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RESEARCH ARTICLE

Recognition of species of Triglidae Family using Deep Learning

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Abstract

This study is performed to classify fish species based on morphometric measurements between main points (fins, head and mouth) on fish image. Three species of Triglidae Family (*Aspitrigla cuculus*, *Chelidonichthys lastoviza* and *Chelidonichthys lucernus*) which has very similar in appearance of shape, color and the fin type are used for the classification. In the first stage, dataset was collected using images of fish species, and then morphometric features were extracted from the fish images using 13 landmarks. Deep Belief Networks is used as a classifier by combining with 3-fold cross validation method. Consequently, 3 fish-species of Triglidae family are separated with a high accuracy rate of 97.61%.

Key Words: Triglidae, species identification, morphometrics, Deep Learning, Deep Belief Networks, fish recognition

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Introduction

Fishes are most diverse group of living vertabrates, with more than 26.400 extant species currently known (Turan 2011). Systematics has sought to organize this diversity by studying aspect of their external and internal morphology. Traditional morphometric measurements have recently been criticized since they concentrate along the body axis with only sampling from depth and breadth, and most measurements are in the head (Turan and Basusta 2001; Turan 1999; Turan 2006). Development of image analyzing methods has invigorated systematic analyses of fish species *(Iscimen et al.2014; Iscimen et al.* 2015). Morphometric features are based on a set of measurements which represent size and shape variations between defining points on the fish.

The various studies have often focused on using morphologic features in taxonomic classification of species of a family. Classical measurements are based on shape features (Fabic *et al*. 2013; Huang *et al*. 2012; Slice 2007), quantitative features (Adams *et al.* 2004; Bookstein 1997), landmark shapes and forms features (Bookstein 1991, 1997; Mitteroecker and Gunz 2009), color, shape and texture features (Chuang *et al.* 2014; Hu *et al.* 2012; Huang *et al*. 2012), fin lengths (Ogunlana *et al*. 2015), centroid-contour distance features from the fins (Chuang *et al*. 2014; Iscimen *et al*. 2014), morphometric, bathymetric and energetic features (D'Elia *et al*. 2014) to categorize fish populations and species. Hence, alternative measures from the body parts of fish can be extracted. Morphologic features of fish from the fins, head and mouth from real-time image were used on species identification (Iscimen *et al*. 2014; Iscimen *et al*. 2015; Turan and Oral 2005).

Deep Belief Networks (DBN) is a machine learning algorithm which has a rapidly increasing popularity in recent years. The DBN is a semi-supervised learning method (Bengio *et al.* 2007). Deep learning (DL) algorithms are the advanced and detailed type of the neural network models. The deep models ensure analyzing deep features and specifications for the speech recognition, image analyzing, diagnosis systems and more. Restricted Boltzmann Machines (RBM) and the Sparse Auto Encoders are the unsupervised algorithms for the DL algorithms. The most powerful advantage of the DL algorithms is having ability of unsupervised and supervised training between the adjacent layers (Bengio *et al.* 2007; Hinton *et al.* 2006; Wang and Shang 2013).

The aim of this study is to propose a morphologic feature based deep fish classification model. Morphologic features which are distances between the fins, head and mouth are extracted using computer based pointing method. Species of Triglidae family (*Aspitrigla cuculus, Chelidonichthys lastoviza, Chelidonichthys lucernus*) are used for species identification and classification with using the DBN. The classification performance of the DBN on species of Triglidae is also evaluated.

Materials and Methods

Model of identification of fish species from Triglidae family is presented in the following subsections. The model consists of collecting data, morphometric feature extraction and deep learning classification (Figure 1).

