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Shape- and Texture-Based Fish Image Recognition System

Chomtip Pornpanomchai*, Benjamaporn Lurstwut
Pimprapai Leerasakultham and Waranat Kitiyanan

ABSTRACT

This research developed a computer system capable of recognizing some fish images. The system known as the "shape- and texture-based fish image recognition system" (FIRS) consists of five subsystems—namely: 1) image acquisition, 2) image preprocessing 3) feature extraction, 4) image recognition and 5) result presentation. The experiment was conducted on 30 fish species, which consisted of 600 fish images as the training dataset and 300 fish images for testing. The system compared two recognition techniques—a Euclidean distance method (EDM) and artificial neural networks (ANN). The system was able to recognize all 30 species of the training fish images with a precision of 99.00 and 81.67% for the ANN and the EDM techniques, respectively. The average access times were 24.4 and 154.43 sec per image for the EDM and ANN techniques, respectively.

Keywords: fish features, fish recognition, image processing, pattern recognition, artificial neural networks

INTRODUCTION

Thailand is a country in Southeast Asia, flanked by the Gulf of Thailand to the south and east and by the Andaman Sea to the west. In the Gulf of Thailand, 241 species from 49 families of marine fish have been recorded during 1991–1998, such as *Terapon jarbua*, *Nemipterus hexodon*, *Epinephelus areolatus*, *Caesio cuning* and *Epibulus insidiator* and others (Ukkrit, 2000). Moreover, 1,746 species of marine fish in 198 families have been identified from the Andaman sea, such as *Gobiidae, Labridae, Pomacentridae, Serranidae, Apogonidae, Blenniidae and Chaetodontidae* and others (Ukkrit, 2011). In addition, there are many large Thai rivers—the Ping, Wang, Yom, Nan, Chao Phraya, Mekong, Mun, Mae Sai, Tapee and Golok rivers among others—which are home to more than 720 freshwater fish species, such as *Rasbora caudimaculata*, *Channa striata*, *Osteochilus hasseltii* and *Sillago maculate* (Beamish *et al.*, 2011; Chomtip *et al.*, 2012). Consequently, it is very difficult even for people who work daily in the fishing industry to recognize all Thai fish species, which exceed 2,700 species. For this reason, this project was established to develop a computer system to identify some Thai fish species. The system aimed to allow users to load an unknown fish picture into a shape- and texture-based fish image recognition system (FIRS) which the system then attempts to identify. Finally, the FIRS displays the recognition results on the system's graphic user interface (GUI).

Many scientists and researchers have developed a variety of fish classification and fish recognition systems for use by the fishing industry,

Faculty of Information and Communication Technology, Mahidol University, Bangkok 10400, Thailand.
* Corresponding author, e-mail: itcpp@mahidol.ac.th

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to observe fish behavior and to aid in fish sorting and counting among other applications. Some brief details of each research technique are provided below.

My SQL tools

Using My SQL tools, Uma *et al.* (2009) developed a fish identification system called "Superimposed Image Description and Retrieval" or "Super IDR". The system was tested by 28 students and the precision of the system was 73.35% in identifying 20 species of fish.

Xitao *et al.* (2011) used a My SQL tool called "Ontology web language" or "OWL" to identify fish species using a fish knowledge-base in My SQL that integrated text mode in both a morphological and lexical style.

Euclidean distance technique

Jia *et al.* (2010) used a computer vision technique to recognize and track fish in a tank. The system studied 6 fish species in about 100 images using Euclidean and k-means methods. The precision of the system was 90%.

Concetto *et al.* (2010) developed a system called "Automatic Fish Classification for Understanding Underwater Species Behavior". The system considered 10 fish species—*Bodianus mesothorax*, *Chaetodon trifascialis*, *Chromis viridis*, *Dascyllus albisella*, *Dascyllus aruanus*, *Dascyllus reticulates*, *Gomphosus varius*, *Hemigymnus fasciatus*, *Plectorhinchus lessonii* and *Pseudocheilinus hexataenia*. A k-means method was applied to classify 100 fish images with 92% precision.

