

Diagnosis of Fish Disease using UKF and Elman Neural Networks

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Abstract: At early stages, identification of fish disease is very difficult because it can prevent from spreading disease underwater. The identification of fish disease is a manual process so far. Hence with a vision of contribution to aquaculture, this new scheme to categorize and detect (Epizootic Ulcerative Syndrome) EUS infected and non fishes are proposed here. The need for an image based automated process arises because the manual process of identification is tedious. This work depends on the prior data base obtained from information fusion study of integrated navigation with GPS/INS. To deal with the uncertainty of error covariance and noise in diagnose the fish disease, the article propose a novel fish disease Identification approach where the Unscented Kalman Filter (UKF) with different covariance. The characteristics like GLCM are pulled out for classification of Non-EUS and EUS affected fish by Algorithms pertaining to Machine Learning to obtain classification accuracy with the help of Elman Neural Network (ENN). This testing was done by MATLAB simulation software with real time database containing images of EUS affected fish.

Keywords: Fish disease, Unscented Kalman Filter, Feed forward neural network and Elman neural network.

1. INTRODUCTION

EUS is a dangerous ulcerative disease which occurs in freshwater and back water fishes in the countries like Japan, Australia, South-East Asia, Eastern USA and of Africa. Nearly 100 types of fishes have been inclined by EUS but however just a pair of reports have been verified by proving the key investigative changes in the characteristic analysis. Mulletts and snakeheads which survive in salt and fresh water are seriously influenced [1]. Exact findings of EUS are necessary to elude confusion with other ulcerative conditions. It is necessary to take note of that ulcer is a non-open clinical injury which might be brought about by frequent unique reasons [2]. All ulcers are not EUS ulcers as they are not in epizootic extents or then again not event in nature. Image processing algorithms are projected to locate out the EUS illness by automatically instead of manual identification. Fish is a nutrition of a huge number of individuals [3- 4]. Different edge detection techniques have been used to recover the quality of fish with the help of several fish pictures.

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2. LITERATURE SURVEY

Fish is a protein rich food for large number of individuals [3- 4]. Various segmentation algorithms are implemented on images of the fishes which are infected and non-infected by EUS. Many of the images obtained were found to be corrupted with salt and pepper noise which was eliminated using a suitable filter. The de-noised images are then focused to characteristic extraction by Principal Component Analysis (PCA) to shrink the dimension of the characteristics. HOG features are extracted by many scientists using Support Vector Machine (SVM)[5] provided a significant performance.

It is a projected one to facilitate the human action from the video stream of HOG highlights and was classified by Probabilistic Neural system (PNN) classifier [6]. The Region of Interest (ROI) is extracted from the video from which the HOG features are extracted and used for shape based identification of the EUS diseased fishes. Experiments are carried out on the KTH database which gives better execution as far as 100% as compared to the other database which gave a performance of 89.8%.

Color markers are used to identify the infected area on the fishes [7, 10]. The main drawback with this method is that false points can be identified as infected area due to automatic allocation as a result of which the normal area could be marked as infected area [8].

3. MATERIALS AND METHODS

Many filters on state estimation are designed to deal with removal of noise present in images [4]. The standard Kalman Filter (KF) is usually used and it is an influential tool for linear systems having dynamic nature. To meet the escalating requirement of complex nonlinear systems, improved versions of KF are used.

3.1. Unscented Kalman Filters (UKF)

The performance of Extended Kalman Filter (EKF) is appreciably restricted to its stability and complexity, which is evaluated by the computation of Jacobian matrix [5, 6]. The probability density of state distribution can be calculated using Unscented Kalman filter (UKF) by unscented transformation, resulting in the estimation accuracy of subsequent mean and covariance of Gaussian random variable which could go up to third order [8,9] is used and the flowchart is given in Figure 1.

