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Classification of Penaeid Prawn Species using Radial basis Probabilistic Neural Networks and Support Vector Machines

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Abstract

This research is to present a new approach for the classification of the Penaeid Prawn Species. The extraction of Texture features based on the Gabor filter is proposed in this method. These extracted features are used for the classification of Penaeid Prawn Species based on Radial Basis Probabilistic Neural Networks and Support Vector Machines. The texture of the prawn image are extracted based on different scales and orientations by which mean and standard deviation are calculated. The resultant Gabor feature values are fed as input to Radial basis Probabilistic Neural Network Classifier for the classification of the species. The experimental results show the performance of the extracted feature vectors for Penaeid Prawn species recognition. The RBPNN gives better recognition when compared with Support vector machines.

Keywords*: We Feature Extraction, SVM, RBPNN, Penaeid Prawn, Species, Gabor*

1. Introduction

The basic need of prawn species recognition system using image processing techniques is increasing day by day. The recognition of prawn species is very important for the farmers of aquaculture. The processing speeds still fail to meet though accurate algorithms are available [1]. At present Penaeid Prawn species recognition has more attention from researchers of various areas like biometrics, image processing, pattern recognition, and neural networks. The different types of Penaeid prawns species used in this research work are *PenaeusIndicus, PenaeusMonodon* and *Vennamei*. Different species can be identified based on different features that vary. The classification can be done by analyzing the prawn features. To classify prawn species the texture features are extracted. Texture is a repetitive pattern in which the elements are kept based on a placement rule. The feature vector contains a set of numerical values derived based on rule that describes the texture. Rather than a point texture occurs over a region or an area. Many features may vary among the different species of the prawn. The classification is done based on the extracted features of the prawn. This difficult and time consuming task was carried out by taxonomists. Prawn species recognition from images is very difficult task in computer vision due to lack of proper representations or proper models. Also different species of prawns take various biological variations which increase the difficulty of recognition. Many prawns exhibit different texture features that are evident and can be very much useful for the species recognition. It is very important to give meaningful

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features for exploring the features of the prawn texture. There are many methods for extracting texture features like Gabor filter, gray-level co-occurrence matrix [2]. These methods give good results to prawn texture analysis but they fail to classify adequately the prawn texture. Now a day's RBPNN and SVM are the classifiers that are popularly used by the researchers for the better accuracy of classification due to best performance. This study is done to compare the performance of the RBPNN and SVM in classifying the Penaeid Prawn species.

2. Image Acquisition

The images of the different prawn species namely *PenaeusMonodon*, *PenaeusVennamei* and *PenaeusIndicus* were shot using SONY 50Xcamera, by maintaining a distance of 20cms between prawn and the camera. The prawn images were taken from top view with white background. In this work 300 image samples of each species of *Penaeidprawn* of different shapes, sizes and orientations were taken. These samples have been collected from different sources like ponds, research centre's, harbors, aqua labs and ports. Some of the images acquired are shown in Figure 1. After image acquisition preprocessing must be done. The main use of image preprocessing is to improve the quality of the image [3] As it is not easy to interpret the images of prawn species, the quality of the image is to be enhanced and make the results much more effective.

Figure 1. Images Acquired

3. Extraction of Features using Gabor Filter

The Gabor filters are defined as group of the wavelets in which each wavelet captures energy at a particular frequency and in a particular direction [4]. The texture features of the Penaeid prawns can be analyzed by the tunable property of scales and orientation of the Gabor filter.

The two-dimensional Gabor Wavelets g(x,y) can be defined as follows(5-7).

$$g(x, y)=\frac{1}{2\pi\sigma_x\sigma_y}\exp\left(-\frac{1}{2}\left(\frac{x^2}{\sigma_x^2}+\frac{y^2}{\sigma_y^2}\right)+2\pi jWx\right) \quad . \tag{1}$$

$$G(U, V) = \exp\left\{-\frac{1}{2}\left[\frac{(U-\omega)^2}{\sigma_u^2}+\frac{V^2}{\sigma_v^2}\right]\right\} \tag{2}$$

Along x-axis W is the frequency of the sinusoidal plane.

σ_x, σ_y, are the constants with respect to x and y axis respectively. Let g(x, y) through generating function.

$$g_{mn}(x, y) = a^{-m}.\ g\ (\tilde{x}, \tilde{y}) \quad (3)$$

m and n are the total number of scales and orientations With, m=0, 1, 2……, M-1, n=0, 1, 2,…N-1,

$$\tilde{x} = a^{-m}(x \cos\theta + y\sin\theta\ ) \quad (4)$$
$$\tilde{y} = a^{-m}(-x \sin\theta + y\cos\theta\ )$$

Where m and n are integers specifying the scale and orientation and Where a >1 and θ=2π/N.

$$\mu_{mn} = \iint |W_{mn}(x, y)| dxdy$$
$$\sigma_{mn} = \sqrt{\iint \left(|W_{mn}(x,y)| - \mu_{mn}\right)^2 dxdy} \quad (5)$$

When Gabor filter is applied to a prawn image then it responds with the output maximally at only some particular edges where the orientation is equal to θ. Based on this the edges at all orientations of the image can be detected. For any image I(x, y) the Gabor wavelet transformation is given as:

$$w_{mn} = \int I(x_1, y_1) g^{*}{}_{mn}(x - x_1, y - y_1) dx_1 dy_1 \quad (6)$$

Where * is the complex conjugate and the Gabor wavelet transformation is denoted by w_{mn}. At orientation m and n. Gabor wavelet transformation for the prawn images is computed at 5 orientation and 4 scales. The mean and standard deviation represents the region for classification.

