

A Hybrid Memetic Algorithm (Genetic Algorithm and Great Deluge Local Search) With Back-Propagation Classifier for Fish Recognition

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Abstract

The aim of this study is to establish a hybrid method to optimize the performance of back-propagation classifier for fish classification by using Memetic Algorithm (MA) (genetic algorithm and great deluge local search). This is to be performed by utilizing the ability of memetic algorithm to optimize the parameters (weight and bias) of the back-propagation classifier (BPC). Recognizing an isolated pattern of interest (fish) in the image is based on robust features extraction. These features are extracted based on color signature measurements that are extracted by Gray histogram technique and Level Co-Occurrence Matrix (GLCM) method. The typical Back Propagation Classifier (BPC) has the slow practice speed and easy for running into local minimum disadvantages. The new system prototype will help in resolving such disadvantages.

Key words: *Back-propagation classifier (BPC), a hybrid memetic algorithm with back-propagation classifier (HGAGD-BPC), Color Histogram Technique, Gray Level Co-Occurrence Matrix (GLCM), Color signature measurements, digital fish images, poison and non-poison fish.*

1. Introduction

Recently, fields like face recognition, fingerprint verification, iris discrimination, chromosome shape discrimination, optical character recognition, texture discrimination and speech recognition are widely experimented and studied. Such areas need fast and accurate computations. One important field is digital image recognition which has been extremely applied and studied recently. Various approaches in image processing and pattern recognition have been developed by scientists and engineers [1]. In this study, a system for recognizing fish images is built. Such system may benefit various fields such as marine experts and biologists. The system input is considered to be an image of specific size and format, the image is processed. Then the system recognizes the given fish into its cluster and categorize the clustered fish into poison or non-poison fish and then into its family.

The proposed system recognizes the isolated fish pattern, then, the image is processed into several phases such as pre-processing and feature extraction before recognizing the pattern of fish. The BPC and

HGAGD-BPC are used for the recognition phase and their results are compared.

1.1 Problem statement

Several efforts have been devoted to the recognition of digital image but so far it is still an unresolved problem. Due to distortion, noise, segmentation errors, overlap and occlusion of objects in color images [1 - 3]. Recognition and classification as a technique gained a lot of attention in the last years wherever many scientists utilize these techniques in order to enhance the methodologies. Moreover, Fish recognition and classification is still an active area in many domains and is considered as a potential research area.

Although advancements have been made in the areas of developing real time data collection and on improving range resolutions, existing systems are still limited in their ability to detect or classify fish, despite the widespread development in the world of computers and software [4, 5]. Thousands of people die every year because they do not have the ability to distinguish between poison and non-poison fishes. Object classification problem lies at the core of the task of estimating the prevalence of each fish species. Solution to the automatic classification of the fish should address the following issues as appropriate [1, 4]:

- Arbitrary fish size and orientation; fish size and orientation are unknown a priori and can be totally arbitrary.
- Feature variability; some features may present large differences among different fish species.
- Environmental changes; variations in illumination parameters, such as power and color and water characteristics, such as turbidity, and temperature. The environment can be either outdoor or indoor.
- Poor image quality; image acquisition process can be affected by noise from various sources as well as by distortions and aberrations in the optical system.
- Segmentation failures; due to its inherent difficulty, segmentation may become unreliable or fail completely.

The vast majority of research based fish classifications point out that the basic problem in the fish classification; they typically use small groups of features without previous thorough analysis of the individual impacts of each factor in the classification accuracy [1, 6, 7, 8].

1.2 Related studies

In pattern recognition domain, such as digital image, color has not been a relevant field of study, since grayscale images involved enough information to solve many different tasks in the pattern recognition. Another reason to avoid the use of the color images is the fact that color images require to upgrade the input hardware (mainly CCD cameras) and that the CPU processing power need to be higher to be able to handle the additional color information [9].