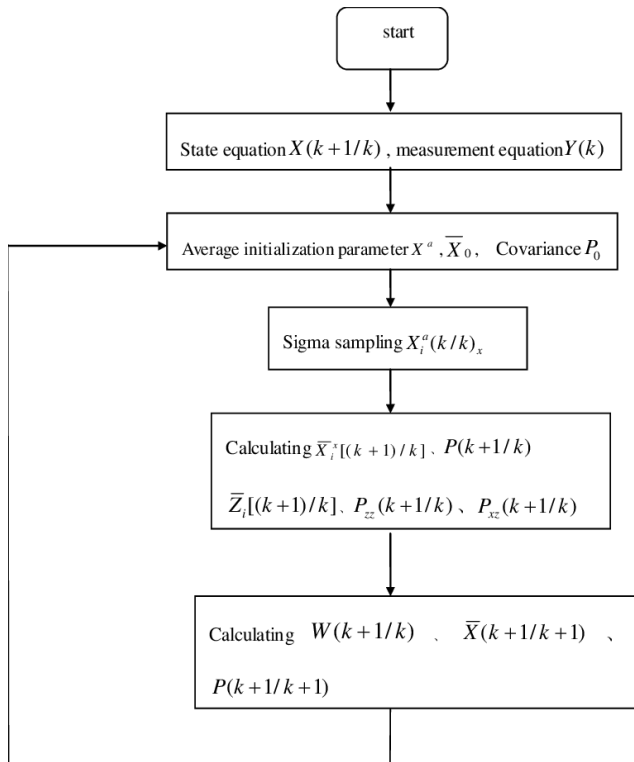


Figure 1. Flowchart for UKF

3.2. Gray level Co-occurrence Matrix (GLCM)

In statistical quality analysis, statistical distribution is computed from the observed intensity values at specified locations relative to the reference image. Based on the number of pixels the statistics are segregated as first, second and other statistics. The features of second order include Gray Level Co-occurrence Matrix (GLCM) for extracting quality information. The relationship among three or more pixels is need for computation of third and higher order statistics. The characteristics [1] extracted from standardized symmetrical GLCM are and is depicted in Figure 2 using a flowchart.

1. Energy value
2. Correlation.
3. Homogeneity
4. Contrast.

3.3. Elman Neural Network (ENN) by Back Propagation Algorithm (BPA)

In such network architecture, no feedback link because data flows from input to output neurons in one way. Networks with recurrent links are used to associate static patterns with output patterns that are serially ordered. Concealed nodes called the hidden layer nodes visualize their own previous output to serve as a channel for subsequent behavior. In recurrent connection network memory is provided. It is treated as a black box where a supervised FFNN uses 2 techniques to learn and predict for which the architecture is shown in Figure 3. The learning process requires the inputs and the desired outputs. The weight updation takes place in the reverse propagation phase after the computation of the Mean Squared Error (MSE) in its forward phase. Always the designed output should be as near as possible to the required output. The designed process takes input and generate, using the concealed state, the most likely output according to its past “training experience”.

That’s why machine learning is called sometimes model fitting as indicated in Figure 4.

