Applications of Meta-Heuristic Algorithm with Back Propagation Classifier for Handling Class of General Fish Models

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Abstract
Pattern recognition is a system that recognizes isolated patterns of interest that could be an image. Many models such as noise, distortion, overlap, and errors in the segmentation results and obstruction of image's objects could occur during the process of image recognition. The aim of this study is to develop a system to recognize isolated fish object in the image based on a combination of significant extracted features using anchor points, texture and statistical measurements. A generic fish classification method could be performed using a hybrid meta-heuristic algorithms (genetic algorithm with Great Deluge (GD) algorithm) with back-propagation algorithm (GAGD-BPC). Thus, it is used to classify the images of fish into dangerous and non-dangerous families, to recognize the dangerous fish families into Predatory and Poison fish family, and to recognize the non-dangerous fish families into garden and food fish family. A prototype to deal with the problem of fish images classification is presented in this research work. The proposed prototype has been tested based on 24 fish families, each family contains different number of species. Therefore, it has performed the classification process successfully. The experimental tests have been performed based on 320 distinct fish images that were divided into 220 images for training phase and 100 images for testing phase. An overall accuracy recognition rate was 83.2%, which was obtained using the proposed GAGD-BPC.

Keywords:
Great deluge (GD) algorithm, Feature Extraction, Back Propagation Classifier, Anchor Measurements and Genetic Algorithm.

1. Introduction

Traditionally, image recognition process was performed based on human skills and senses. However, this has made not accurate and insufficient recognition process. With the advent of computers, they gained their place in this research area, which was obvious to think of using them in such important process. Many approaches were used for image processing and pattern recognition [1-7]. In this research work, a prototype for image recognition using anchor points, texture and statistical measurements is introduced. The focus of this study is on fish images classification to benefit many fields such as agriculture, industrial and marine field. The system input is to be a fish image of specific size and format. The features of the fish images will be extracted using the anchor points, texture and statistical measurements in order to be classified using the meta-heuristic algorithm into dangerous and non-dangerous and then to recognize the dangerous fish families into Predatory and Poison fish family for the purpose of recognizing the non-dangerous fish families into garden and food fish family.

A number of studies have been conducted in the field of image recognition. Nevertheless, it is still an active area of research due to many problems such as distortion, errors in the segmentation results, overlap and obstruction of objects in digital images [3, 4, 6-8]. Based on recent studies, the developed fish recognition systems still have many limitations such as the low ability in detection and classification of fish. Moreover, a high number of deaths occur every day due to inability to differentiate dangerous from non-dangerous fishes [4, 8].

In literature, Anderson et al., [5] has introduced a way to apply image processing techniques in the context of gray-level images to detect and identify fish in natural underwater environments. To achieve accurate segmentation, thresholds methods for automatic image are explained, implemented, and applied in conjunction with back subtraction. One method can be used to improve segmentation is the use of thinning edge procedure. Biometric principles such as WARP and Gabor filters are applied to extract feature data. Indeed, machine learning techniques such as Boltzmann machines, convolutional neural networks, and deep belief networks are trained to perform the classification.

The Gabor filter is usually used in several image processing applications. The output of the filter allows locating any edge's identification in an image. The process of feature extraction and classification is based upon using some known physical features of the fish images. For example, the E.morio fish has a distinct pattern at the edge of the tail that is much lighter in color than the rest of the fish. This pattern is small in width and runs for most of the tail. Gabor filters could be used to highlight this line on the tail and to classify the images based on the presence or absence of the line [5].

It is important to determine a set of anchor/land mark points on the size and shape measurements. The detection of such points helps to find a set of anchor points related for patterns of interest. Therefore, the geometrical features

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were calculated using the angle and distance measurements and these features were obtained from the shape and size measurements of fish object after detecting the anchor/landmark points over the fish images [9].

