An Automated Fish Species Classification and Migration Monitoring System

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Abstract—The quantification of abundance, distribution, and movement of fish is critical to ecological and environmental studies of fish communities. To properly manage, regulate, and protect migratory fisheries it is essential to accurately monitor numbers, size, and species of fish at specific fish passages during migratory seasons. Currently, all monitoring is done manually with significant time and financial constraints. An automated fish classification system will simplify data gathering and improve data accuracy.

In this research, 22 images of 9 target species were recorded. The contour of each image was extracted to form a closed curve for shape analysis. A new shape analysis algorithm was developed for removing edge noise and redundant data points such as short straight lines. A curvature function analysis was used to locate critical landmark points. The fish contour segments of interest were then extracted based on these landmark points for species classification. By comparing individual contour segments to the curves in the database, accurate pattern matching was achieved.

***Index Terms*—Landmark points selection, shape-based fish classification, shape analysis, fish migration monitoring system**

I. INTRODUCTION

The quantification of abundance, distribution, and movement of fish is critical to ecological and environmental studies of fish communities. This includes assessing the use of fish by-pass facilities, estimating entrainment at canals and dams, studying behavioral responses of fish to environmental and weather changes, and collecting counts and sizes of fish at multiple points along migration routes. Hydroelectric facilities, diversion dams, and reservoirs on most western rivers block fish migration routes. Passageways are often installed to allow fish movement through these structures. Monitoring fish movement at these passageways can provide important management and ecological information about fish migration patterns. On the Columbia River, for example, run strengths can be estimated and the destination of the strongest runs can be determined through monitoring fish in these passageways. At the present time, approximately 50 percent of the US Bureau of Reclamation (USBR) passageway facilities on the Columbia and Snake River count and monitor fish passages. All monitoring is done by human observers with significant time and financial costs. To reduce the cost of manual fish tracking, video taping has been implemented. However, the typically poor image quality obtained makes it difficult for biologists to identify species from these recorded images, further complicating the data acquisition process.

An automated fish identification system is urgently needed to replace the present error-prone procedure. The automated Fish Recognition and Monitoring (FIRM) system is being developed for biological and scientific use. The FIRM system utilizes high-resolution images taken from a near-infrared camera. The images are run through shape analysis and classification algorithms. From this information species composition, densities, fish condition, size, and timing of migrations can be estimated. This automated data collection process will significantly reduce manual labor costs, automatically create a database of observations, and provide a more accurate source of information.

Similar research has been published for monitoring and measuring fish for various applications. A stereo imaging system was built to relate salmon morphology to mass [1]. It allows salmon farmers to make accurate decisions on feeding, grading, and harvesting strategies. Fuzzy C-Mean (FCM) was also used for fish recognition. This approach requires a priori knowledge of the analyzed data [2]. A stereo vision system was built to measure fish size, growth, determine the feed and medication, and harvest timing [3]. Fish behavior and movement patterns were analyzed to monitor the presence of acute toxicants in water [4]. Fish orientation was measured for optimal cutting for fish processing [5]. The system was later improved using statistical pattern recognition for finding the cutting position. The above studies focused on monitoring the size of individuals of the same species in fish farms or fish processing facilities. However, none of the work addressed the

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fish classification and monitoring needs for research on free-swimming, migratory populations of fishes.

To accurately monitor and classify free-swimming fish populations, the species classification system must be invariant to rotation in three dimensions (the fish may be turned in azimuth or elevation), size, and shape deformation while the fish is in motion. Thus, it is not acceptable to use Fourier coefficients or moments for the entire fish contour because these methods and the aforementioned do not account for three-dimensional rotation. To remedy this, it necessary to instead extract features from the fish that can then be evaluated for classification purposes. The FIRM system under development can be installed at the fish passageways or other facilities in lakes or rivers where fish can be guided through a narrow passage and images can be taken at a close range. As a fish swims through this narrow passage, a glass viewing windows allows images to be taken of the passing fish.

In this paper, Differential Motion Analysis (DMA) was used to detect the presence of fish and a linear threshold was applied to the difference image to extract closed shape contours. A shape analysis algorithm was modified to remove redundant data points while preserving the significance of the curve. A curvature function analysis was then used to determine critical landmark points for piecewise curve matching and comparison. Fish shape characteristics and shape description methods are discussed in Section III. Calculation, evaluation, and classification of the similarity measure for shape-based classification between the test shape and shapes in the database are included in Section IV. Conclusions and future work are discussed in Section V.

II. Fish Detection and Contour Extraction

A. Fish Contour Extraction

Subtraction of images acquired at different time can detect the motion of an object [6]. It is also a simple way of detecting the presence of an object, assuming a stationary camera position and constant illumination. The only minor variation between frames is the water turbulence. The average of a few frames without objects can provide a background image, $f(x, y)$, as shown in Fig. 1 (a). The difference between the averaged background image and the image taken at a different time, $g(x, y)$ in Fig. 1 (b), detects any object distinct from the background. Fig. 1 (c) is a binary image of the difference and was calculated as

$$\begin{aligned} d(x,y) &= 0 \quad \text{if } |f(x,y) - g(x,y)| \leq threshold \\ &= 1 \quad otherwise \end{aligned}$$

Images shown in Figs. 1(a) and 1(b) were digitized from a recorded video, which are of the similar quality of the images from the monitoring systems that are currently available. The image quality from the image acquisition system that is currently being built will be improved dramatically with better lighting and a high-resolution machine vision camera. We used these digitized images from the recorded video to illustrate the fish contour extraction process.