Recently, many researchers have begun to take color information into consideration. In the texture analysis field, many classical feature extraction algorithms have been enhanced to process color textures and new ones have been researched. Muñiz and Corrales [9] have presented a new approach to extend grayscale texture analysis methods. By means of the band rationing technique, the authors suggested that they can modify any feature extraction algorithm to take the advantage of color information and achieve higher classification rates. To prove this extreme, the authors have selected three standard techniques, namely, Gabor filters, Wavelets and Co-occurrence Matrices. For testing purposes, 30 color textures have been selected from the Vistex database. The authors performed a number of experiments on that texture set, combining different ways of adapting the former algorithms to process color textures and extract features from them. Their experimentation results indicated that the standard three techniques (i.e. Gabor filters, Wavelets and Co-occurrence Matrices) show higher classification rate of features extracted from color texture compared to feature extracted of grayscale texture. For example, the Gabor data obtained in the color texture feature 95.24% while in the grayscale obtained 87.86 %, and the Wavelet data obtained in the color texture 93.81% while in the grayscale obtained 86.19%.

Arivazhagan et al. [10] applied a discrete wavelet transform (DWT) on a set of color texture images and statistical features such as; mean and standard deviation were extracted from the approximation and detail regions of DWT decomposed images, at different scales. In order to improve the success rate of the classification, the co-occurrence matrix is calculated for original image, approximation and detail sub-bands of 1-level DWT decomposed images and additional features called Wavelet Co-occurrence Features (WCF) were also extracted. It is found that the success rate is improved much by combining wavelet statistical and co-occurrence features.

The authors conducted a number of experiments with 20 color texture images and the size for each image 512*512 obtained from Vistex color texture image which is presented in VisTex [11], for different color models such as YUV and HIS color space. In the experimental results, the color texture classification is done by a combination of wavelet statistical features (WSFs) and different wavelet co-occurrence features. Results show a high accurate classification rate, for instance, it is found that the mean success rate is the highest, i.e. 97.81% for YUV and 97.80% for HSI for the combinations of WSFs and WCFs. An example of color texture is presented in Figure 1.



Fig.1: Example of color texture

2. Materials and Methods

This study had focused on 300 fish images which are collected from both the Global Information System (GIS) on Fishes (fish-base) and the department of fisheries, Ministry of Agricultural and Agro-based industry in putrajaya, Malaysia. The used data is acquired on the 22nd. August, 2008.

2.1 The feature selection approach

Feature extraction refers to a process by which fish attributes are computed and collected from color signature measurements through the GLCM method. The goal of a feature extraction determines the largest set of features.

2.2 Differentiation Between Poison and Non-Poison Fish Families Based on Color Signature

According to studies and classification of fish biologists [4, 12], the ventral colorations constitute are very important features that might be used to discriminate different fish species.

On the other hand; the colors of the ventral part of fishes are to differentiate between the poison and non-poison fish families. The poison fish families have very colorful ventral part and the non-poison fish families are obviously have one or two different appearance color on the ventral part of the fishes.

Referring to the case study above, the fish ventral part color is used in this research by assigning a color signature to each fish family. This is done by subtracting out a crop from the patterns of interest (fish object).

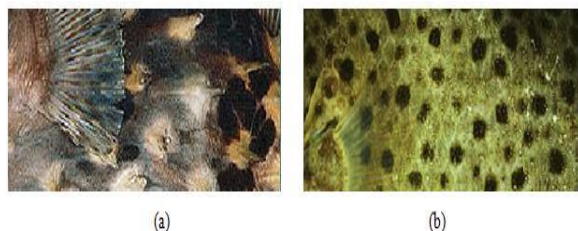


Fig. 2: crop out of color signature for ventral part of two different poison fish families, (a) Porcupine family (b) Trigger family.

Figures 2 and 3 show samples of ventral part of fish families (poison and non-poison) cropped out from fish images that are used in this research. Two cropped out segments of ventral part for poison fish families are shown in Figure 2, and six cropped out segments of ventral part for non-poisons fish families are shown in Figure 3.