Edge detection is an initial step in identifying an image object. Shrivakshan and Chandrasekar [10] have made a comparison among Edge Detection Techniques with a case study of how to identify a shark fish type. Bad sensitivity to noise is one of the main drawbacks in Gradient-based algorithms due to the static characteristics of the kernel filter dimension and its coefficients. Hence, it cannot be adjusted to any given image. A novel edge-detection algorithm is required to provide solutions with minimal error levels, and hence it should be adaptable to the different image noise levels. This condition could help in determining the valid image noise produced contents. While the performance of the Canny Algorithm is determined by the variant Gaussian filter standard deviation parameters and its threshold values, the Gaussian filter size is controlled by the larger size and the greater value. It is necessary for noisy images as well as detecting larger edges to know rule of that larger size of Gaussian filter, more noise produced. Subsequently, the edge localization has less accuracy than the larger scale of the Gaussian. A new algorithm is desired for smaller values to adapt these parameters since changing these parameters will help user to modify the algorithm to outfit different environments. Although the detection algorithm of canny edge has a better performance than Sobel, the detection algorithm of Prewitt and Robert's operator is costly. Under the noise conditions, the images evaluation showed that Canny, LoG, Sobel, Prewitt, Roberts's are exhibited better performance respectively. Other methodologies used for edge detection are many, namely the Gradient and Laplacian transformation. Although Laplacian performs better for some features (such as the fins), it still suffers from bad performance for some of the lines [10].

However, Adebayo and Olumide [7] proposed a fast and accurate system capable of classifying fish images into distinct classes based on their physical forms. The system comprises three items: image-processing, feature extraction and classification method. Fish feature vector is obtained through the product of Single Value Decomposition (SVD)extracted from fish block images. Training and testing the proposed fish classification system are done using Artificial Neural Network (ANN). Experimental test was carried out to determine the species of query fish images. As a result, thirty-six fish images were tested with 94% recorded as correct classification results. Badawi and Alsmadi [4] developed a system to recognize isolated fish object in the image based on a combination between significant extracted features using anchor points, texture and statistical measurements. A generic fish classification was performed using hybrid meta-heuristic algorithms, genetic algorithm with iterated local search with back-propagation algorithm (GAILS-BPC), to classify the images of fish into dangerous and non-dangerous families. The proposed system has been tested based on 24 fish families, each family contains different number of species. The experimental tests have been performed based on 320 distinct fish images. The 320 distinct fish images were divided into 220 images for training phase and 100 images for testing phase. An overall accuracy recognition rate was 80.5% obtained using the proposed GAILS-BPC.

Furthermore, Al smadi et al., [8] realized a fish object in the fish images using the blend between the effective extracted features from the measurements of color texture. Therefore, Gray Level Co-occurrence Matrix (GLCM) was used to extract a number of features to be used in the classification process based on back-propagation classifier. They have developed a method to handle fish classification problem. The method segments the fish image using the measurements of color texture. The performance of the proposed method has been conducted based on 20 different families of fish, with different number of species per family. The dataset consists of 610 fish images; 500 fish images were used for training process and 110 fish images were used for testing process. The overall accuracy of the back propagation classifier was 84%. On the other hand, many applications to handle different models by using numerical or analytical algorithms can be found in [18-29].

The paper is organized as follows. In Section 2, we present the methodology of such biological models. In Section 3, the representation of statistical measurements is presented based upon the great deluge algorithm. In Section 4, experimental results are simulated to show the reasonableness of the methodology. Finally, some conclusions are summarized in the last section.

2. Primaries and Methodology

This work has been applied on 320 fish images obtained from Global Information System (GIS) on Fishes (fish-base).

2.1 The feature selection scheme

The main goal of the feature selection approach is to determine the biggest set of significant features in order to use it for successful fish images recognition.

2.1.1 Gabor Filter (GF):

In image processing, Gabor filter (GF) is used for edge detection, which relies on the representations of orientation and frequency [10]. GF behaves like the human perception system, which particularly belongs to suitable texture differentiation and representation. GFs are connected to the Gabor wavelets. They can be implemented and used for a number of rotations and expansions [10]. In image processing field, GF is very beneficial for edge detection. This work uses the GF for fish images recognition. Four image quality features (Standard Deviation, Contrast, Homogeneity, and Mean) will be calculated based on the obtained image from the GF. Figure 1 shows the results of applying GF.