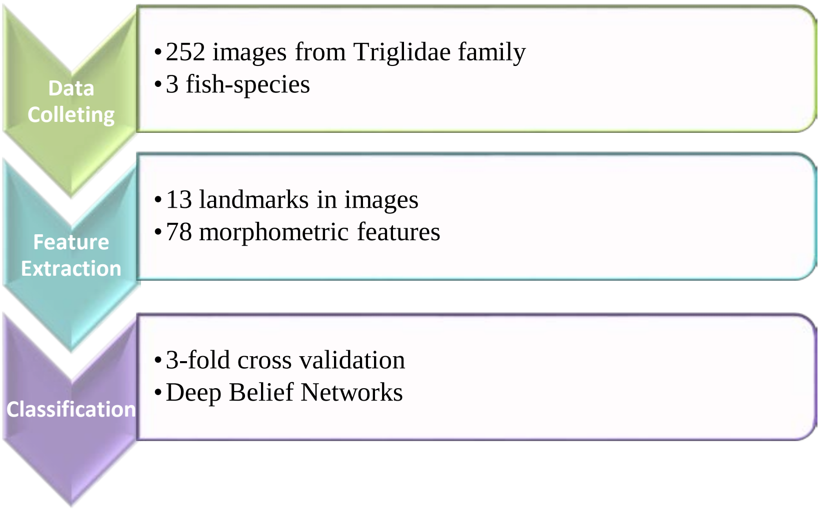

Figure 1. Structure of proposed fish recognition model

Database

The images of species from Triglidae family were taken in a standard composition with the same options of backgrounds, calibration tools and from different distances. A coin was used as a calibration tool to get real actual metrics from the images. Species of Triglidae family having two dorsal fins were used for the analysis. Dataset consists of images of the 3 different species, 22 images from *Aspitrigla cuculus*, 94 images from *Chelidonichthys lastoviza* and 136 images from *Chelidonichthys lucernus*.

Feature Extraction

Main descriptive 13 landmarks (Figure 2) such as starting and ending of fins, head and mouth on fish-species images were manually pointed using software which is developed in MATLAB. The metrics between marked points on fish images were calculated using radii distance algorithm and dataset was created using the extracted morphometric features. Thus, 78 distances from 13 landmarks were extracted for the three fish-species. Feature extraction was described and detailed in (Iscimen *et al*. 2014).

Classification and Performance Measurement

DL is a machine learning algorithm that ensures high classification performances using unsupervised training of the first layer of artificial neural networks. It consists of both supervised learning and unsupervised learning phases (Bengio *et al.* 2007; Hinton *et al.* 2006).

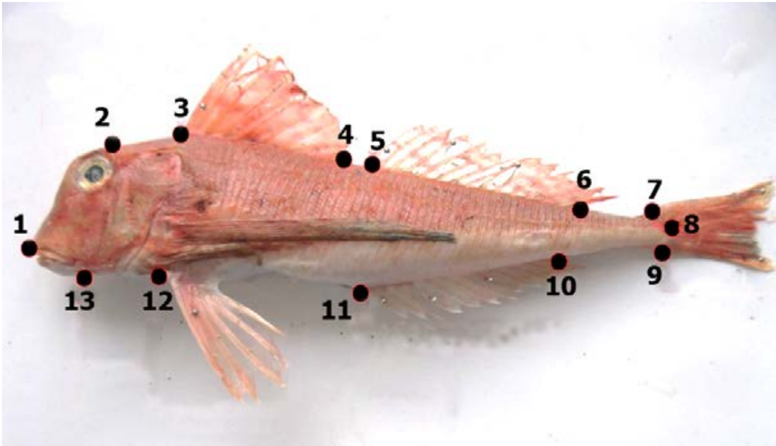

Figure 2. Utilized landmarks from fish species with two dorsal fins

The DBN algorithm is the most widely known model of the DL. The DBN transfer the input data to the next layer by encoding a Restricted Boltzmann Machine (RBM) in the first layer. The main difference between the DBN and neural network is using at least two hidden layers in model. The DBN consists of hidden layer size number of RBMs (Bengio *et al.* 2007; Hinton *et al.* 2006; Lopes and Ribeiro 2014). Energy and probability formulation of the DBN are seen below (Bengio *et al.* 2007):