Dah *et al.* (2008) developed fish species recognition by applying contour matching and a Euclidean distance method. The system was used on six fish species—Speckled Dace, Whitefish, Cottid, Utah Sucker, Salmon and Brown Trout—and had a precision of 97%.

Principal component analysis

Matai *et al.* (2010) used principal component analysis (PCA) to recognize fish images. The experiment was conducted on four species of rock-fish (*Sebastes Constellatus*, *S. levis*, *S. miniatus*, *S. rubrivinctus*) and one species of butterfly fish (*Scythe butterflyfish)*. The precision of the system was 90%.

Charles and Itsuo (2012) applied an active appearance model (AAM) with PCA on a smartphone to identify fish species. The system was tested on 15 fish species—*Chromis atripectoralis*, *Premnas biaculeatus*, *Pseudanthias bicolor*, *Amphiprion clarkii*, *Pomacentrus coelestis*, *Chrysiptera cyanea*, *Zebrasoma flavescens*, *Amphiprion frenatus*, *Sphaeramia nematoptera*, *Amphiprion perideraion*, *Amphiprion sandaracinos*, *Gnathanodon speciosus*, *Pseudanthias squamipinnis*, *Microcanthinae strigatus* and *Abudefduf vaigiensis*. The precision of the system was 94%.

Neural networks technique

Masato *et al.* (2008) applied the neural networks technique in an image processing approach for automatic fish sorting of four species of fish (Urumeiwashi, Maiwashi, Kibinago and Katakuchiiwash). They achieved a precision of 100% for the training data set and 66.7% for untrained data set.

Sebastien *et al.* (2000) developed an intelligent system for automated fish sorting and counting. The system employed the neural networks technique for sorting five species of fish—Bowfin, Copper Redhorse, Largemouth Bass, Northern Pike and Walleye. The system used 1,200 fish images with a precision of 88.75 and 77.88% for the training and untrained data sets, respectively.

Mutasem *et al.* (2010) developed a fish recognition system by applying back-propagation neural networks. The system was applied to 20 fish species with 350 fish images and resulted in 86% precision.

Frank and Daan (2001) reported a fish species recognition system using computer vision and a neural networks system based on 251 fish images of six fish species—Sole, Plaice, Whiting, Dab, Cod and Lemon Sole. The precision of the system was 98%.

Thus, there have been many studies that considered an automatic system to identify many fish species for many purposes. In the current research, the FIRS was applied to more than 30 fish species using the Euclidean distance and a neural networks technique for recognition.

MATERIALS AND METHODS

The experiment was conducted using the following computer hardware specifications: 1) CPU Intel® Core ™ i5-2410M 2.3 GHz, 2) Memory DDR3 4GB and 3) Hard disk 600 GB. The computer software used Microsoft Windows 7 (Microsoft Corp.; Redmond, WA, USA) as the operating system and MATLAB R2013a (The MathWorks Inc.; Natick, MA, USA) for the development tool.

The process of analysis and design describes the system conceptual diagram and system structure chart. The details of each element are described below.

System conceptual diagram

The FIRS starts with the user taking a fish image using a digital camera. Then, the fish image is entered into the computer system for recognition, which involves the system comparing the fish image with all the fish images in the system database. Finally, the system displays the recognition results, as shown in Figure 1.

System structure chart

For a better understanding and more detail of each operation of the system, the FIRS structure chart which elaborates on how each model works is shown in Figure 2. The fish image recognition system consists of five main process modules: 1) image acquisition, 2) image preprocessing, 3) feature extraction, 4) image recognition and 5) result presentation.

Image acquisition

This module takes a fish image taken from a birds-eye-view angle as an input of the system. The system reduces the fish shadow by taking the fish photo on a white plastic plate which has fluorescent bulbs below. Samples of fish images are shown in Figures 3a–3d. All fish images are taken with a black color reference object 3 × 3 cm square.

Image preprocessing

The image preprocessing module consists of six submodules: 1) size adjustment, 2) grayscale conversion, 3) black and white conversion, 4) noise removal, 5) edge detection and 6) object segmentation.

1. Size adjustment

The input image is resized to 800 × 600 pixels using 'nearest-neighbor' interpolation. Neighborhood pixels are used to consider the new pixel value. This process also helps maintains consistency and reduces the processing time. An example is shown in Figure 4a.

