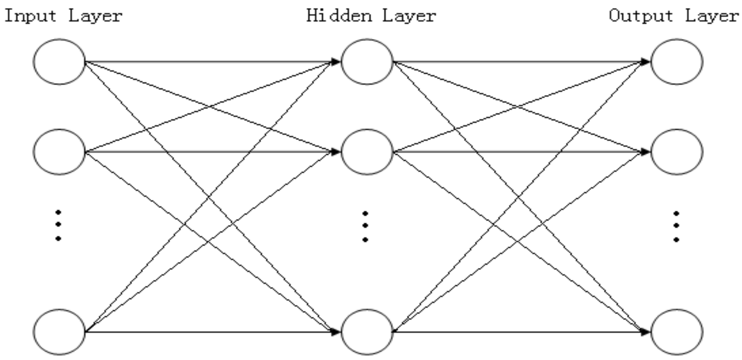


Fig. 6 The topological diagram of the standard BP artificial neural network model

The information transfers from nodes to nodes of different layers, and the degrees of the connections are controlled by the connected weights. The output of every node of the hidden layer and the output layer are calculated by

$$\left.\begin{aligned} s_j &= \sum_{i=1}^{n} \omega_{ji} \cdot x_i - \theta_j \\ b_j &= f\left(s_j\right) \end{aligned}\right\} \tag{2}$$

where $j = 1, 2, ..., p$; p denotes the number of nodes in the hidden or output layer, ω_{ji} is the connected weight, θ_j is threshold value, $f(\cdot)$ is activation function. The connected weights are adjusted during training by employing a method known as error back propagation. The weights change equations on the output layer and the hidden layer, and the hidden layer and the input layer are respectively (Ilunga and Stephenson 2005)

$$\left.\begin{aligned} \omega_{kj}^{o}\left(n+1\right) &= \omega_{kj}^{o}\left(n\right) + \alpha\delta_k^o b_k \\ \omega_{ji}^{h}\left(n+1\right) &= \omega_{ji}^{h}\left(n\right) + \alpha\delta_j^h x_i \end{aligned}\right\} \tag{3}$$

where, i is unit node in the input layer, j is unit node in the hidden layer, k is related to the output layer, α is learning rate, n is iterations, δ_k^o and δ_j^h are error factor of the output units and the hidden units respectively, the superscript "o" represents the output layer, the superscript "h" denotes the hidden layer. The computing formulas of δ_k^o and δ_j^h are shown as the following

$$\left.\begin{aligned} \delta_k^o &= \left(E_k - b_k^o\right) b_k^o \left(1 - b_k^o\right) \\ \delta_j^h &= \left(\sum_{k=1}^{q} \omega_{kj}^{h} \cdot \delta_k^o\right) b_k^h \left(1 - b_k^h\right) \end{aligned}\right\} \tag{4}$$

where: E_k is the expectant output, q denotes the number of nodes of output layer. The standard BP artificial neural network algorithm can be summarized as follows:

(1) initialize the connection weights and threshold values of the network;

(2) select a sample from the net train set as the input of the network;
(3) calculate the output value or output vector of the network;
(4) calculate the correction errors of the hidden and output layer;
(5) modify the connection weights and threshold values from the hidden layer to the output layer, as well as the input layer to the hidden layer;
(6) repeat steps (3), (4) and (5) until the errors are acceptable.

