Ship Identification Using Probabilistic Neural Networks (PNN)

Leila Fallah Araghi, Hamid Khaloozade , Mohammad Reza Arvan

Abstract— **This paper proposed ship classification based on covariance of discrete wavelet using probability Neural Network A set of ship profiles are used to build a covariance matrix by discrete wavelet transform using Neural Network.**
It is found that this method for ship classifier design offers good class discriminacy when trained with 5 ship classes. This method can discriminate noisy ship very well. Simulation results are very promising.

Index Terms— **covariance matrix, wavelet transform, probability Neural Network.**

I. Introduction

The challenge in studying the incised ship graffiti found on various buildings in the Bahamas is not in the interpretation of them as different ship types[1] .Ship classification is very important, in recently years many methods has been used for ship classification, in ship classifier identification of noisy image is very important. Many researchers has been worked in this area such as: Eric Besnard et al used Neural Network-based Response Surface Method for reducing the cost of computer intensive optimizations for applications in ship design.[1] Jorge Alves et al reported two experimental systems for ship classification from infrared FLIR images. In an edge- histogram approach, we used the histogram of the binned distribution of observed straight edge segments of the ship image [2].

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K. Michelle Vanhorn proposed that how ships were built in the eighteenth century as indicated by the archaeological and literary evidence. With a limited number of shipwreck excavations from the period, only tentative conclusions can be drawn about differences between ship types and the evolution of ship building techniques [3].

S. Musman worked on Automatic Recognition of ISAR Ship Images [4]

In the similar work Klepko, et al worked on Automatic pattern Recognition of ISAR Ship Images [5]. V. Gouaillier et al reported on an evaluation study of a ship classifier based on the Principal Components Analysis (PCA) [6]

Jorge A. Alves et al used invariant moments as input to a neural network, and train on silhouettes of polyhedral ship models. They obtained 70% accuracy with five classes and real infrared images. [7]. Jorge Amaral Alves explored a moment-based method for ship-type recognition. Numerical simulations were carried out with a set of five three-dimensional ship models. Moment-invariant signatures were used as the input to a neural-network classifier. The classifier achieved a 87.5% correct classification rate (within the set of test-models) for a complete range of point of view around the input ship model [8]

II. Ship Classification

Maneuvering large ships in rivers and confined waterways is a challenging and potentially hazardous task. Because ships are slow to respond to changes in the surrounding environment

And their own rudder movements [7] Five ship types ARE choosen to be included in the recognition class and therefore be modeled: namely, an aircraft carrier, a frigate, a destroyer, a research ship (Point Sur), and a merchant ship. The five models are shown in Figure 1.

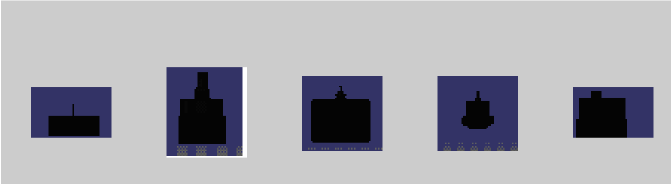

Figure 1: Views of the three-dimensional ship models

In this paper the covariance matrix of discrete wavelet transform of ship image has been used for Ship Classification using Probabilistic neural networks following figure shows the structure of Ship Classifier system that has been design in this paper. The output of neural network is the class of ship. This system can classify the noisy ship image very well...

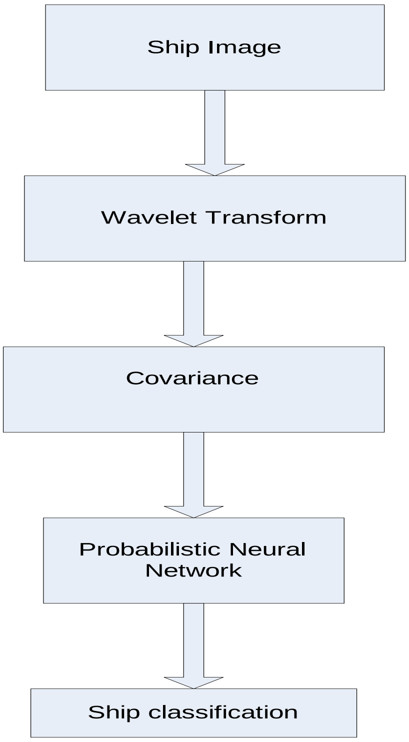

Figure 2: the structure of ship classifier system

III. A REVIEW ON PROBABILISTIC NEURAL NETWORK [3, 9, 10, 11]

The probabilistic neural network was developed by Donald Specht. His network architecture was first presented in two papers, Probabilistic Neural Networks for Classification, Mapping or Associative Memory and Probabilistic Neural Networks, released in 1988 and 1990, respectively. This network provides a general solution to pattern classification problems by following an approach developed in statistics, called Bayesian classifiers.

The probabilistic neural network uses a supervised training set to develop distribution functions within a pattern layer. These functions, in the recall mode, are used to estimate the likelihood of an input feature vector being part of a learned category, or class. The learned patterns can also be combined, or weighted, with the a priori probability, also called the relative frequency, of each category to determine the most likely class for a given input vector. If the relative frequency of the categories is unknown, then all categories can be assumed to be equally likely and the determination of category is solely based on the closeness of the input feature vector to the distribution function of a class.

Probabilistic neural networks can be used for classification problems. When an input is presented, the first layer computes distances from the input vector to the training input vectors and produces a vector whose elements indicate how close the input is to a training input. The second layer sums these contributions for each class of inputs to produce as its net output a vector of probabilities. Finally, a competed transfer function on the output of the second layer picks the maximum of these probabilities, and produces a 1 for that class and a 0 for the other classes. The architecture for this system is shown below [3].