Based on the mean and standard deviation a database of all the feature values is created from which a Gabor feature matrix can be formed. The resultant feature vector is given as

$$f=[\mu_{00}\sigma_{00},\ \mu_{01}\sigma_{01},\ \ldots\ldots\ldots\ldots\ldots\mu_{3,5}\sigma_{3,5,}] \quad (7)$$

This feature vector can be used for classification of the Penaeid prawn species.

4. Methodology

4.1. Radial Basis Probabilistic Network (RBPNN) Classifier

After the extraction of the prawn features from the images then the next step is to recognize the texture of the prawn based on Radial basis probabilistic networks. The RBPNN is fundamentally developed from the probabilistic neural networks and radial basis function neural networks [8-11].Therefore Radial basis probabilistic network classifier consists of two networks. And RBPNN also covers the drawbacks of these models. The RBPNN consists of four layers: one input layer, output layer and two hidden layers. The first hidden layer usually consists of hidden centers from a set of training data and second hidden layer actually sums the outputs generated by the first hidden layer based on the Classes to which the hidden centers belong. Usually weightvalues of the hidden layer which is second is 1.The last layer is the output layer, and it does the nonlinear mapping by performing tasks like classification. Orthogonal least square algorithms is used for Training of the network so that quick convergence will be there along with good accuracy. The algorithm is as follows:

$$y_i^{\,o} = \sum_{k=1}^{M} W_{ik} h_k(x) \quad (8)$$

$$h_k(x) = \sum_{i=1}^{n_k} \phi_i(x, c_{ki}) \sum_{i=}^{n_k} \phi_i\left(\|x - c_{ki}\|_2\right), k = 1,2....M$$ x is the input (9)

$y^o i$ is the output of the i^{th} neuron. W_{ik} is the weight matrix $h_k(x)$ is the k^{th} output n_k is the hidden center vector for k^{th} class of the hidden layer. The kernel function is $\phi_i\left(\|x - c_{ki}\|_2\right)$ and can be written as follows.

$$\phi_i\left(\|x - c_{ki}\|_2\right) = \exp\left(\frac{-\|x - c_{ki}\|^2{}_2}{\sigma^2}\right) \tag{10}$$

If there are m training samples then it can be shown as

$$Y^0 = HW \tag{11}$$

where W is the weight matrix

$$W = R^{-1}\hat{Y} \tag{12}$$

$$H = Q\begin{bmatrix} R \\ L \\ 0 \end{bmatrix} \tag{13}$$

$Q^T Y = \begin{bmatrix} \hat{Y} \\ Y \end{bmatrix}$ where Q is an orthogonal matrix with n rows and n columns. (14)

4.2. Support Vector Machine

Support vector machines (SVM) identify the patterns and analyses that is used for classification. The basic idea of SVM is to split the data in an optimal way. If a set of training samples is given where each marked belongs to one or more classes, Support Vector Machine maps the features non-linearly into n dimensional feature space when provided with a feature set represented in the space In SVM inputs are given in the form of the scalar products. An attribute in SVM is called as a predictor variable and the feature is a transformed attribute [12]. The feature vector defines the hyper plane. To separate the clusters of different classes Hyper plane is constructed as shown in the Figure2The margin represents the distance between hyper plane and support vectors. SVM analysis tries to positions the margin in such a way that space between it and support vectors are maximized.

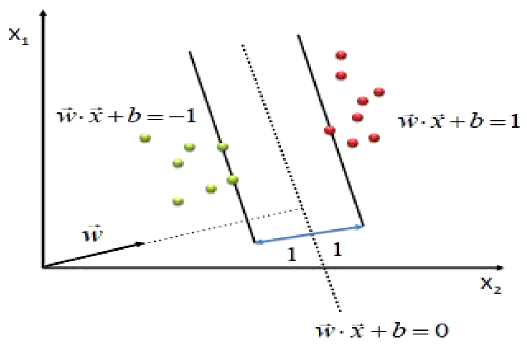

Figure 2. Support Vector Machine

Design of SVM

The Hyperplane [13] is shown as

$$\sum_{i=1}^{N} \alpha_i d_i P(x, x_i) = 0 \qquad (15)$$

Where $P(x, x_i) = \varphi^T(x)\varphi_1(x)$

It shows inner product of two matrices input matrix a and inputs a_i.

