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A biometric-based model for fish species classification

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ABSTRACT

Fish identification is crucial for the survival of our threatened fish species. In this paper, a novel and robust biometric-based approach was proposed to identify fish species. The proposed approach consists of three phases. In the first phase, different features were extracted from fish images. In this phase, Weber's Local Descriptor (WLD) and color moments were used to extract texture and color features, respectively. Due to the high dimensionality of WLD features, in the second phase, Linear Discriminant Analysis (LDA) was applied to reduce the number of features and to discriminate between different classes. In the third phase, the AdaBoost classifier was used to identify fish species. We have collected a dataset that consists of four classes/species. To validate the results of the AdaBoost classifier, a comparison between three well-known classifiers (Naive Bayesian, *k*-Nearest Neighbor, and Multilayer Perceptron) was performed. The experimental results proved that our approach achieved excellent results (approximately 96.4%). Moreover, our model has been tested against different real challenges such as image rotation and image translation, and the proposed model achieved promising results.

1. Introduction

Fish sorting by species is vital for industry, food production, and to protect and manage marine fisheries. At present, many commercial fishing boats or vessels classify fish manually into different species under the EC regulations (3703/85, 1986) (Commission et al., 1986). However, the manual process is time-consuming and requires many labors and hence increases costs. Therefore, a fully automated fish sorting or classification system is needed to solve problems of manual process (Benson et al., 2009; Hasija et al., 2017).

It is reported that animal recognition/identification can be achieved using many different methods which could be classified as electronic, mechanical, and biometric methods (Gaber et al., 2016). There are many examples related to the mechanical methods such as jaw and fin tags. However, mechanical methods have many limitations such as (1) they are not suitable for large-scale identification systems and (2) they take more time than other modern methods (Rusk et al., 2006). Electronic methods such as using *Radio Frequency Identification* (RFID) to identify animals depend mainly on attaching one device that contains a unique identification number with fish individuals. Another device is called reading device and it is used to communicate with animals and interpret the animal code. However, the attached device may get lost, damaged, or removed (Gaber et al., 2016). The limitations of electronic and mechanical methods can be addressed using biometric-based methods.

In biometric-based methods, many biometric markers have been proposed to identify animal individuals uniquely (Gaber et al., 2016; Tharwat et al., 2016a). This method has addressed the weaknesses of electrical and mechanical methods. Similar to a biometric-based recognition of human, many biometric animal markers have been utilized to identify animal individuals (Gonzales Barron et al., 2008; Rusk et al., 2006; Corkery et al., 2007; Tharwat et al., 2016a). For example, a retina-based identification system used retinal vessels which can be extracted from a retinal image as a unique identifier (Gonzales Barron et al., 2008). Moreover, animal face recognition was also employed in Peirce et al. (2001); Corkery et al. (2007). In addition, the DNA biometric was also utilized to identify meat and animal products that produced from each specific animal (Jiménez-Gamero et al., 2006). Despite this method achieves a higher identification rate than the other biometric methods, it is not cost-effective, intrusive, and it is time-consuming (Rusk et al., 2006).

In this paper, we have collected a dataset consisting of four species,

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namely: *Argyrosomus regius, Sardinella maderensis, Scomberomorus commerson, and Trachinotus ovatus*. These four species were selected because they have specific nutritional and functional importance; hence, these species are common in Egypt and different areas in the world. The Weber's Local Descriptor (WLD) and color moments methods were adopted to extract texture and color features, respectively. Due to the high dimensionality of the WLD features, Linear Discriminant Analysis (LDA) technique was used to reduce the number of features and to increase the separability between different classes. The class label of an unknown sample can be predicted using the AdaBoost classifier, which matches the features of the unknown sample with the features of labeled or training data.

The rest of the paper is organized as follows: Section 2 summarizes the related work of the fish identification system based on information technology. Section 3 gives overviews of the techniques and methods that are used for the proposed approach while Section 4 summarizes our approach in details. Experimental results and discussions are presented in Section 5. Finally, conclusions are summarized in Section 6.

2. Related work

There are many automated fish identification systems have been proposed (Iscsmen et al., 2014; Hnin and Lynn, 2016; Shafait et al., 2016). Cadieux et al. proposed an intelligent system for automated fish sorting and counting (Cadieux et al., 2000). They employed the Neural Networks (NN) for classification, and for the features, they utilized some shape features including moment invariants, Fourier descriptors, and nine shape features, and they achieved an accuracy that ranged from 70.8% to 72.7%. In another research, Lee et al. introduced a system for fish recognition and migration monitoring (Lee et al., 2004). Their system depends on extracting a shape and then applies shape matching for fish recognition. They matched the whole shape and several shape descriptors, such as Fourier descriptors, polygon approximation, and line segments, were tested, and they revealed accuracy near to 60%. Rova et al. used the deformable template matching to extract texture features and Support Vector Machine (SVM) for classification, and their model revealed 90% accuracy rate (Rova et al., 2007). Instead of using one type of features as in Cadieux et al. (2000); Lee et al. (2004); Rova et al. (2007), our model combined the color and texture features.