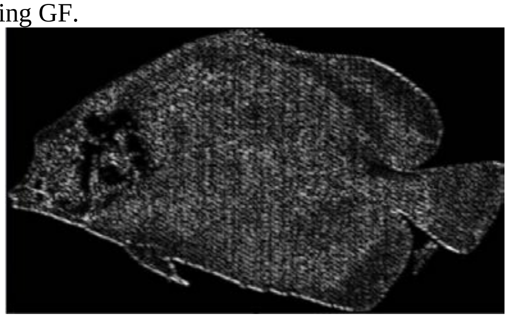

Figure 1. Application outcome of GF

2.1.2 Anchor points location detection:

A number of anchor points should be determined as labeled on the fish shape measurements. In the last few years, anchor point detection was aimed in many research works in the field of pattern recognition. Point detection is applied to find a significant set of points that will help in obtaining the anchor measurements for patterns of interest (fish object). In this work, the goal of anchor point detection is to determine twenty-three labeled points (as labeled in Figure2 in the fish shape measurements) that will help in determining the location of each feature for recognition of fish images. After that, the geometrical features will be calculated using the determined anchor points for the fish classification purpose. After detecting the whole anchor points over the fish object, significant features will be extracted using distance and angle measurements.

2.1.3 Shape measurements:

Shape measurements are used to calculate the edge and distance measurements of the fish object and then to determine the significant similar and dissimilar parts for each fish family. Moreover, the classification procedure based on the measurements of vector's angles using three points will lead to obtain higher classification accuracy such as caudal fin angle and fish head angle [4, 9]. Therefore, a number of features can be determined and extracted such as radius of fish eye and pectoral fin length by using distance measurements.

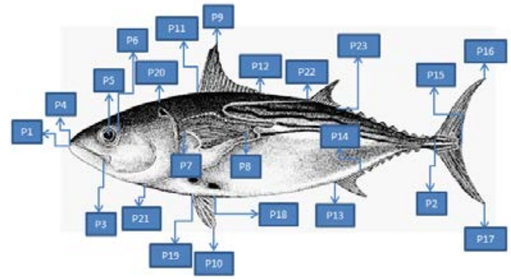

Figure 2. Locations of anchor points measurement.

Shape features were calculated using distance and angle measurements. The distance measurement is the distance between twenty-three anchor points: P1, P2, P3, P4, P5, P6, P7, P8, P9, P10, P11, P12, P13, P14, P15, P18, P19, P20, P21, P22, P23 (see Figure 2). The angle between three anchor points over the fish object can be found by calculating the angle measurements: ((P9, P4, P10), (P9, P16, P10), (P20, P4, P21), (P16, P15, P17), (P15, P10, P17), (P15, P9, P16), (P9, P15, P10) and (P16, P4, P17)). Table 1 and 2 explained the selected anchor points, the feature calculation using distance, and angle measurements as explained in the following subsection.

2.2 Measuring Tools

Distance measurements are considered very useful tools in the field of pattern recognition to extract robust features in order to enhance the classification accuracy. In the field of algebraic geometry, the distance $Dis(A, B)$ between the points $A = (a_1, a_2)$ and $B = (b_1, b_2)$ will be calculated by the following formula:

$$Dis = \sqrt{(\Delta a)^2 + (\Delta b)^2} = \sqrt{(a_2 - a_1)^2 + (b_2 - b_1)^2} \qquad (1)$$

The twenty-three anchor points shown in Figure 2 show the length between anchor points. Therefore, fifteen features were obtained using the formula of the distance measurement as shown in Table 1.

The angle is a union of two line segments with a common endpoint. The common endpoint is defined as the vertex of the angle, whereas the rays represent the sides of this angle [11]. It can be written as follows: if $\angle B$ represents the vertex angle and A, B represent the points of the two sides, the angle will be represented as $\angle CEJ$ or $\angle JEC$. Therefore, the distance between two points (C, E) can be calculated using the distance equation (1). Once the distances of the two sides are obtained, the internal angle θ will be obtained automatically. Here, the cosine rule is the single available choice. The angle θ will be calculated by the following formulas:

$$b^2 = a^2 + c^2 - (2ac \times cos(B)), \qquad (2)$$

$$\cos B = \frac{a^2 + c^2 - b^2}{2ac}. \qquad (3)$$

Table 2 illustrates the nine features calculated using the angle measurements based on the anchor points displayed in Figure 2.