2. Grayscale conversion

After adjusting the size of an image, the system converts the fish image into a grayscale image. The value range of the grayscale level is 0–255, as shown in Figure 4b. Equation 1 is used to convert the red-green-blue RGB image to a grayscale image.

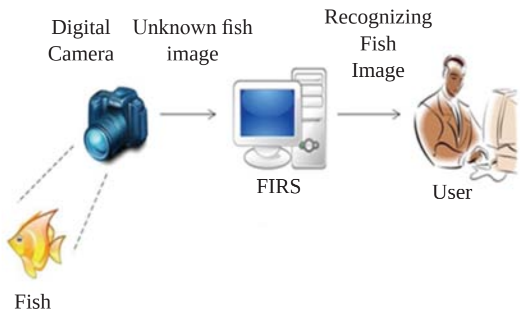

Figure 1 Fish image recognition system conceptual diagram.

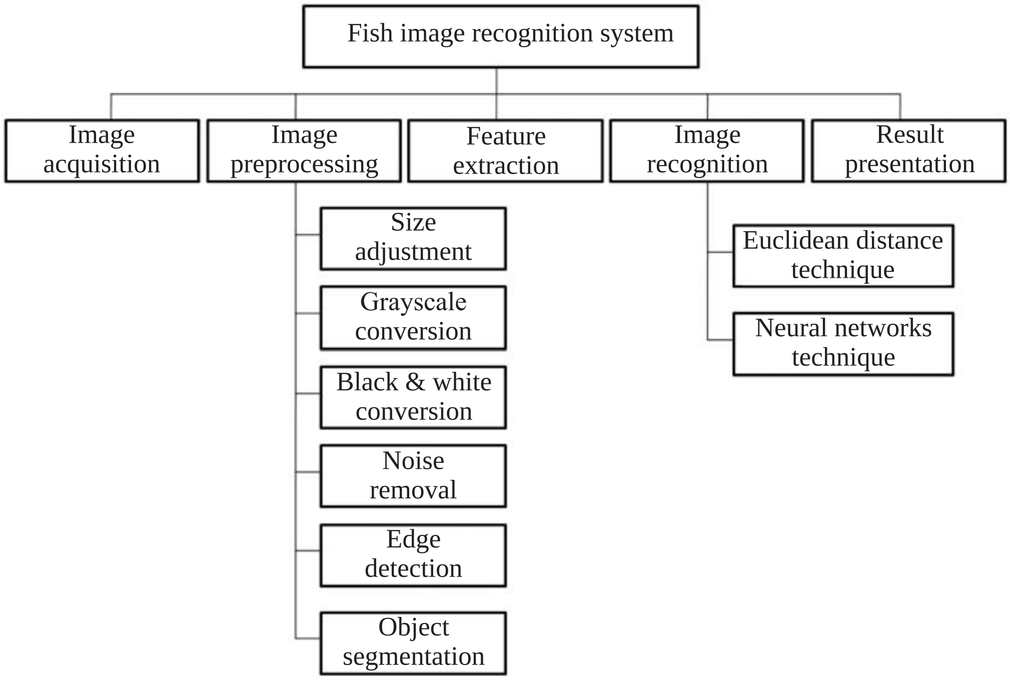

Figure 2 Shape- and texture-based fish image recognition system structure chart.

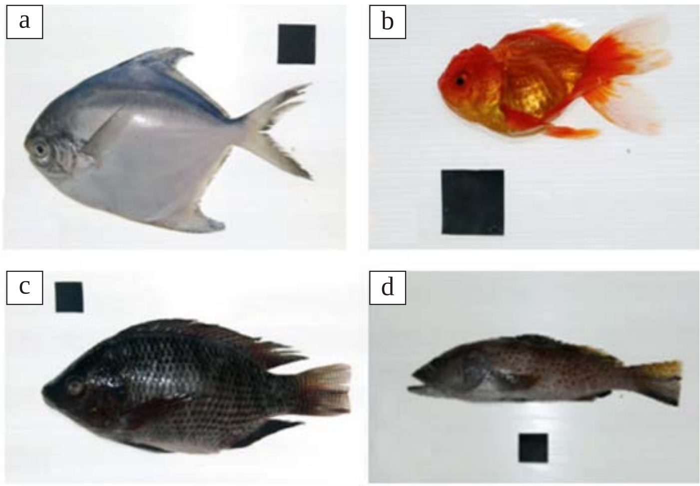

Figure 3 Sample of fish images (a) *Pampus argenteus* (b) *Carassius auratus* (c) *Oreochromis niloticus* and (d) *Epinephelus areolatus*. The black scale reference square is 3×3 cm square.