Chamba et al. extracted 85 features, which consists of geometric features (e.g. area, perimeter, and elongation), color features (e.g. hue, gray levels, and color histograms), motion features, and texture features (e.g. entropy and correlation). They also employed the quadratic Bayes classifier for classification, and they achieved 85.77% accuracy rate (Chambah et al., 2003). Spampinato et al. classified 320 fish images which were collected from 10 different classes and they revealed 92% accuracy rate (Spampinato et al., 2010). They extracted texture and shape features such as Gabor features and Fourier descriptors, and they employed discriminant analysis classifier. Larsen et al. also used shape and texture features with linear discriminant classifier to classify three species and they obtained a recognition rate of 76% (Larsen et al., 2009). Three different biometric techniques (Euclidean network technique, quadratic network technique, triangulation technique) were employed with Naive Bayesian classifier in Iscsmen et al. (2014), and the accuracy was 93.10% for seven species and 75.71% for 15 species. Due to the uncontrollable environment, fish species were also classified using video images as in Shafait et al. (2016). They aimed to classify and track fish in a real environment. In all mentioned studies, one single classifier was used. However, our model employed the AdaBoost classifier which is based on combining the outputs of different single classifiers to improve the classification robustness.

3. Preliminaries

This section provides overviews of the algorithms and methods that were used in the design of the proposed model.

3.1. Weber's Local Descriptor (WLD)

WLD is an image descriptor method which describes the image as a histogram of Differential Excitation (ξ_j) and Orientation (ϕ_t) (Chen et al., 2010; Gaber et al., 2016). WLD is originally inspired by Weber's Law that was proposed by Ernst Weber in the 19th century, where the ratio between an increment threshold and the background intensity is constant, and this law can be formally expressed as follows:

$$\frac{\Delta I}{I} = k \tag{1}$$

where ΔI is the increment threshold, I represents the initial intensity or an image background, k is the constant value even if I is changing, and the fraction $\frac{\Delta I}{I}$ is the *Weber law* or *Weber fraction* (Chen et al., 2010).

In the WLD method, the features are extracted from each pixel in an image. The WLD algorithm has three main steps (1) finding differential excitations, (2) calculating the gradient orientations, and (3) building the histogram. In the first step of the WLD algorithm, the differential excitation of the image is computed for each pixel in the input image, and the gradient orientation is then calculated. In the third step of the WLD algorithm, the differential excitation and gradient orientation are combined to form a WLD histogram (Chen et al., 2010; Gaber et al., 2016). More details about each step are explained below.

3.1.1. Differential excitation

In this step, the differential excitation (ξ) for each pixel is calculated. First, the differences between the center pixel x_c and its surrounding neighbors are calculated as follows:

$$v_s^{00} = \sum_{i=0}^{p-1} (\Delta x_i) = \sum_{i=0}^{p-1} (x_i - x_c) \tag{2}$$

where p is the number of neighbors and $x_i (i = 0, \ldots, p-1)$ is the intensity of the ith neighbor of x_c. Fig. 1 shows an illustrative example to calculate the differential excitation where the number of neighbors for x_c was eight, i.e., $p = 8$. The number of neighbors or the patch/window size is a user defined parameter. As shown in the figure, four filters, f_{00}, f_{01}, f_{10}, and f_{11}, are used to calculate v_s^{00}, v_s^{01}, v_s^{10}, and v_s^{11}, respectively, where, v_s^{00} is the difference between x_c and its neighbors, $v_s^{01} = x_c$, $v_s^{10} = x_5 - x_1$, and $v_s^{11} = x_7 - x_3$. The ratio between the differences v_s^{00} and v_s^{01} is then calculated as follows, $G_{\text{ratio}}(x_c) = v_s^{00}/v_s^{01}$. The arc-tangent function is then applied on $G_{ratio}(\cdot)$ to get the differential excitation of (x_c), as in Eq. (3).

$$\xi(x_c) = G_{\text{arctan}}[G_{\text{ratio}}(x_c)] = \arctan\left[\sum_{i=0}^{p-1}\left(\frac{x_i - x_c}{x_c}\right)\right] \tag{3}$$

3.1.2. Orientation

In this step, the orientation of the current pixel (x_c) is computed by calculating the differences in the horizontal and vertical directions as follows:

$$\theta(x_c) = \arctan\left(\frac{v_s^{11}}{v_s^{10}}\right) = \arctan\left(\frac{x_7 - x_3}{x_5 - x_1}\right) \tag{4}$$

The gradient orientation is then quantized by transforming it into T dominant orientation, where θ is mapped to $\acute{\theta}$ as follows (Gong et al., 2011):

$$\acute{\theta} = \text{arctan2}(v_s^{11}, v_s^{10}) + \pi \tag{5}$$

where