3.2 Improved BP artificial neural networks

The standard BP artificial neural network adopts the gradient-descent rule as the learning rate of the connection weights and threshold values. The connection weights and threshold values are modified from the negative direction of the gradient, without considering the previous experience. Therefore, this training is slow rate of convergence and liable to trap in local minimum value. In order to solve these problems, this paper analyzes various improved methods, and employs both the momentum factor and the self-adjusting of learning rate methods. The formula of the additional momentum method is shown as following

$$\omega(n)=\omega(n-1)+\Delta\omega(n)+\eta\left[\omega(n-1)-\omega(n-2)\right] \tag{5}$$

where $\omega(n)$, $\omega(n-1)$ and $\omega(n-2)$ corresponds to the weight of the state of n, $n-1$ and $n-2$, respectively; η $(0<\eta<1)$ is the momentum factor. The self-adjusting algorithm of learning rate can determine the value of step length. The basis idea is that if the connection weights are far from stable point (the training will reach the goal), the value of learning rate will become large, if the connection weights approach stable point (that is, the output error approaches 0), the value of learning rate will become small (Li and Xu 2010). The computational formula of the learning rate self-adjusting method as follows

$$\eta(t)=\frac{\eta_{\max}-t\left(\eta_{\max}-\eta_{\min}\right)}{t_{\max}} \tag{6}$$

where: $\eta_{\max}$ is the maximum learning rate, $\eta_{\min}$ is the minimum learning rate, $t_{\max}$ is the maximum iterations, t denotes the current iterations.

4. Experimental results

We carry out a series of experiments to examine the effect of each of our modifications on the results. On this trial, our goal is to achieve classification of different speeds of the ship wakes. The five kinds images of the ship wake at different speeds are chose in this work, the classified and recognized process is shown as in the Fig. 7.

In order to better deal with the wakes image, the image is pre-processed by the wavelet and discrete cosine transform. In addition, the statistical characteristics of the histogram are further extracted, which can well describe the most important characteristic of the image. When these statistical characteristics are turned into a sample feature vector, they will greatly reduce the dimensions of the histogram feature vectors. In the statistical characteristics of histogram, the means, standard deviation, contrast, entropy, energy, skewness, kurtosis and correlation are common features employed. This paper selects the means, standard deviation, contrast, energy, skewness and kurtosis of the LBP histogram as the input feature vector of each ship wakes image. The wakes images at five ship's speed are identified by the Arabic numbers 1, 2, 3, 4 and 5, respectively. And the extracting features are stored on the net training database. Therefore, every piece of the data will be a seven-dimensional vector, the first dimension is the category ID, and the rest are the feature vectors of the wakes images. In the database, the 134 samples have been chosen as analysis data, in which the quantity of the samples are 30 respectively at 8 knots, 16 knots and 17 knots ship wakes image, and the quantity of the samples are 22 at 12 knots and 18 knots ship wakes image. In addition, in these 134 samples, 90 of them are training set, the rest are test set.

Generally speaking, the nodal points of the hidden layer have important influence on the performance of neuron network, so it is necessary to fittingly select the nodal points of the hidden layer. This paper gives the relation between the classification error and the nodal points of the hidden layer, as indicated in figure 8, the partial data are shown in Table 1, the Fig. 8 illustrates the relation curve at 500, 600 and 700 iterations, respectively.