$$GR = 0.299*R + 0.587*G + 0.114*B \quad (1)$$

where GR is gray, R is red, G is green and B is blue.

3. Black & white conversion

After obtaining the grayscale image, the system converts it into a black and white image using a single value, threshold T. Otsu's method (Reza and Cheriet, 2012) maximizes the between-class variance and is applied to each input image to determine the T value, so that the T value of each image is different, depending on the illumination. Each pixel is coded as black (0) if the gray value is greater than T, otherwise it is white (1). The result of the image after this conversion process is shown in Figure 4c.

4. Noise removal

Normally, the image contains noise or unwanted parts, for instance, spot, dust, and water droplets. This process remove these objects if their size is less than 300 pixels. In addition, the system also fills in any open area in the object. Thus, this process produces an enhanced binary image, as shown in Figure 4d.

5. Edge detection

The system applies the 'Sobel' edge detection technique (Rebecca and Folorunso, 2009) to the black and white image. There are two 3 × 3 templates used in this technique. Template "a" (Figure 5a) is applied to determine the difference in the horizontal axis and template "b" (Figure 5b) is used for the vertical axis. The result from the edge detection submodule is shown in Figure 4e.

6. Object segmentation

In this experiment, the system is based on a two-object image. The noise, only a small part of the image, is removed in the noise removal process as discussed previously. The system segments the objects from the black and white image to produce two objects—the fish body and the reference object (as shown in Figure 4f). The smaller object is assumed to be the reference object. The result from the process is used to calculate the input size ratio.

a

1	0	1
-2	0	2
-1	0	1

b

1	2	3
0	0	0
-1	-2	-1

Figure 5 Sobel edge detection templates for: (a) Horizontal axis, (b) Vertical axis.

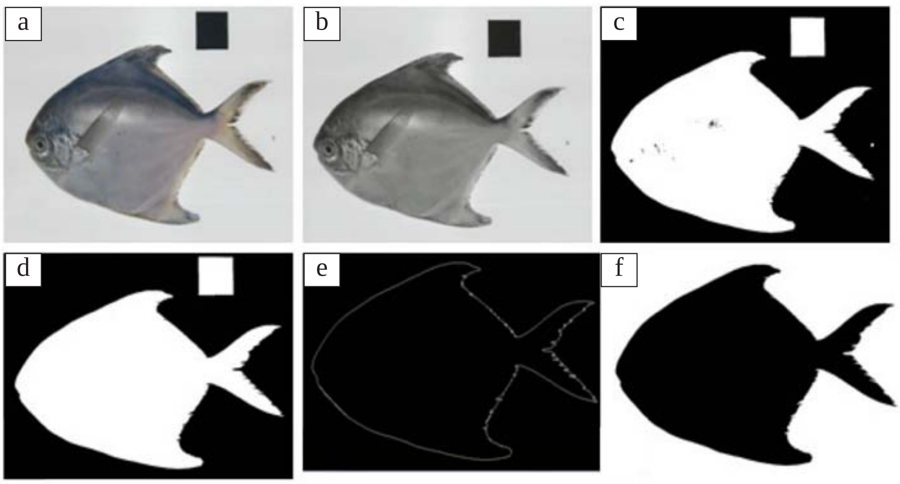

Figure 4 Image in each preprocessing step: (a) Size adjustment, (b) Grayscale image, (c) Black and white image, (d) Noise removal, (e) Edge detection and (f) Object segmentation. The black scale reference square is 3 × 3 cm square.