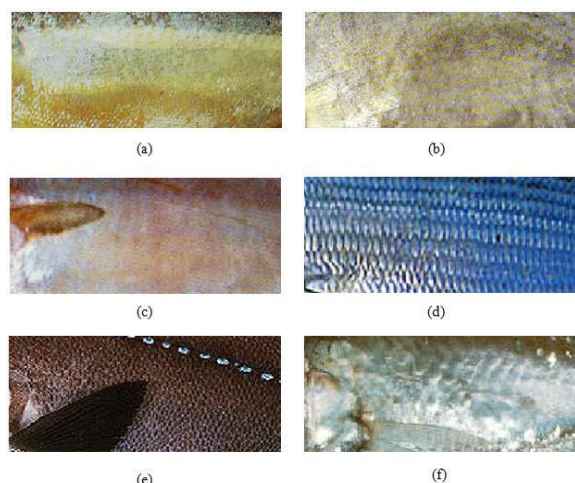


Fig.3: crop out of color signature for ventral part of six different non-poison fish families, (a) Acropomidae family (b) Leiognathidae family (c) Megalopidae family (d) Albulidae family (e) Anomalopidae family (f) Caesionidae family

Both Figures (2 and 3) show the differentiation between fish families based on color of the fish ventral part, especially between poison and non-poison fish families. This differentiation helps to classify the fish images into poison and non-poison, and hence into its regarded family.

2.3 Calculation of Color Signature Features of Fish Images Based on Fish Ventral Part

Some authors recommended using of a combination of color and texture features. Therefore; texture features are computed in grayscale and are combined with color histogram. Then combined features are sent to a classifier for color texture classification [13, 14, 15].

This research proposed a combination between the features extracted based on image segmentation method (color histogram) and those features extracted based on the feature extraction method (GLCM). Fifteen features are extracted based on color signature of fish images using

color histogram and GLCM methods. Compared to the previous studies in the literature, such as Nery et al. [4] who extracted only 8 features based on the ventral part of the fish. In this research, 25 features have been extracted using color histogram technique and GLCM. Experimentally; the number of the extracted features is minimized to 15 features based on selecting only one feature among the converged features values. Figure 4 illustrates the complete process of extracted features from the color signature of fish images.

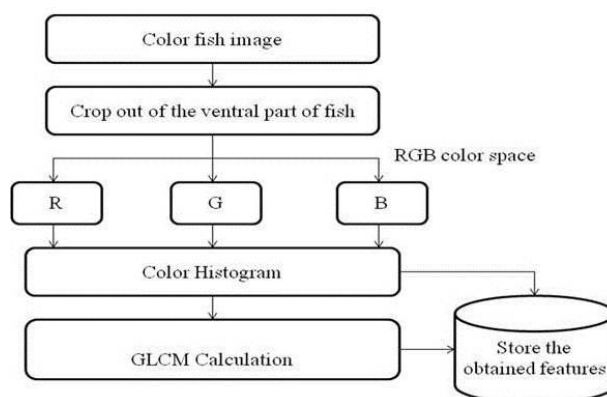


Fig.4: The extracted feature model based on color signature

In the color signature extraction, six distinct steps occur in processing. The first is the image acquisition. It is imperative that images, that are included in the database, are to be digital and of high quality color. The second step is to subtract a crop out of the ventral part from the pattern of interest (fish object). The third step is the extraction of the color value from captured crop using RGB color space. Color values are represented as vectors in the form of 3D-RGB color space. Since the color histogram technique deals with 2D matrix only, therefore, the RGB matrix has been divided into three individual matrixes (R, G, and B) as shown in Figure 4. The fourth step, is to obtain the color histogram from each matrix R, G, and B. The median features and the variance features are obtained directly from the color histogram technique. The fifth step is commenced after obtaining the color histogram technique, in which three features (Standard deviation, Homogeneity, Energy) are extracted using the GLCM.

The three GLCM operations (Standard deviation, Homogeneity, Energy) are performed based on the one direction as vertically (0^0) in the extracting features from color signature of fish images. In gray and color texture measurements GLCM are performed based on the four directions as horizontally (90^0), vertically (0^0), and two diagonally (45^0 and 135^0). These measurements were determined experimentally in this research. The final step is to store the obtained features from the color signature of fish images. The outline of extracted features from color signature is shown in Figure 5.

