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A Survey on Underwater Fish Species Detection and Classification

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Abstract— Fish species recognition is a challenging task for research. Great challenges for fish recognition appear in the special properties of underwater videos and images. Due to the great demand for underwater object recognition, many machine learning and image processing algorithms have been proposed. Deep Learning has achieved a significant results and a huge improvement in visual detection and recognition. This paper mainly reviews some techniques proposed in past years for automatic fish species detection and classification.

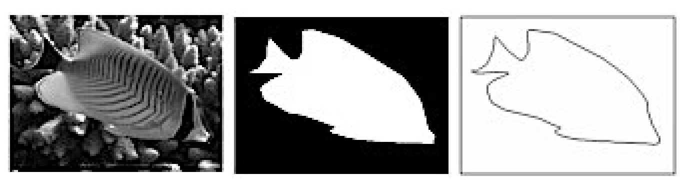
Keywords— Fish Recognition;Fish Classification;Feature ExtractionImage Processing;Neural Network;Deep Learning.

I. INTRODUCTION

Live Fish recognition in the open sea is a challenging task. They have been investigated for commercial and environmental applications like fish farming and meteorological monitoring. Traditionally, aquatic experts have employed many tools to examine the appearance and quantities of different types of fish using methods such as casting nets to catch and recognize fish in the ocean, diving to observe underwater, using photography[1], combining net casting with acoustic(sonar)[2].Quantity of collected data is not enough using these methods. They are not well equipped to capture normal fish behaviors. Nowadays, much more convenient tools like hand-held video filming devices, Embedded video cameras are also used to record underwater animals. Fish presence and their habit at different times can also be observed. This equipment has produced large amounts of data and informatics technology like computer vision and pattern recognition are required to analyze and query large about videos. Statistical details about specific oceanic fish species distribution ,besides an aggregate count of aquatic animals can assist biologists resolving issues ranging from food availability to predator-prey relationships. Since fish can move freely and illumination levels change frequently in such environments, the recognition task is challenging. The challenges faced during classification of underwater fish species include noise, distortion, overlap, segmentation error and occlusion. As a result, this task remains an eminent research problem. Prior research is mainly restricted to constrained environments and the datasets were probably small. The accuracy also is very unsatisfying under constraint and unconstraint conditions.Many scientists in the field of ecology collect large amounts of video data to monitor biodiversity in their species applications.But manual analysis of this data is time consuming. However this large scale analysis is important to obtain the knowledge to save ecosystem that have a large impact on the human population. So tools for automatic video analysis need to be developed. In this paper we first discuss about some techniques based on shape, color, texture and hierarchical classification approaches used for fish detection and classification. The last section review about deep learning based techniques.

II. LOW-LEVEL FEATURE BASED APPROACH

Many fish species have similar size, color and shape which makes the identification process very difficult. This section reviews species recognition based on geometric features such as size and shape and appearance features such as color and surface texture.



Fish Contour .This figure is from paper[5]

This paper [3] presents the design of an automated fish species recognition and monitoring system. Several shape-based recognition methods were implemented on the prototype system for testing. Curvature function analysis is used to find critical landmark points on the fish contour. Fourier descriptors of a bend- angle function for shape description meet all invariant requirements. For recognition process, power spectrum and phase angle information is calculated as shape descriptors. Since the performance of these shape methods did not give satisfactory result, a new method called Turn Angle Distribution Analysis(TADA) was developed and tested on larger database. This method allows the contour for the current image to be matched against species-specific contours.300 images of 6 species were tested for recognition with impressive results. TADA algorithm is easy to set up and does not require extensive training. Computational overhead is low and small number of parameters are used.

FIRS[4] proposes five subsystems for image recognition. They are image acquisition, image preprocessing, feature extraction, image recognition and result presentation. To recognize the fish image it employs Artificial Neural Network(ANN) and Euclidean distance method(EDM).It extracts eight main fish features. Dataset consists of 900 fish images of 30 fish species.600 fish images are used for training and 300 fish images for testing. FIRS recognize all 30 species of training fish images with a precision of 99.00% for ANN and 81.67% for EDM. The ANN gave better precision than EDM but EDM uses less processing time than ANN. To have better precision rate FIRS system need to access more fish features and must have a larger database of fish images.