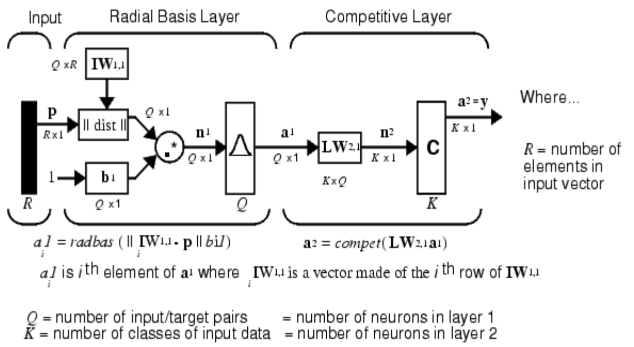

Figure 3: structure of neural network

It is assumed that there are Q input vector/target vector pairs. Each target vector has K elements. One of these elements is 1 and the rest are 0. Thus, each input vector is associated with one of K classes.

The first-layer input weights, IW1, 1 (net.IW {1, 1}), are set to the transpose of the matrix formed from the Q training pairs, P'. When an input is presented, the || dist || box produces a vector whose elements indicate how close the input is to the vectors of the training set. These elements are multiplied, element by element, by the bias and sent to the radbas transfer function. An input vector close to a training vector is represented by a number close to 1 in the output vector a1. If an input is close to several training vectors of a single class, it is represented by several elements of a1 that are close to 1.

The second-layer weights, LW1, 2 (net.LW {2, 1}), are set to the matrix T of target vectors. Each vector has a 1 only in the row associated with that particular class of input, and 0's elsewhere. (Use function ind2vec to create the proper vectors.) The multiplication Ta1 sums the elements of a1 due to each of the K input classes. Finally, the second-layer transfer function, compete, produces a 1 corresponding to the largest element of n2, and 0's elsewhere. Thus, the network classifies the input vector into a specific K class because that class has the maximum probability of being correct [9].

The Probability Neural Network is based on baesian classification and the estimation of probability density function it is necessary to classify the input vectors into one of the Bayesian optimal manner [10].

The PNN introduced by Specht is essentially based on the well-known Bayesian classifier technique commonly used in many classical pattern-recognition problems [11].

Consider a pattern vector 'x' with 'm' dimensions that belongs to one of two categories K1 and K2. Let F1(x) and F2(x) Bethe probability density functions (PDF) for the classification categories K1 and K2, respectively [11].

From Bayes' discriminant decision rule, 'x': belongs to K1 if:

$$\frac{F_1(x)}{F_2(x)} > \frac{L_1}{L_2} \cdot \frac{P_2}{P_1}$$

(1)

Conversely, 'x' belongs to K2 if

$$\frac{F_1(x)}{F_2(x)} < \frac{L_1}{L_2} \cdot \frac{P_2}{P_1}$$

(2)

where L1 is the loss or cost function associated with misclassifying the vector as belonging to category K1 while it belongs to category K2, L2 is the loss function associated with misclassifying the vector as belonging to category K2 while it belongs to category K1, P1 is the prior probability of occurrence of category K1, and P2 is the prior probability of occurrence of category K2treated at length in a variety of statistical textbooks. If the th training pattern for category K_1 is x_j, then the Parzen estimate of the pdf for category K_1 is given by equation (3) as[11]:

$$F(x) = \frac{1}{(2\pi)^{m/2}\sigma^{m} n} \sum \exp\left[\frac{(x - x_j)^{T}(x - x_j)}{2\sigma^{2}}\right]$$

(3)

IV. SIMULATION RESULT

In this paper covariance matrix of discrete wavelet transform of ship image has been used as input of probabilistic neural network. This method for ship classifier design offers good class discriminacy when trained with a 5 ship classes. This method can classify noisy ship image.

For example following figure shows noisy image that has been used as input of neural network and the output of system classifier.

The neural network can classify ship image very well.

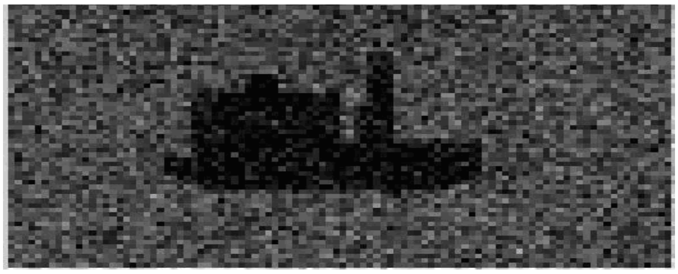

Figure 4.a: noisy image, input of system classifier

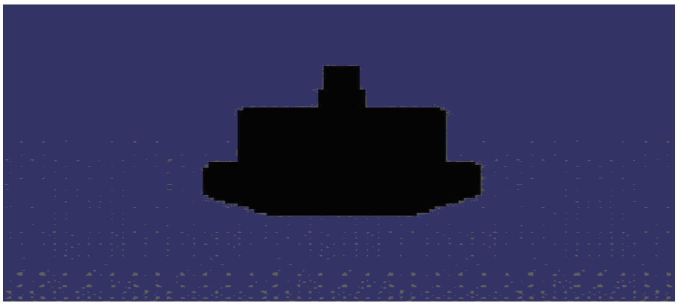

Figure 4.b: output of system ship classifier

V. CONCLUSION

This paper proposed ship classification based on covariance of discrete wavelet using probability Neural Network A set of ship profiles are used to build a covariance matrix by discrete wavelet transform using Neural Network

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