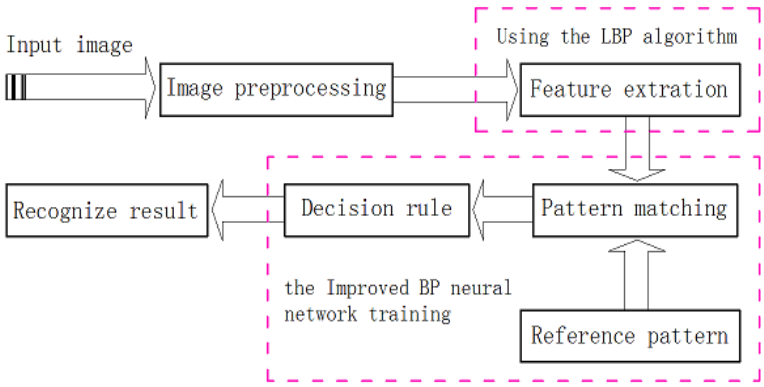
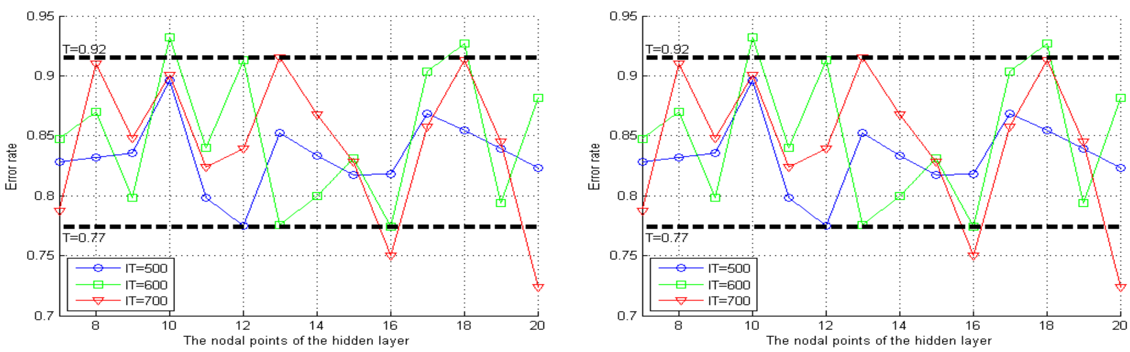


Fig. 7 The flowchart of ship wake image classification

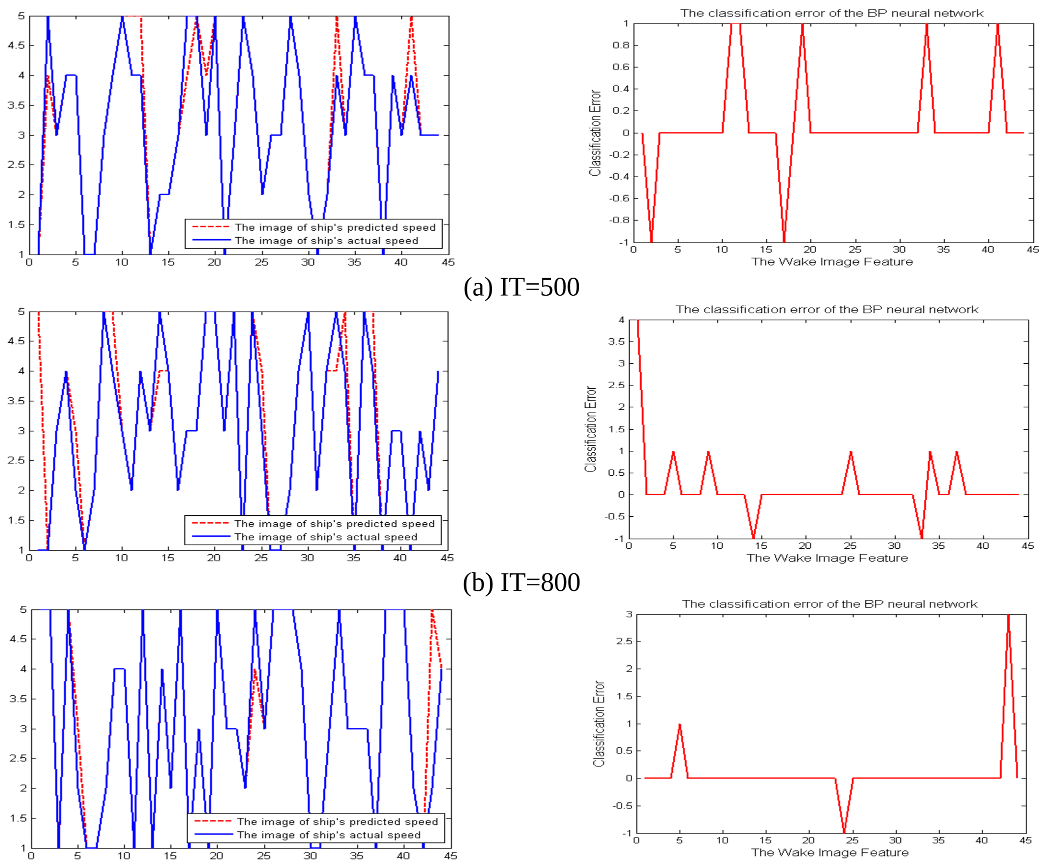


(a) using the additional momentum method (b) using the learning rate self-adjusting method