In this paper[5],an automatic fish classification system that operates in the natural underwater environment is proposed. Texture features are combined with shape descriptors preserved under affine transformation. Using statistical moments of grey-level histogram, spatial Gabor filtering and properties of the co-occurrence matrix, texture features are extracted. Shape features are extracted using CurvatureScaleSpace transform and the histogram of Fourier descriptors of boundaries. Affine transformation is applied to the acquired images to represent 3D fish shape. This describes the different views while fish move in the water. Two types of affine invariant features are used. Principal Component Analysis is used to reduce many values in vector produced by texture and the boundary features of affine transformation .For large amount of data, K-fold cross validation method was used.320 images of 10 different fish species are used. The use of color features for a better fish description is considered to be the future work.

This paper[6] recognizes isolated pattern of fish, as the system acquire an image consisting of pattern of fish. The image is processed into several phases like image preprocessing and feature extraction before recognizing the pattern of fish. The image is processed and then recognized the given fish into its cluster. The clustered fish are categorized into poison or non-poison fish and categorizes the non-poison fish into its family. Image segmentation is based on color texture measurements. The Gray Level Co-occurrence Matrix(GLCM) is used for the extraction of feature values from color texture. In the color texture ,we extracted the GLCM’s feature from the whole pattern of interest(fish) which differs from previous studies which considered only small parts of the pattern of interest. Shape characters of fish play a important role in fish recognition based on color texture measurements. Different feature values obtained from the shape characters helps to distinguish between each family.

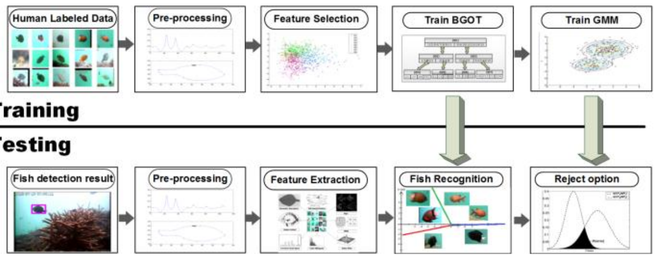
In this paper[7],an algorithm for shape and color descriptors are generated from fish images. Fish bending and deformations will not affect the descriptors. The descriptors crudely sort the fish. A shape grid is derived from the shape of the fish. From the shape grid, a set of descriptors is obtained. These shape descriptors are normalized to make them invariant to size by dividing them with the square root of the area of fish. They can be used as a set of variables to sort the fish by species. Average R,G,B values obtained from the tail and nose elements of the shape grid is used to sort the fish by species. Discriminant analysis is used to process the shape descriptors and the color data and it employs linear combinations of variables which is used to distinguish between the different species of fish.

III. HIERARCHICAL IMAGE CLASSIFICATION

Hierarchical classification inherits from the divide and conquer tactic. A customized classifier is trained with special features at each level. Hierarchical classification has several advantages. It divides all classes into certain subsets and leaves similar classes for a later stage. This strategy balances the load of any single node. This method applies customized set of features to classify specific classes. It achieves better performance on similar classes. This method also exploits the correlations between classes and find the similar group.

This paper[8] proposed a hierarchical classification approach for live fish recognition. Heuristic method is used to construct an automatically generated Balanced Guaranteed Optimized Tree(BGOT).66 types of features are extracted from the color, shape and texture properties from different parts of the fish. Forward Sequential Feature Selection(FSFS) is used to reduce the feature dimensions. The features selected from FSFS are used by Support Vector Machine(SVM).BGOT is used to control the error accumulation in hierarchical classification. Data is acquired from a live fish dataset with 3178 fish images of 10 different species. The automatically generated hierarchical tree achieves about 4% better accuracy compared to state-of-the-art technique.

In this paper[9] a novel rejection system in a hierarchical classification method for fish species recognition is proposed. A Gaussian Mixture Model(GMM) is applied at the leaves of the hierarchical tree as a reject option. This model evaluates the posterior probability of testing samples.2626 dimensions of features such as color, shape and texture properties from different parts of the fish are computed and normalized. FSFS is used which utilizes SVM as a classifier. FSFS is used to select a subset of effective features that distinguishes samples of a given class from others. The reject function is combined with a Balance-Guaranteed Optimized Tree(BGOT) hierarchical method.



Frame work of GMM for Fish Recognition. This figure is from original paper[9].

This paper[10] proposes a novel Balance-Enforced Optimized Tree with Reject(BEOTR) option classifier for live fish recognition. This paper contributes on a hierarchical classification method suited for greatly unbalanced classes, classification-rejection method to clear up decisions and reject unknown classes. It also contributes on the application of the classification method to free swimming fish. The Grabcut algorithm[11] is employed to segment fish from the background. A streamline hypothesis is proposed to align the fish images to the same direction. BEOTR process the fish samples from an imbalanced dataset. A GMM model is applied after the BEOTR method to evaluate the posterior probability of testing samples and provide the reject option. The reject option filters out less confident results such as noise, classification errors or unknown classes. BEOTR achieves 6% better accuracy compared to SVM and other hierarchical classifiers.