- Step 1: digital fish image acquisition.
- Step2: subtract a crop out of the ventral part from the fish object.
- Step 3: extract the color value from captured crop using RGB color space, and divide the RGB matrix into three individual matrixes (R, G, and B).
- Step 4: color histogram is obtained from each R, G, and B color matrixes .
- Step 5: the color signature features are calculated depending on color histogram technique to extract two features (the median features and the variance features), then the GLCM is used to calculate three features (Standard deviation, Homogeneity, Energy).
- Step 6: store the obtained features in the data storage.

Fig.5: The outline of extracted features from color signature

Eventually, fifteen color signature features have been calculated from the color histogram. These fifteen features are divided into 3 groups covering all three individual color histogram matrixes (R, G, and B). Each matrix contains 5 common features with different values.

2.4 Genetic Algorithms (GA) Evolutionary Process

Recently, many researchers use Genetic Algorithms (GA) to solve their problems, as long as they know how to encode solutions of a given problem to chromosomes in GA, and compare the fitness of solutions. The secret behind the success in GA is the representation and meaningful fitness evaluation. It helps in discovering good solutions rapidly for difficult high-dimensional and complex problems [16].

There are two elements required for any problem before a genetic algorithm can be used to search for a solution and they are:

- There must be a method of representing a solution in a manner that can be manipulated by the algorithm. Traditionally, a solution can be represented by a string of bits, numbers or characters.
- There must be some method of measuring the quality of any proposed solution, using a fitness function.

2.5 Great Deluge Algorithm

The great deluge algorithm is a local search procedure that was introduced by Dueck [17]. The idea of great deluge comes from the analogy that a person climbing a hill and try to move to any direction of finding a way up to keep his feet dry as the water level rises during a great deluge. The pseudo code for the great deluge algorithm is shown in Figure 6.

Algorithm Great Deluge

Begin

- $s := \text{initial solution};$
- Set initial water level $WL_{\text{initial}};$
- Set final water level $WL_{\text{final}};$
- Calculate the decay rate $\beta;$

Repeat

- generate an $s' \in N(s)$
- if $f(s') \geq f(s)$ then $s = s'$
- $WL = WL - \beta;$