Table 1: fifteen extracted features from the determined anchor points.

No.	Feature Name	Anchor points
D1	Fish length without the caudal fin	$Dis(P1, P2)$
D2	Fish width without the upper and lower fins	$Dis(P11, P19)$
D3	Mouth length of fish	$Dis(P1, P3)$
D4	Distance between the right- end of mouth and the eye center	$Dis(P3, P5)$
D5	Radius of the fish eye	$Dis(P5, P6)$
D6	Pectoral fin length	$Dis(P7, P8)$
D7	Length of first dorsal fin (spinous)	$Dis(P11, P12)$
D8	Anal fin length	$Dis(P13, P14)$
D9	Caudal fin length	$Dis(P2, P15)$
D10	Pelvic fin length	$Dis(P19, P10)$
D11	Head width	$Dis(P20, P21)$
D12	Length of second dorsal fin (soft rays)	$Dis(P22, P23)$
D13	Distance between the right- end of mouth and the eye center	$Dis(P3, P5)$
D14	Distance between the right-end of first dorsal fin and the start of second dorsal fin	$Dis(P12, P22)$
D15	Distance between end of the pelvic fin and the start of the anal fin	$Dis(P18, P13)$

Table 2: the nine features that calculated using the determined anchor points

No.	Feature Name	Anchor description
A1	The angle of lower triangle	P15, P10, P17
A2	The angle of upper triangle	P15, P9, P16
A3	Caudal fin Angle	P16, P15, P17
A4	Fish head Angle	P20, P21, P1
A5	Front triangle angle	P9, P15, P10
A6	the whole fish angle	P16, P4, P17
A7	Eye-end mouth Angle	P1, P3, P5
A8	Second caudal angle	P9, P4, P10
A9	Rear triangle angle	P9, P16, P10

3. Statistical Measurements

In this section, statistical measurements are conducted using the features extracted from fish images that belong to 24 fish families in order to determine and obtain the significant features. These features will help to get high recognition accuracy and to recognize the fish images into its dangerous or non-dangerous family. Table 3 shows the correlation results based on the features that were extracted using anchor points measurements, where these statistical measurements were obtained from [4].

Based on the statistical results obtained from the extracted features, the correlation value between some extracted features (head, eye and caudal angles) are different and considered good features that can be used in this work to enhance the classification accuracy. For example, the correlation value between the head and eye angles in the dangerous fish families are negative (which means that as the head angle increases the eye angle decreases), and the correlation value between the caudal and eye angle is also negative. But in some non-dangerous fish families, the correlation value between the head and eye angle is positive (which means that as the head angle increases the eye angle increases) and the correlation values between the caudal and eye angles are also positive. Thus, the obtained correlation values of the extracted features are varied from family to another and they will increase the differentiation between the fish families: poison, non-poison, wild and food fish families.

Table 3: Correlation results based on the features extracted using anchor points measurements.

Fish Family #	Correlation (Head_ Angle, Eye _Angle)	Correlation (Caudal _ Angle, Eye _Angle)
1	-0.10	-0.10
2	-0.22	-0.12
3	-0.23	-0.20
4	0.11-	-0.13
5	-0.11	-0.11
6	-0.21	-0.13
7	-0.24	-0.21
8	0.12	-0.14
9	-0.13	-0.59
10	-0.60	0.67
11	0.18	-0.087
12	-0.83	-0.39
13	-0.44	0.13
14	-0.70	-0.20
15	0.38	0.27
16	-0.56	-0.27
17	-0.11	0.34
18	-0.17	0.03
19	-0.36	-0.21
20	-0.35	0.22
21	-0.01	-0.29
22	-0.34	-0.17
23	-0.12	0.01
24	-0.30	0.39