Features extraction

Based on the fish image and the reference object in Figure 4a, the system found the following fish and reference object characteristics: 1) fish width is 668 pixels, 2) fish length is 1,098 pixels, 3) fish area is 394,664 pixels, 4) fish boundary is 4,045 pixels, 5) reference object side length is 141 pixels. The process identified eight fish features based on the fish and reference object characteristics. Each feature has the following details.

1. Width ratio (WR) – the ratio between the fish and the reference object width. The WR in Figure 4a is equal to 668 / 141 or 4.74.

2. Length ratio (LR) – the ratio between the fish and the reference object length. The LR in Figure 4a is equal to 1,098 / 141 or 7.79.

3. Area ratio (AR) – the ratio between the fish and the reference object area. The AR in Figure 4a is equal to 394,664 / (141 × 141) or 394,664 / 19,881or 19.85.

4. Width and length ratio (WLR) – the ratio between the fish width and the fish length. The WLR in Figure 4a is equal to 1,098 / 668 or 1.64.

5. Boundary ratio (BR) – the ratio between the fish and the reference object boundary. The BR in Figure 4a is equal to 4,045 / (141 × 4) or 4,045 / 564 or 7.17.

6. Average red color (AR) – the average red color in the fish image. The AR in Figure 4a is equal to 119.78.

7. Average green color (AG) – the average green color in the fish image. The AG in Figure 4a is equal to 119.29.

8. Average blue color (AB) – the average green color in the fish image. The AB in Figure 4a is equal to 123.96.

Image recognition

There are two submodules in the image recognition module—the Euclidean distance (ED) submodule and the neural networks submodule. The FIRS compares the recognition precision of these two methods and each submodule has the following details.

1. Euclidean distance

The ED measures the similarity between every feature of an unknown fish image and every feature of each training data set in the FIRS. The lowest ED value indicates both fish images are very similar. The ED formula is shown in Equation 2.

$$ED = \sqrt{\sum_{i=1}^{n} (X_i - Y_i)^2} \qquad (2)$$

where ED is the Euclidean distance value, n is number of features (in the FIRS = 8), X_i is the value of feature *i* in the system database and Y_i is the value of feature *i* in an unknown image.

2. Artificial neural network

The artificial neural network (ANN) recognizes the fish image by using the neural networks structure: 8-20-30 (as shown in Figure 6). The 8 input nodes are equal to 8 features of each fish image and the 30 output nodes are equal to 30 kinds of fish image in the training dataset.

Result presentation

The result presentation process shows the fish recognition results. The graphic user interface (GUI) of the system is shown in Figure 6, which has the following details.

1. Image box – there are two image boxes—namely, the input unknown fish image

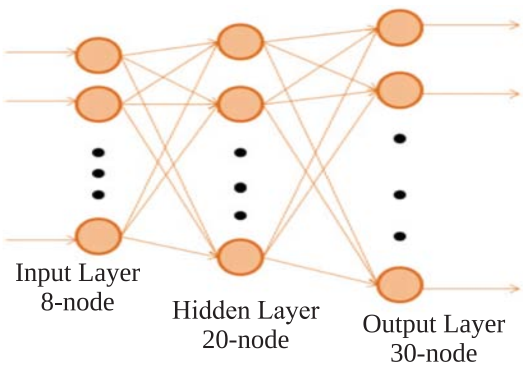

Figure 6 Fish image recognition system artificial neural network structure.

(Figure 7 label number 1) and the recognition image box (Figure 7 label number 2).

2. Text box – there are two text boxes—namely, the browse image file text box (Figure 7 label number 3) and the recognition fish details text box (Figure 7 label number 4). The recognized fish details include the common and scientific names of the fish, its habitat and other details.

3. Command button – there are three command buttons—namely, the recognition process button (Figure 7 label number 5), the reset button (Figure 7 label number 6), for refreshing the FIRS screen and the report button (Figure 7 label number 7), for printing the fish details on paper.