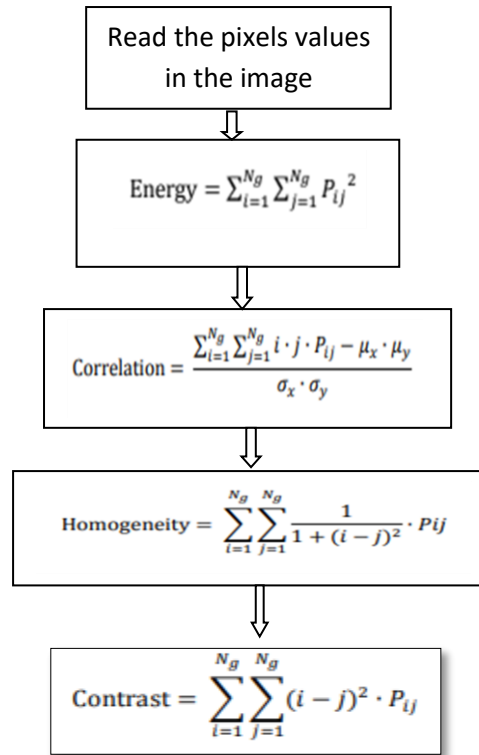


Figure 2. Flowchart for GLCM computation

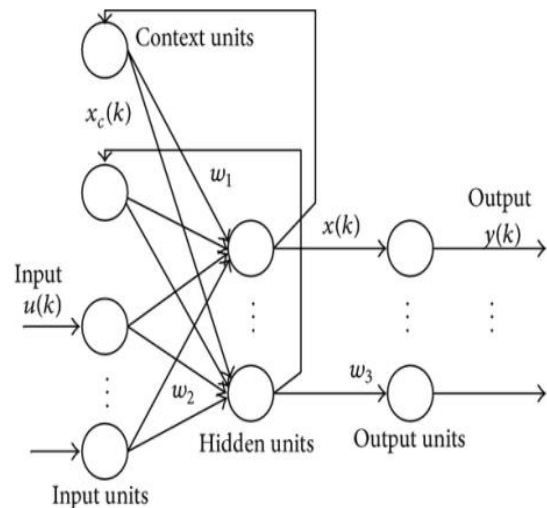


Figure 3. Architecture for Elman Neural network

4. METHODOLOGY

A water proof video camera is attached to the bottom of the ship which when navigation through the sea water captures the video of the fishes. This video is segregated into frames. Then the noise removal is done using UKF followed by GLCM feature extraction. To classify the EUS non-infected and infected fishes the characteristics are undergone for working out and testing the ENN with BPA as shown in Figure 5.



5. RESULTS AND DISCUSSION

A total of nearly 233 samples relating to the images of the fishes affected by EUS and non-infected by EUS are collected. Nearly 173 samples are used for working out and remaining 60 samples are used for testing. These images may or may not be corrupted by noise. If the samples are corrupted by noise, then it is eliminated using UKF. The efficiency of UKF is estimated using Standard Deviation of the error which states that the value is only in the range of 900×10^{-4} to 1800×10^{-4} . Then GLCM features in Table 1 are extracted from the filtered output. These features are used to train and test the ENN with BPA to sort the EUS infected and non-infected fishes as shown Figure 7. The experimentation is done using MATLAB simulation software.