Else

```

if  $f(s') > WL$  then  $s = s'$ ;
until stopping criterion;
end;
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Figure 6: A Great Deluge Algorithm [17]

Inserting a great deluge algorithm within a genetic algorithm is considered an effective way to produce a high quality solution rather than using a genetic algorithm alone [18, 19].

This research applied a great deluge algorithm to improve the solution quality (weight) by increasing the number of fitness costs. This helps to enhance the exploitation process during the searching process.

2.6 Neural Network (NN) Model

The multilayer feed forward neural network model with Back-Propagation Classifier (BPC) for training is employed for classification task as shows in Figure 7 which illustrates our implemented neural network that contains three layers, namely, the input layer, the hidden layer and the output layer. The number of neurons is varied from layer to another (except The output layer consist of 20 neurons since we need to classify 20 fish families [1, 2, ..., 20], each of which correspond to one of the possible family's that might be considered) in order to determine the suitable number of neurons for both input and hidden layers, therefore, obtaining high accurate results.

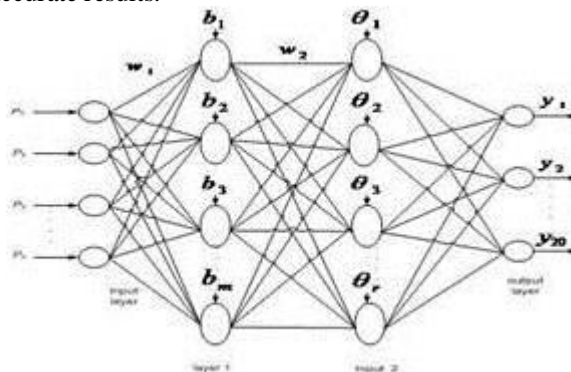


Fig.7: Topology structure of a three-layer feed-forward NN

The developed Back-Propagation Classifier (BPC) is trained with Termination Error (TE) 0.01 in 411 epochs the value of learning constant (Learning Rate LR) used is 0.1. In our experiment the neural network is built with number of input features, three layers and different numbers of neurons in order to achieve the goal.

Table 1: Number of input features and neurons for each layer

Classifier	Number of input features	NO. Neurons in layers		
		Layer #1	Layer #2	Layer #3
BPC	15	23	30	20
HGAGD-BPC	15	25	35	20

Table 1 shows the number of input features and number of neurons for each layer that are determined experimentally.

3. A Hybrid Memetic Algorithm (MA) With Back Propagation Classifier

The MA is used in this work to optimize the weights required by the BPC. This is accomplished by initializing a population of diverse weights covering large possibilities of determining the best suited weight for the algorithm's learning process.

The parameter learning process, based on MA technique and BPC, involve a two-step learning process, in the first step, the initial parameters of the neural network are tuned by the MA .in the second step, the BPC is introduced to train the initial NN to yield optimal values of weight and biases in the NN.

Basically, the MA is a derivative-free stochastic optimization method based on the features of natural selection and biological evolution. It has several advantages over other optimization algorithms. It can be applied to both continuous and discrete optimization problems. Compared with the BPC, the MA is less likely to get trapped in local optima [1, 20 - 25]. This can be avoided by implementing some genetic operators and mechanisms, such as producing new population using solutions crossover and/or mutation. It is a computational model inspired by population genetics. It has been used mainly as function optimizers and it has been demonstrated to be an effective global optimization tool, especially for multi-model and non-continuous functions.

The MA evolves a multi-set of elements, called a population of individuals. Each individual X_i ($i= 1, 2, 3, \dots, p$) (where p is the size of the population) of population X represents a solution of the problem. Individuals are usually represented by strings and each element of which is called a gene. The value of a gene is called its allelic value, and its range is usually restricted to $[0, 1]$, but it can also be continuous and even structured. This research use real-valued strings in proposed approach, a binary representation. The MA is capable of maximizing a given fitness function F computed on each individual of the population. The flowchart of proposed hybrid learning algorithm is illustrated Figure 8.