$$E(v,h) = \sum_i f_i(v,h) = -bv - ch - Wvh \qquad (1)$$

$$P(v,h) = \frac{e^{-E(v,h)}}{\sum_x e^{-E(v,h)}} \qquad (2)$$

$E(v,h)$ represents for energy function, $P(v,h)$ represents for the probability function, v is input layer vector, h is hidden layer vector, b and c are the biases of input and hidden layers respectively and W is weight vector. The DBN is a two stage learning algorithm. Each RBM is created between two adjacent layers RBM. RBM are energy-based reduction methods. The DBN has two stage learning. In the first stage, RBM are trained using input dataset in unsupervised training and weights and biases of neurons are calculated with the aid of conditional probability of greedy layer-wise algorithm from the first layer to forward. In the second stage, the DBN model is unfolded to neural network model and the weights and biases that were calculated in the unsupervised learning and the parameters that are calculated as a result of RBMs are optimized using supervised learning with gradient descent and ascent algorithms in unsupervised stage to reach higher classification performances. Each layer is trained by the activation outputs from the previous layer. The used unsupervised learning is called as pre-training. At the second stage, (Bengio *et al*. 2007; Lopes and Ribeiro 2014; Wang and Shang 2013).

Performances of classification processes are calculated in terms of sensitivity (Equation 3), specificity (Equation 4) and accuracy (Equation 5) according to confusion matrix. Positive (P) and negative (N) represent the prediction of classifier, True (T) and false (F) represent the prediction of real class.

$$Sensitivity = \frac{TP}{TP+FN} \tag{3}$$

$$Specificity = \frac{TN}{TN+FP} \tag{4}$$

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \tag{5}$$

Results

A specialized deep identification model for three species of Triglidae family was achieved. The total number of images was 252 from the three species which were taken in a standard composition of fish with the same options such as backgrounds, calibration tools. The manually pointed 13 landmarks were determined in the images and 78 morphometric features were extracted using radii distance in centimeters between the landmarks. Features were normalized to 0-1 for the DBN classification.

System was tested using 3-fold cross validation technique (Wong 2015). In this technique, dataset randomly divided into 3 folds with the same number of instances. Two folds are utilized training the classifier; remaining fold is selected for testing the trained classifier. Accuracy, sensitivity and selectivity of each fold were calculated for 3 times for each fold of dataset and mean of them was calculated as results. Thus, all instances were used independently in both training and testing respectively.

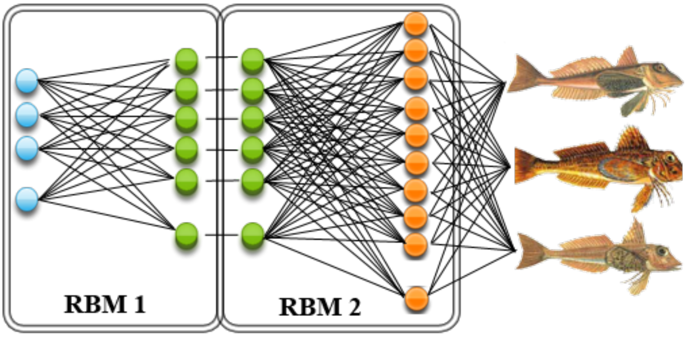

Figure 3. Proposed DBN model

The DBN that was used in fish-species recognition model has one input layer with 78 neurons, 2 hidden layers and 3 output neurons (Figure 3). Each input neurons belongs one morphometric feature from dataset. Greedy layer-wised pre-training on 2 RBMs was used in pre-training phase of the DBN with 500 epochs. The DBN has 2 hidden networks with 120, 360 numbers of neurons. Each fish-species was represents by an output. Model parameters : learning rate is 0.01, sigmoid output function, activation function of hidden layers during unfolding process in supervised phase is logistic sigmoid function to update weights and biases. After supervised and unsupervised learning process, performance measurements were calculated. Crosstab of the DBN is seen in Table 1.