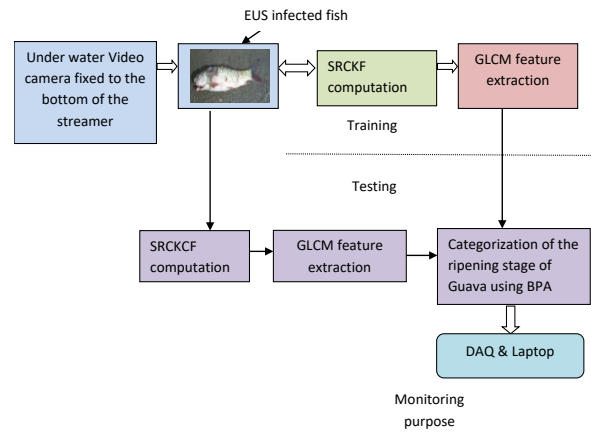


Figure 5. EUS identification in fishes under the sea water

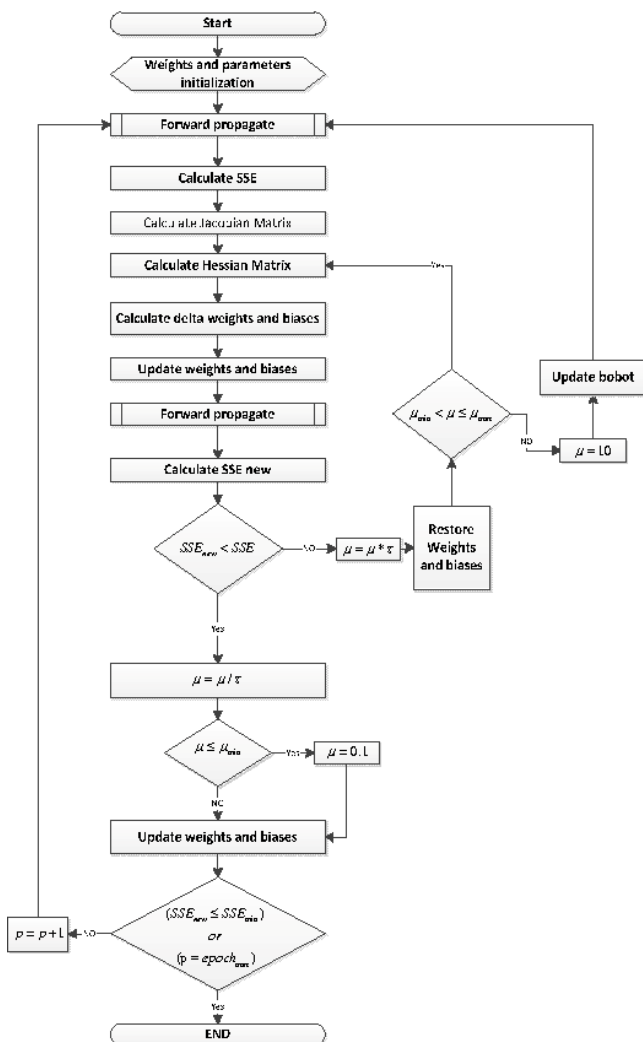


Figure 4. Flowchart for Elman neural network trained with BPA

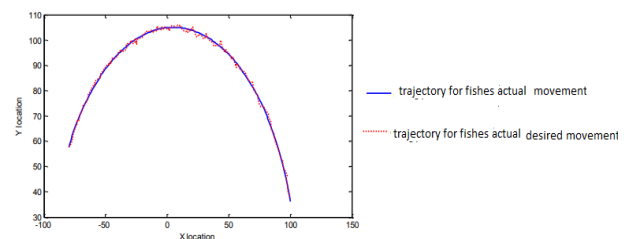


Figure 6. Performance Evaluation of UKF

Table 1. Feature extraction

S.No	Energy	Correlation	Homogeneity	Contrast	Status of the fish
1.	12678	0.6	134	22	EUS infected
2.	15334	0.8	126	21	EUS infected
3.	13416	1	115	24	EUS infected
4.	2469	0.2	1221	68	EUS non-infected
5.	3692	0.4	1569	62	EUS non-infected
6.	4221	0.1	1328	60	EUS non-infected

6. CONCLUSION

The proposed work concludes that the suggested combination gives optimal classification efficiency of 98% to identify the EUS affected and non-affected fishes after applying this intelligent learning algorithm. EKF paved way to eliminate the noise for better increase in classification efficiency. The testing has been completed with real time images of the EUS disease affected and non-affected fish images dataset. It automatically detects the fishes affected by EUS disease.



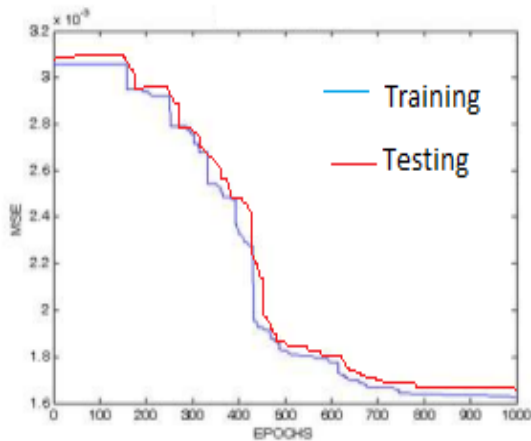


Figure 7. Training and Testing for identification of EUS infected and non-infected fishes by ENN

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