This model describes the hybridization between MA and BPC by using the MA to optimize the parameters of the BPC. All the parameters of the BPC are encoded to form a long chromosome and tuned by the MA. Then, as a result of the MA process, the BPC is used to train the network [1].

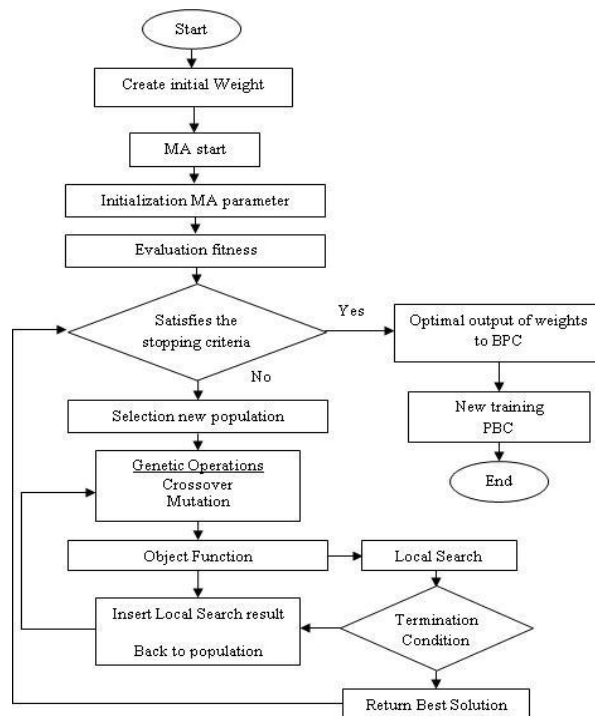


Fig. 8: Flowchart of the Hybrid Learning Algorithm Method

3.1 Initialization

Initially, many individual chromosomes solutions are randomly generated to form an initial population [26]. MA begins with an initial population represented by chromosomes. A chromosome is a set of solutions from one population. It can be taken and apply to form a new population. Figure 9 shows the gene, chromosome, and population presentations.

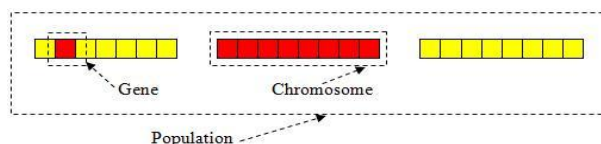


Figure 9: Representation of Gene, Chromosome and Population

The expectation is the new population (offspring) will be better than the old one. According to the degree of fitness, the offspring will be selected. This process is repeated until the best solution is fulfilled. Each chromosome represents a possible solution by a set of parameters. The population size depends on the nature of the problem, but typically contains several hundreds or thousands of possible solutions [1].

3.2 Chromosome Representation

A BPC can be represented by a directed graph, encode on a chromosome with each parameter (weights and biases). The parameters are memorized by a row matrix $C = (c_i), i = 1, 2, \dots, N$, where N is the number of all NN parameters. We can write the chromosome as

$$C = [W_1, W_2, b_1, b_2, \dots, b_m, \theta_1, \theta_2, \dots, \theta_r]$$

Where W_1 denotes the connective weight of link between the input layer and the first hidden layer, W_2 is the connective weight of link between the first hidden layer and the second hidden layer, b_1, b_2, \dots, b_m are the biases of neurons of the first hidden layer, $\theta_1, \theta_2, \dots, \theta_r$ are the biases of neurons of the second hidden layer.

$W_1, W_2, b_1, b_2, \dots, b_m, \theta_1, \theta_2, \dots, \theta_r$ are the real values of the connective weights, biases respectively, as shows in figure 7.

3.3 Roulette Wheel Selection

Roulette Wheel Selection is the simplest selection schema; it is developed by Baker [27]. This is a stochastic algorithm and involves the following technique:

1. The individuals are mapped to contiguous segments of a line, such that each individual's segment is equal in size to its fitness.
2. A random number is generated and the individual whose segment spans the random number is selected.
3. The process is repeated until the desired number of individuals is obtained (called mating population).

Two chromosomes in the population will be selected to undergo genetic operations for reproduction by the method of spinning the roulette wheel [23]. It is believed that high potential parents will produce better offspring (survival of the best ones). The chromosome having a higher fitness value should therefore have a higher chance to be selected as a parent as shows in Figure 10 which represent an example of three segment areas represent three solutions (A, B, and C), in which each segment area has its size determined by the fitness of the solution. The higher fitness has the highest probability to be selected in successive iterations.

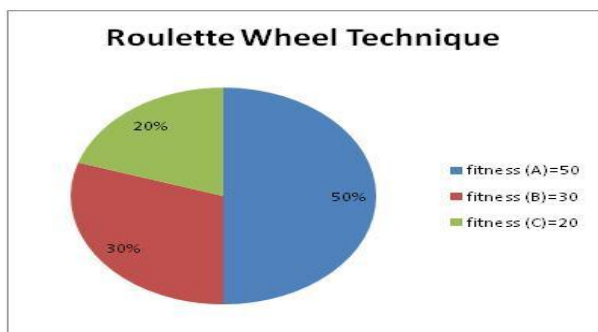


Fig. 10: Roulette Wheel technique

The basic part of the selection process is to stochastically select from one generation to create the basis of the next generation. The requirement is that the fittest individuals have a greater chance of survival than weaker ones. This

replicates nature in that fitter individuals will tend to have a better probability of survival and will go forward to form the mating pool for the next generation. Weaker individuals are not without a chance. In nature such individuals may have genetic coding that may prove useful to future generations.

3.4 Single Point Crossover

This is the simplest method of crossover, which generate one or two child string by random selection of crossover site within the length of pattern string. Single point crossover is done by choosing a random point. The chromosomes of the parents will be cut from that point, and the resulting sub-chromosomes will be swapped. As shown in Figure 11.