Fig. 8 the relationship between the classification error and the nodal points of the hidden layer

Table 1 Illustrative dataset to explain the classification error using the learning rate self-adjusting method

The nodal points of the hidden layer	Iterations(IT)		
	500	600	700
7	0.78750	0.82858	0.84762
8	0.83214	0.86984	0.90988
9	0.79816	0.83530	0.84834
10	0.89642	0.93182	0.90064
11	0.79864	0.84000	0.82422
12	0.77492	0.91278	0.83944
13	0.85254	0.77530	0.91556
14	0.83334	0.79958	0.86786
15	0.81714	0.83112	0.82834
16	0.81818	0.77386	0.75000
17	0.86848	0.90364	0.85778
18	0.85454	0.92666	0.91334
19	0.83944	0.79384	0.84476
20	0.82302	0.88182	0.72374



(a) IT=500

(b) IT=800

(c) IT=1000

Fig. 9 The classification forecasting and error of wake image

Table 2 Wake target recognition rate based on the proposed method

Iteration (IT)	Vessel's speed					average correctness rate
	8 knots	12 knots	16 knots	17 knots	18 knots	
500	0.9000	0.8889	0.8571	0.7500	0.6667	0.8181
800	1.0000	1.0000	0.9167	0.7778	0.6667	0.8667
1000	1.0000	1.0000	1.0000	0.9286	0.6667	0.9191

From the Fig. 8, we can find that the classification error values are concentrated in restricted regions, like the dotted path in the figure. Therefore, in the case of this work, the nodal points of the hidden layer have little effect on the output of the network. This paper designs a BP neural network model with three layers, as shown in Fig. 6. Due to the dimensions of the input feature vectors are 6, so the input nodal points are 6. And according to the empirical theory that the numbers of the hidden layer's nodes are about twice the nodal points of the input layer, so the hidden layer's nodal points are 12. Because the unspecified ship wakes images are five groups' images at different speeds, the output layer has five nodes. The connection weights and threshold values are to adjust according to the network prediction error when the BP neural network training. The Fig. 9 is the result of the network training by the additional momentum with the learning rate self-adjusting method, this work gives the classification forecasting and error curves at IT=500, 800 and 1000, respectively. The classified accuracy of the network is as shown in the table 2, from the results of the classification, we can see that the ship wake image classification algorithm based on the BP neural network has a high accuracy, and recognize the categories of the speeds that the wake image belongs to, this method has an average correctness rates over 80%. In addition, we also construct the nearest neighbor classification method for this experiment; the result of this approach is that the average recognition rate is only 46.15%. Regarding the nearest neighbor classification approach, the readers may be found in the literature.

5. Conclusions

This paper has introduced the LBP algorithm and put forward the improved BP neural network model for the ship wakes target recognition. The results of experiment show that the new method is feasible by the classification and recognition of the wakes image at five ship speeds. Furthermore, this paper achieves the anticipated results using the additional momentum with the learning rate self-adjusting method, and obtains the following conclusions:

(1) It is feasible that the ship wakes images are classified and recognized by our proposed method.

(2) In general, the nodal points of the hidden layer have greatly influences on the precision of the BP neural network forecast. But in the case of this experiment, the numbers of the hidden layer's node units can effect little changes in the result of the output.

(3) The experimental results show that the convergence only based on the learning rate self-adjusting method is poor; sometimes this method is apt to trap the local optimum. The proposed method may overcome these shortcomings to a certain extent.

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