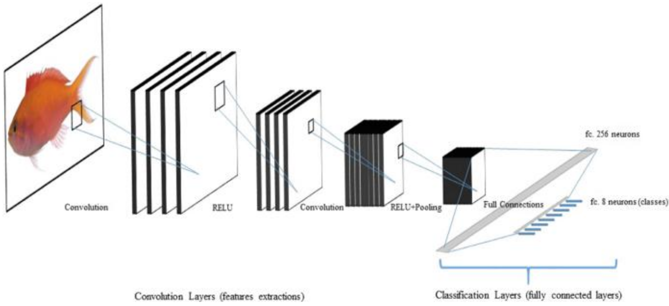
IV. DEEP LEARNING BASED APPROACH

Since 2012 Neural Network came back as a strong possibility for classification tasks. By integrating convolutional layers, Deep neural Network(DNN) are able to create features vectors and classify them. Neural Network is a mathematical model which tries to mimic human brains[12].Like SVM, neural networks may classify feature vectors after a training phase. A neural network is composed of interconnected nodes called neurons and each neuron of each layer receives a signal from the neurons of the previous layer. This signal is altered according to an activation function and transferred to the neurons of the next layer. Each layer of a neural network except the first one which receives the feature vector and the last one are called hidden layers. To make a network able to build its own feature, a simple network is moved to Convolutional Neural Network(CNN).Each convolutional layer transforms the signal sent from the previous layer using convolutional kernels, an activation function breaking the linearity and a pooling phase that reduces image and strengthens the learning by selecting significant pixels. The last convolutional layer concatenates all the information in one feature vector and sends it to another layer or to a classifier.

This paper[13] proposes two supervised machine learning methods to automatically detect and recognize coral reef fishes in underwater HD videos. The first method relies on the extraction of HOG features and use of a SVM classifier. The second method is based on Deep Learning. The Histogram of oriented Gradients characterizes an object in an image based on its contours. HOG features gives a better results in a complex classification, where a fish can be hidden in coral reefs or occluded by another fish. SVM is a supervised methods to classify feature vector.The deep learning method approach efficiently recognizes fishes on different resolutions.Deep learning architecture used in this method follows the GooLeNet with 27 layers,9 inception layers and asoft-max classifier.

This paper[14] proposes a system for aquarium family fish species identification. It identify and classify eight family fish species with 191 species. The system is built using deep Convolutional Neural Network(CNN).It is made up of two convolutional layers for feature extraction and two fully connected layers for classification. The proposed system is a simple version for AlexNet[18]. QUT Robotics fish dataset consisting of 3,960 images. The proposed system achieves 85.59% testing accuracy when compared to AlexNet which achieves 85.41% over untrained benchmark dataset.

This paper[15] proposes the use of object proposal classification for fish detection. Convolutional Neural Network(CNN) are applied to object proposals for detection and species classification. The detection approach constitutes generation of bounding box, extraction of CNN features for each proposal and classification of each bounding box proposal as fish or background. The background subtraction algorithm[16] uses a probabilistic background model that represents each pixel as a mixture of Gaussians. The result of this algorithm is a binary mask that identifies pixels of background. An Erosion filter is applied to this mask to obtain background mask to separate nearby fishes. Then the Blob detection method[17] is used on both masks to obtain bounding box proposals. A binary SVM is used for classifying each bounding box proposal as fish or background. The generated proposals is used to extract CNN features from AlexNet. The activations of the 7^{th} hidden layer(relu7) in the convolutional network is chosen as features.



Abstract view of the CNN architecture.This figure is taken from paper[14]

A novel technique based on convolutional neural networks is proposed in this paper[19] for fish classification.The noise in the dataset are first removed.Image pre-processing is done using gaussian Blurring,Morphological operations,Otsu's thresholding and Pyramid Mean Shifting.A grey level histogram is created from the gray scale image for noise removal.the outline of the fish object is obtained using Pyramid Mean shifting with the kernel function k.The enhanced image is feed to CNN for the classification of Fish Species.This method gives an accuracy of 96.29%.

V. CONCLUSION

This survey paper discuss various types of approach for fish recognition. Various techniques for image pre-processing is discussed. Fish recognition using low level features, hierarchical classification and deep learning is discussed.Features has to be enhanced for larger dataset and also to obtain 100% accuracy.

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