RESULTS AND DISCUSSION

The FIRS process was conducted on 30 fish species consisting of 600 fish images for the training data set and 300 fish images for testing. The precision rates of the EDM were 81.67, 1.60 and 2.33% for match, mismatch and unknown, respectively (Table 1) and the precision rates of the ANN were 99.00 and 1.00% for match and mismatch, respectively (Table 2). The average access times were 24.4 and 154.4 sec per image for the EDM and ANN, respectively. The ANN gave higher precision rates than the EDM but the average access time for the EDM was 6.3 times faster than the ANN. Based on the experimental results in Tables 1 and 2, the FIRS produced some mismatch results with *Terapon jarbua* because it has very similar features to *Barbonymus gonionotus*, *Lactarius lactarius* and *Eleutheronema tetradactylum*.

In previous studies into fish recognition systems, some researchers applied a semantic identification method to retrieve a fish image in the fish database (Yixin *et al.*, 2005; Uma *et al.*, 2009). The system described each part of a fish (head, fin, body, tail et cetera) and then compared each part of the fish image to the system database. Finally, the system identified the fish by using a semantic classification. It is very difficult for researchers

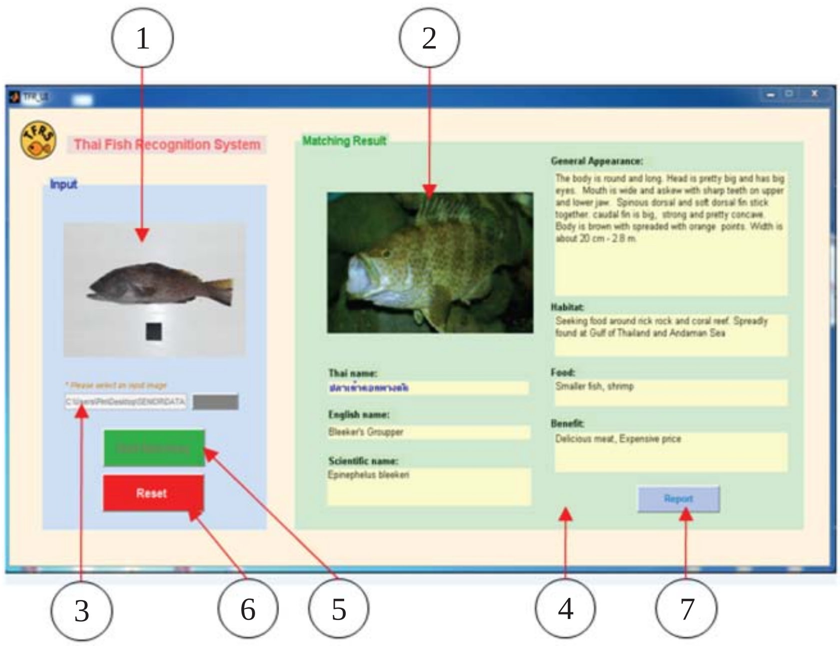

Figure 7 Fish image recognition system graphic user interface. The numbers refer to key information (1, 3 = image and file location of fish to be identified; 5, 6, 7 = command buttons; 2, 4 = information on recognized fish)

to describe fish characteristics in a text mode and then compare and map the database information to the fish image. Some researchers applied the relationship between fish length and fish weight to identify the fish species, but this technique was considered time consuming (Beamish *et al*., 2011). Due to the fast development of digital camera technology, image processing techniques have made it very easy to recognize a fish species by using only the fish image. Many researchers have applied image processing techniques to recognize a fish. Normally, shape, color, contour and texture features are applied to recognize a fish (Frank and Daan, 2001; Jia *et al*., 2010; Matai *et al*., 2010; Mutasem *et al*., 2010).

Table 1 Experimental results by Euclidean distance method.