3.1 Genetic Algorithm

Genetic Algorithm (GA) is a population based heuristic approach that simulates the procedure of natural selection. GA is used to generate new solutions useful to solve difficult problems based on sample solutions in a population. GA contains three main phases, area selection technique attempts to select and recombine other two solutions from the population. Goldberg in [12] has recommended different types of selection techniques such as Tournament Selection, Truncation Selection and Roulette Wheel Selection. A crossover operator performed for a mating process is the genetic way to find a new solution (with better fitness value) in the search space. A mutation operator is considered as a local search to find the neighbor solutions and to update the population in order to improve the quality of the search space by generating better solutions (new solutions with better fitness value) [12].

3.2 Great Deluge Algorithm

This work uses the Great Deluge algorithm for increasing the quality of solution (weight) through increasing the fitness number, which helps in enhancing the process of exploitation during the searching process.
Table 4 shows the parameters setting of the of great deluge algorithm. Great Deluge Algorithm is incorporated into the employed genetic search process to improve the exploitation process rather than the exploration process.
GD algorithm [13] is one of the local search procedures in meta-heuristic approaches that accepts the solution if improves its quality. It also accepts the worse solutions if the quality is better than that at the boundary level. In the initialization phase, the level is set to the quality of the initial solution and it is then increased or decreased (based on maximization or minimization approaches) by fixed rate, which is initialized as β. The search will be continued until the quality value reaches the estimated quality function or the number of iterations passes the threshold number of iterations that has been set in the initialization phase. The pseudo code for the GA is shown in Figure 3.

Table 4: Parameters of the great deluge algorithm.

Great Deluge Generation	**700**
Initial water level	0
Final water level	100

```
Great deluge (GD) algorithm
Begin
s:=initial solution;
Set initial water level WLinitial;
Set final water level WLfinal;
Calculate the decay rate β;
Repeat
generate an s' ε N(s)
if f(s') =f(s) then s = s'
WL = WL -β;
Else
If f(s') > WL then = s';
until stopping criterion;
end;
```

Figure 3. Pseudo code for the GA.

3.3 Neural Network Model

The neural network with BP algorithm is used for training and classification purpose as illustrated in Figure 4, which shows the applied neural network model that involves three layers. The neurons number in the input and hidden layer is selected based on the experiment conducted in this work in order to decide the suitable neurons number to enhance the classification accuracy [4, 14], whereas the number of neurons in the output layer is twenty four since the proposed GAGD-BPC is required to classify twenty four fish families.
In the experimental part, the back-propagation classifier is implemented with a set of input features. According to [15], back-propagation classifier is suffering from some drawbacks such as getting trapped in the local optima and low convergence rate. In order to overcome these drawbacks, this work proposed a hybrid meta-heuristic algorithm (GAGD-BPC). The meta-heuristic algorithm is utilized to solve the problems in the optimization fields, and it is highly effective in getting trapped in the local optima compared to the traditional back-propagation algorithm. Table 5 specifies the number of neurons needed for each neural network layer and the input number of the extracted features.

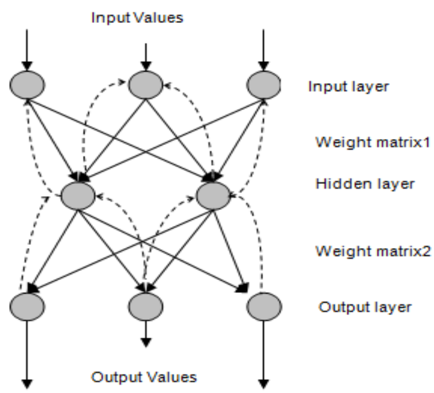

Figure 4. Neural network model consists of three layers.

Table 5: Number of neurons needed for each neural network layer with input number of the extracted features.