Where $$W = \sum_{i=1}^{N} \alpha_i d_i \varphi(x_i) \qquad (16)$$

$$\varphi(x) = [\varphi_0(x), \varphi_1(x), \ldots, \varphi_{m_1}(x)]^T \qquad (17)$$

$\varphi_0(x)=1$ for all x.

The function of the kernel is given as

$$P(x, x_i) = (1 + x^T x_i)^2 \qquad (18)$$

The lagrange multipliers {} for i =1…N that maximize function Q( ) is given by

$$Q(\alpha)\sum_{i=1}^{N} = \alpha_i - \frac{1}{2}\sum_{i=1}^{N}\sum_{j=1}^{N} \alpha_i \alpha_j d_i d_j P(x_i, x_j) \qquad (19)$$

With the constraint as

$$\sum_{i=1}^{N} \alpha_i d_i = 0 \text{ for i=1,2..N.} \qquad (20)$$

The linear weight vector W_0 is calculated using the formula:

$$W_0 \sum_{i=1}^{N} \alpha_{0,i}\, d_i \psi(x_i) \text{ where } W_0 \text{ represents the bias } b_0 \qquad (21)$$

5. Experimental and Results

The proposed system is implemented in MATLAB 7.11 by implementing the RBPNN and SVM Model. The Front End is designed using GUI environment. To perform the classification correctly large database is required. 300 images of prawn species have been collected and kept in the database. For the extraction of Prawn features we have to convert all the colour prawn images into gray scale before processing. The original images of three species of prawns are shown in Figure 3 and the gray scale images are shown in Figure 4.

Figure 3. Original Images

Figure 4. Gray Scale Images

All the Penaeid prawn images are resized to 256 X 256 pixels. Among many types of image formats like png, tiff, bmp, jpeg or jpg, we are choosing jpeg format of the image because jpeg format takes less memory space, easily viewable from internet, use millions of colours and perfect for many types of images. 25 % of the Penaeid prawn samples for each type of species is taken as testing set and the remaining 75% of the samples for a training set. For getting the accurate results, the Gabor parameters were being tested with different values of scales (m) and orientations (n) as shown in Figure 5.

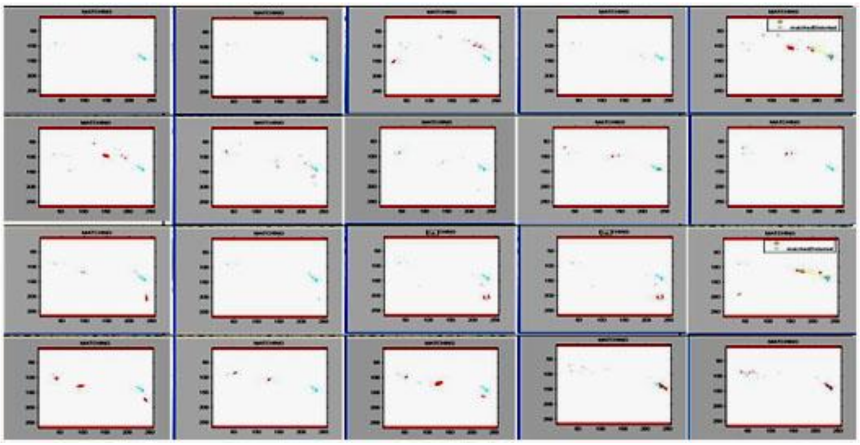

Figure 5. Gabor Features Extracted

The average recognition rates are shown in Table 1.Three different prawn species were used for identification. They are Peaneaus Monodon, Vennamei and Indicus. The results are being compared with average recognition rate.

Average recognition rates are shown in Table 1.

Table 1. Average Recognition Rates

Gabor Filter Features	Recognition rate using RBPNN	Recognition rate using SVM
m=4,n=6	53.71	50.48
m=5,n=6	62.58	68.22
m=6,n=6	69.03	71.45
m=7,n=6	67.42	73.06
m=4,n=5	52.90	52.10
m=5,n=5	64.19	67.42
m=6,n=5	66.61	69.84
m=7,n=5	69.84	71.45
m=4,n=4	56.13	54.52
m=5,n=4	67.42	66.61
m=6,n=4	69.84	70.64
m=7,n=4	69.84	72.26
m=8,n=4	70.56	71.45

From Table 1, it can be found that the orientation n=4 achieves the best performance in prawn species recognition and the overall recognition rate of the PenaeidPrawn species can be improved when orientation n=4 and increasing the scales. By taking more features of Gabor filter accuracy can be improved in the classification of prawn species but computations will be delayed. By comparing the effectiveness of the Gabor features with SVM and RBPNN, it shows that RBPNN classifier achieves better results when the feature vectors has low-dimensions, and also the SVM gives better classification accuracy while the dimension of feature vectors is high.

6. Conclusion

In this research paper for PenaeidPrawn Species recognition Gabor features and RBPNN classifier are used. The training of the neural network was done using orthogonal least square algorithms for classifying feature vectors and are tested on different orientations and scales. The RBPNN can give similar results as SVM, when the dimension of the feature vectors is high. It has been identified in experiment that RBPNN got an accuracy of higher classification when the dimensions of feature vectors are low.

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