Table 2. Crosstab of the DBN classifier for three fish species

	Aspitrigla cuculus	***Chelidonichthys lastoviza***	***Chelidonichthys lucernus***
Aspitrigla cuculus	20	0	1
C. lastoviza	0	93	2
C. lucernus	2	1	133

Discussion

In the present study, deep belief networks that applied as a classifier by combining with 3-fold cross validation method has been successfully recognized and classified *Aspitrigla cuculus*, *Chelidonichthys lastoviza* and *Chelidonichthys lucernus* species of Triglidae family with a high accuracy rate of 97.61%.

Table 2. Comparison of fish recognition studies according to features, classifiers and performance measurements

Author	**Features**	**Classifier**	**Classes**	**Accuracy**
Huang *et al*. (2012)	Shape, texture, color	Hierarchical classifier	15 species	97.50
Ogunlana *et al.* (2015)	Body and five fin metrics	Support Vector Machines	2 species	78.59
Iscimen *et al.* (2015)	Centroid-contour distance	k-NN	15 species	95.00
Iscimen *et al.* (2014)	Biometric distance metrics	Naïve-Bayes Classifier	15 species	75.70
Chuang *et al.* (2014)	Size, shape and texture	Hierarchical classifier	7 species	94.00
This study	Morphometric measures	DBN	3 species	97.61

As it is seen in Table 2, various features from various numbers of fish species were utilized in fish recognition models. Different kinds of classifier, mostly similarity-based and hierarchical classification algorithms were preferred. Due to the variety of classifiers and features in studies (Table 2), it is hard to compare this method with the other studies. On the other hand, the present performed model of fish recognition and classification achieved to 97.61%, 99.55% and 99.12% of accuracy, specificity and sensitivity, respectively. The extracting morphometric features is one of the most popular methods in image analysis techniques. The powerful landmarks are pointed in the image and the distances between the all landmarks are calculated using radii distance function. The 3 of fish-species images that are used in the proposed model were so similar and are difficult to recognize in simplistic ways. DL algorithms are the methods that include both feature extraction and classification stages together, but in our proposed model the morphological features were directly presented to classification stages. The model extracted RBM-based features from the morphological features and the DBN classified the extracted RBM features. The morphometric based DBN features were classified using a semi-supervised DL model with pre-training phase. The other methods on DL algorithm have a rising popularity in image recognition and so on. The accuracy rate of 97.61% is achieved on fish species recognition performing the DBN. The achieved performance shows that DL algorithms are successful for evaluating the morphometric features on fish recognition models.

In the future works, the fish images may be directly utilized as features using the DBN and the other DL algorithms such as Convolutional Neural Networks. The number of the landmark may be increased to get specific and characteristic feature combinations.

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Derin Öğrenme Kullanılarak Triglidae Familyasının Türlerinin Tanınması

Öz

Bu çalışma, balık resimlerindeki ana noktalar (kuyruk, baş ve ağız) arasındaki morfometrik mesafeler baz alarak balık türlerinin sınıflandırılmasını gerçekleştirmektedir. Sınıflandırma için kuyruk türü, renk ve şekil gibi çok benzer görünüşlere sahip olan Triglidae familyasından 3 balık türü (*Aspitrigla cuculus, Chelidonichthys lastoviza* ve *Chelidonichthys lucernus*) seçilmiştir. Birinci aşamada, balık türlerinin resimleri toplanarak very seti oluşturulmuştur, sonra balık resimlerinden 13 merkezi nokta kullanılarak morfometrik öznitelikler çıkarılmıştır. Derin İnanç Ağları, 3-parça çapraz doğrulama metoduyla kombine edilerek sınıflandırıcı olarak kullanılmıştır. Sonuç olarak, Triglidae Familyasından 3 balık türü %97.61 yüksek başarımla ayrıştırılmıştır.

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