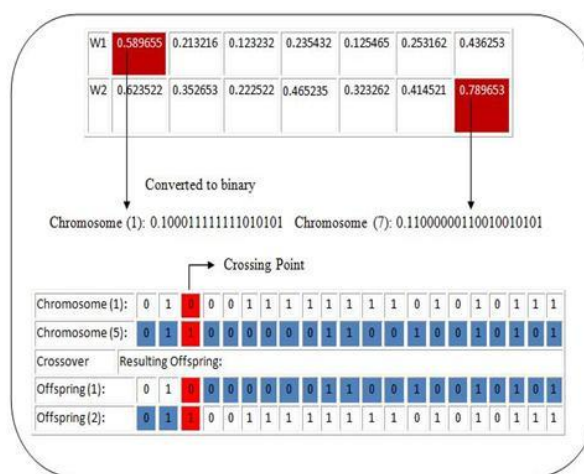


Fig. 11: Single point crossover

3.5 Mutation

The purpose of mutation in MAs is to allow the algorithm to avoid local minima by preventing the population of chromosomes from becoming too similar to each other, thus slowing or even stopping evolution. A variable is selected with a certain probability and its value is modified by a random value. This reasoning also explains the fact that most MA systems avoid only taking the fittest of the population in generating the next but rather a random (or semi-random) selection with a weighting toward those that are more fit. A simple mutation example shown in Figure 12.

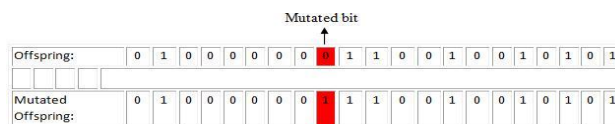


Fig. 14: Mutation process

In this study, a non-uniform mutation method is chosen. Non-uniform mutation changes one of the genes of the parent based on a non-uniform probability distribution.

3.6 Fitness Function

The fitness function is dependent on problem and is used to evaluate the performance of each individual. The fitness function of calculating the performance of each individual is performed by computing the percentage Variance Account Function (VAF) between two signals. The VAF is calculated as follows:

$$V = 1 - \frac{\text{variance}(y - y_{est})}{\text{variance}(y)} * 100\%$$

Where y is the real output, y_{est} is the estimated output of a model. VAF is computed for the two signals to result the output v . The VAF of two signals that are the same is 100%. If they differ, the VAF will be lower. When y and y_{est} have multiple columns, the VAF is calculated for every column in y and y_{est} . VAF is often used to verify the correctness of a model, by comparing the real output with the estimated output of the model.

3.7 Stopping Criterion

A generation consists of the production of a new population in a generational algorithm. A similar definition is used for a steady-state algorithm. A maximum number of generations usually defines the stopping criterion in genetic algorithms. However; when it is possible to achieve an ideal fitness (i.e. optimal weight), this can also serve as the stopping criterion. In this work, a maximum generation number is used, regardless of whether the ideal fitness is achieved or not. Other criteria are possible, such as a measure of diversity loss or a lack of fitness improvement.

3.8 Testing the System

As shown in Table 2, the accuracy of classification test results for each fish family (20 families) based on the color signature features, which vary from a family to another. From Table 2, the obtained results by the BPC method indicate a high accuracy of each fish family's recognition percentage, which lie between 82% - as minimum percentage of accuracy - and 90% - as a maximum percentage of accuracy.

The HGAGD-BPC obtained high accurate results and outperforms the BPC for all fish families except the last family where both classifiers (BPC and HGAGD-BPC) obtained the same classification accuracy (90%). The accuracy of HGAGD-BPC's results in the classification process lie between the minimum percentage of accuracy equals to 88% and the maximum percentage which is 94%. Some of the results obtained by the BPC (for instance) are close to the minimum percentage (e.g. Scombridae) are due to the color features similarities (e.g. Leiognathidae). This causes a noise identification interruption to the proposed classifiers to classify properly. This indicates that the GAGD-BPC performed

better and more accurate than the BPC in differentiating between extracted features set.

Table 2: The accuracy of recognition test results for each fish family based on the color signature features

Family Name	BPC%	HGAGD-BPC%
<u>Acestrorhynchidae</u>	87	89
<u>Acropomatidae</u>	88	90
<u>Albulidae</u>	82	88
<u>Anomalopidae</u>	83	88
<u>Caesionidae</u>	83	89
<u>Drepanidae</u>	84	92
<u>Istiophoridae</u>	84	90
<u>Leiognathidae</u>	82	90
<u>Megalopidae</u>	82	88
<u>Platycephalidae</u>	84	92
<u>Priacanthidae</u>	85	91
<u>Scombridae</u>	82	92
<u>Siganidae</u>	84	91
<u>Sillaginidae</u>	84	93
<u>Stromateidae</u>	84	94
<u>Triacanthidae</u>	85	91
poison/Red Snapper	86	89
poison/Trigger	90	92
poison/Porcupine	89	93
poison/Thorn	90	90