Scientific name	M	S	U
Rastrelliger brachysoma	10	0	0
Pangasius pangasius	9	0	1
Terapon Jarbua	2	8	0
Nemipterus hexodon	8	2	0
Cynoglossus macrolepidotus	10	0	0
Dermogeny pusilla	9	1	0
Liza subviridis	9	1	0
Barbonymus gonionotus	7	3	0
Oreochromis niloticus	9	0	1
Katsuwonus pelamis Linnaeus	6	4	0
Oreochromis niloticus niloticus	7	3	0
Prisipomoides typus	9	0	1
Epinephelus areolatus	10	0	0
Paratromateus niger	9	0	1
Salaroides leptolepis Bleeker	7	3	0
Lactarius lactarius	9	1	0
Caesis cuning	9	0	1
Sillago maculata	8	2	0
Arius truncatus Curier & Valennennes	7	3	0
Pampus argenteus	9	1	0
Hypophthalmichthys molitrix	9	1	0
Labeo rohita	8	2	0
Psettodes erumei	4	5	1
Auriglobus Modestus	8	2	0
Zonichthys Nigrofascita	9	1	0
Chitala Chitala	10	0	0
Drepane punctata	8	1	1
Eleutheronema tetradactylum	6	4	0
Carrassius auratus	10	0	0
Pterophyllum altum	10	0	0
Total	245	48	7

M = match, S = mismatch, U = unknown
Each fish species used 10 images for testing.

The current research used an image processing method that applied simple shape and color features to recognize a fish image. Moreover, the FIRS added the fish size feature calculated by comparing the fish pixels with the reference object pixels to recognize a fish image. The results using simple shape, color and fish size features with the ANN method were good. The FIRS was easy to implement on a typical computer and it was easy to recognize a fish species by using only eight fish features.

This research can contribute to building a computer system which can help people to recognize fish images for many purposes including: the study of interesting fish, the study of fish ecology and the investigation of threatened

Table 2 Experimental results by artificial neural networks method.

Scientific name	M	S	U
Rastrelliger brachysoma	10	0	0
Pangasius pangasius	9	0	1
Terapon Jarbua	8	2	0
Nemipterus hexodon	10	0	0
Cynoglossus macrolepidotus	10	0	0
Dermogeny pusilla	10	0	0
Liza subviridis	10	0	0
Barbonymus gonionotus	10	0	0
Oreochromis niloticus	10	0	0
Katsuwonus pelamis Linnaeus	10	0	0
Oreochromis niloticus niloticus	10	0	0
Prisipomoides typus	10	0	0
Epinephelus areolatus	10	0	0
Paratromateus niger	10	0	0
Salaroides leptolepis Bleeker	10	0	0
Lactarius lactarius	10	0	0
Caesis cuning	10	0	0
Sillago maculata	10	0	0
Arius truncatus Curier & Valenennes	10	0	0
Pampus argenteus	10	0	0
Hypophthalmichthys molitrix	10	0	0
Labeo rohita	10	0	0
Psettodes erumei	10	0	0
Auriglobus Modestus	9	1	0
Zonichthys Nigrofascita	10	0	0
Chitala Chitala	10	0	0
Drepane punctata	10	0	0
Eleutheronema tetradactylum	10	0	0
Carrassius auratus	10	0	0
Pterophyllum altum	10	0	0
Total	297	3	0

M = match, S = mismatch, U = unknown
Each fish species used 10 images for testing.

and endangered fish species. This research applied the simple ANN technique with a simple computer system. Therefore, it is possible to implement the FIRS on a mobile system, which is very suitable for students and fisheries staff who must carry portable devices. The following topics deserve consideration for future development of the FIRS: 1) increase the number of fish species and fish images in the system database, 2) develop the capability to recognize a fish from an image taken in the real environment not just in a controlled environment, 3) increase the number of fish features, including skin texture (for example, body stripes and scatter spots) and the size of fish organs (for example, eyes, fins and jaw) to recognize the fish image and 4) implement the package on a client-server-based computer system.

CONCLUSION

The FIRS fulfilled the research objective by extracting eight main fish features and recognizing some fish species by using image processing technique. Based on the experimental results, the FIRS employed the ANN and EDM techniques to recognize the fish image with precision rates of 99.00 and 81.67%, respectively. The ANN gave better precision rates than the EDM but the EDM used less processing time than the ANN. There were 30 fish species and 900 fish images in the FIRS database but there are a lot of fish species in the world. This study represents just an initial project to recognize fish image for many purposes. Many fish species have similar size, color and shape, which makes them very difficult to identify. To increase both the species recognition and the recognition precision rate, the FIRS needs to access more fish features in the recognition procedure and to have a larger database of fish images in the system. Finally, the FIRS needs to be implemented in a world-wide-web-based system, which can help people to share global fish information.

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