Classifier	**No. Neurons in layers**			**Input number of input extracted features**
	Input .Layer	H. Layer #1	Output. Layer #3	
BPC	25	40	24	30
GAGD-BPC	25	40	24	30

4. Experimental Results

In the experimental results, the test results of the recognition accuracy per family (24 fish families) were obtained based on 30 combined extracted features using anchor points detection, Gabor filter and statistical measurements. More specifically, these extracted features were trained and tested using GAGD-BPC. Therefore, the obtained results indicated the success of the features extraction and recognition methods as obtaining high classification accuracy compared with previous methodologies reported in the literature. Thus, the percentage of the recognition results lies between the worst accuracy result (81%) and the best accuracy result (88%).
The variations in the accuracy results are due to the similarity of shape and texture in the most fish families that might contain the original pixel values, causing similar extracted features values. Hence, these features increase the complexity of the extracted features trained and classified using the proposed GAGD-BPC. On the other hand, some fish families have its own species-specific-traits that help GAGD-BPC to classify the fish families. For example, some fishes of the non-poison family have the same angle of upper triangle with other dangerous fish families although these non-poison fishes have several dissimilar features such as the distance between the right-end of first dorsal fin and the start of second dorsal fin; Pelvic fin length and Head width are usually dissimilar from one fish family to another. The recognition accuracy results for each fish family using the features extracted from shape measurements, statistical and texture measurements are illustrated in Table 4.
In particular, the families of the dangerous fish were recognized successfully with high classification accuracy. This is because the species-specific traits of the dangerous fish families (different shape compared with other families) differ than other non-poison and poison families of fish. Moreover, the overall accuracy of recognition training results is 80%, and the overall accuracy of recognition test results is 83.2% as shows in Table 6.

5. Conclusion and Discussion

The extracted features from the proposed methods (anchor points, texture and statistical measurements) especially GAGD-BPC classifier perform better compared to other traditional methods such as [6, 7, 16, 17] in terms of speed and recognition accuracy. Anchor points and texture measurements methods are less affected by the fish expression and the global variations in the appearance of fish object inside the image.
Likewise, the developed hybrid classifier GAGD-BPC outperforms the traditional BPC based on the extracted features using Gabor filter, angle and distance tools. ILS with GA significantly improves the recognition accuracy of the BPC through enhancing and optimizing the weights used in the training and testing the BPC. Table 4 shows the obtained results using the developed GAGD-BPC and compared to BPC.
This paper proposed a novel methodology for general fish classification based on significant combined features extracted from texture and shape measurements using Gabor filter, anchor points detection, and statistical measurements. 4 features were extracted using Gabor filter; 24 features were extracted using angle and distance tools; and 2 features were extracted using statistical measurements. Subsequently, the combined extracted feature were used to recognize the fish images using the hybrid meta-heuristic algorithm (genetic algorithm with great deluge (GD) algorithm). The hybrid meta-heuristic algorithm was also combined with backpropagation classifier (GAGD-BPC) to classify the fish images into dangerous and non-dangerous. Thus, it can be used to classify the dangerous fish families into predatory and poison fish family and hence to recognize the non-dangerous fish families into garden and food fish family. The proposed features-extracting methods and the meta-heuristic algorithm significantly improved the recognition accuracy of the BPC through enhancing and optimizing the weights used in the training and testing BPC.

Table 6: Recognition test accuracy results based on anchor points, texture and statistical features for each fish family.

	Family Name	BPC%	GAGD-BPC%
Dangerous fish families	Carcharhinus Leucas	80	82
	Carcharodon Carcharias	79	81
	Atractosteus Spatula	80	82
	Hydrocynus Goliath	80	81
Poison fish families	Red Snapper	81	84
	Trigger	87	88
	Porcupine	82	84
	Thorn	82	87
	Acestrorhynchidae	82	86
	Acropomaatidae	83	84
	Albulidae	80	82
	Anomalopidae	82	83
	Caesionidae	83	84
	Drepanidae	80	82
	Istiophoridae	83	83
	Leiognathidae	82	82
	Megalopidae	80	83
	Platycephalidae	80	81
	Priacanthidae	80	84
	Scombridae	80	84
	Siganidae	82	83
	Sillaginidae	78	84
	Stromateidae	80	82
	Triacanthidae	80	83
Overall accuracy		81%	83.2%

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