This is due to its intelligent and iterative behavior that provides more possibilities in finding and improving good or optimal weights for the classification process. In contrast with GAGD-BPC, the BPC method search and select weights randomly and provides no improvement of the obtained weight.

4. Results

The methods have been implemented in MATLAB programming language on a CPU Core 2 Duo 2.33 GHZ. We have considered fish images from different families, obtained from Global Information System (GIS) on Fishes (fish-base) and department of fisheries. For experimental purpose, 610 hundred fish images families are considered, 410 fish images for training and the rest 200 for testing. Table 3 describes the overall training and testing accuracy obtained based on robust features extracted from color signature using BPC.

Table 3: Description of the overall accuracy of training and testing

Description	Results
Overall training accuracy	88%
Overall testing accuracy	84%

In addition, the problem in fish recognition is to find meaningful features based on the features extraction. An efficient classifier that produce better fish images recognition accuracy rate is also required. As shown in Table 3 the overall training accuracy equals to 88% and the overall testing accuracy equals to 84%.

Table 4 describes the fitness cost and the overall accuracy of training and testing for the color signature features. The results shown in the Table are the overall accuracy outcome for both training and testing accuracy obtained from the trained the HGAGD-BPC. The fitness cost and the overall training and testing accuracy was 96%, 93% and 91% respectively.

Table 4: the overall accuracy outcome for both training and testing accuracy obtained from the HGAGD-BPC

Description	Results
Fitness cost	96%
Overall training accuracy	93%
Overall testing accuracy	91%

5. Discussion

According to studies and classification of fish biologists [4, 12], the ventral colorations constitute are very important features that might be used to discriminate different fish species. In this paper the feature extraction is done based on color signature, utilizing color histogram technique and GLCM method. Therefore; two features were extracted for each matrix using color histogram technique. Three features were extracted using GLCM method. Finally, these features are stored in a database to be utilized by the proposed classifiers. The extracted features from color signature was done based on ventral part of the fish, which proved to be the suitable region of pattern of fish to extract the color features from. It has been determined by observations and recommendations from previous studies and classification of fish biologists [4].

6. Conclusion

Fifteen features have been extracted from color signature based on ventral part of the fish as shown in the second section. Nine of these features were extracted from the color histogram using GLCM method and 6 features have been extracted directly from the color histogram. The experimental results suggest that our feature selection methodology can be successfully used to significantly improve the performance of fish classification systems. Previous approaches proposed

feature descriptors and do not analyze their impact in the classification task as a whole. A general set of 15 features and their corresponding weights is proposed. These features may be used as priori information by the classifiers. Moreover, the study presents a hybrid memetic algorithm (genetic algorithm and great deluge local search) with back-propagation classifier for fish classification. The performance of the BPC has been improved significantly by the hybridization of the MA with the BPC. It is proved to be much better than the BPC. The experiments showed the effectiveness and robustness of the MA incorporated by the BPC. The HGAGD-BPC has outperformed BPC method and previous methodologies by obtaining better quality results but with a high cost of computational time compared to the BPC method. The overall accuracy obtained using the traditional BPC was 84%, while the overall accuracy obtained by the HGAGD-BPC was 91% on the test dataset used.

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