The binary image contains small pixel clusters (blobs) from water turbulence or image noise. These small blobs in the difference image were removed with a morphological opening operator before we extracted the fish contours. A fast eight-neighborhood contour trace algorithm was developed to extract the x and y-coordinates of the fish contour as shown in Fig. 1 (d).

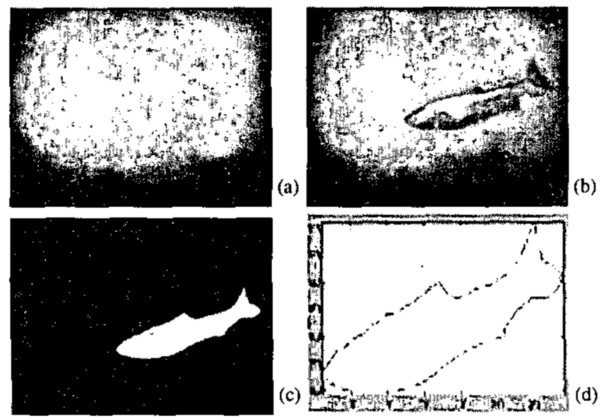

Fig. 1. Images digitized from video tape, (a) background image, (b) with fish, (c) binarized difference image (d) extracted fish contour.

B. Fish Detection and Tracking

After the small blobs being removed, size and location of the remaining large blobs were used to determine the presence of fish and initiate the edge detection process. For small fish, the edge detection process can be initiated immediately after the entire fish is in the viewing window. This can be determined by examining if the large blobs are touching the image boundary. For large fish that are longer than the viewing window width, two image processing tasks will have to be performed, one for the anterior portion of the fish and the other for the posterior portion. Through this blob analysis, multiple fish can be detected and tracked.

III. Shape Characters and Descriptions

Nine species of fish were included in the development of the shape description and shape-based classification algorithms. Differentiation among these species requires reliable characters that can be obtained from the shape of the fish as they move through the passageway. The following is a list of shape characters that have been identified as critical information.

A. Shape Characters

1) ***Adipose fin*** - The adipose fin is a small, non-retractable fin found in salmonids and whitefishes located dorsally, posterior to the dorsal fin and anterior to the caudal fin (Fig. 2). This character is useful to separate the catostomids (suckers) from the salmonids.

2) ***Anal fin*** - This character is useful for separating Pacific salmon and trout from steelhead and bull trout.

3) ***Caudal fin*** - Salmon and steelhead have a relatively straight (truncate) posterior margin to the caudal fin, whereas bull trout have a shallow, but distinct fork.

4) ***Head and body shape*** - Subtle differences in shape specific to each species can be determined by analysis of identifiable landmarks such as the tip of the nose, insertion of fins, and operculum margin that describe the shape of the body and head.

5) ***Size*** – Size can be used to differentiate between large, intermediate, and small species. Total length (from the tip of the snout to the end of the tail) is the size measurement most easily determined.

6) ***Length/depth ratio of body*** - Salmon typically has a deeper body (higher ratio) than do the other large species such as steelhead. Steelhead would rarely have a depth/length ratio greater than about 0.21, whereas salmon typically is greater than that (about 0.23 or higher).

While any of these characters alone may not provide absolute identification, combining them should provide sufficient information to separate the various species in multivariate space. The images of those individuals that cannot be confidently identified with the assessed traits can be stored and examined manually by trained staff. The ability to correctly identify the majority of the fish passing through the fish passageway with a remote system significantly reduces labor costs.

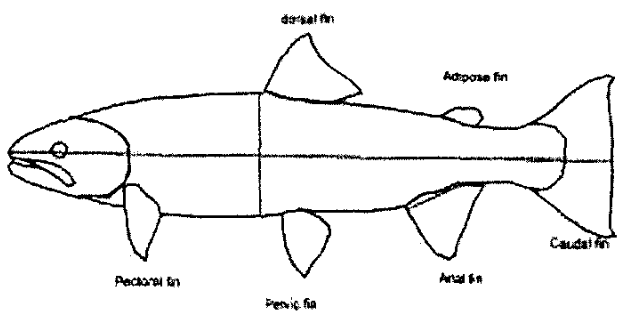

Fig. 2. Outline of steelhead rainbow trout illustrating measurements to be used to differentiate among species.

B. *Data Reduction*

To effectively compare the fish shape characters shown in Section 3.A for classification, landmark points must be identified to determine the location of the fins. These landmark points separate the curves of the fins from the curve of the fish body for fin location and shape character comparison. Shape descriptors and classification algorithms must be invariant to translation, rotation, and scaling because fish could swim into the viewing area from different angles, locations, and with varying size.

In order to accurately classify fish species, it is first necessary to reduce the number of data points obtained in the fish contour extraction algorithm, averaging about 6000 data points per contour, to a reasonable number that can be evaluated for landmark feature relevance. We found that a reduced data set of 40 points was sufficient to retain the important shape features of the fish and calculate landmark points.

Many of the data points obtained in the contour extraction algorithm are redundant and provide unnecessary information. Additionally, we want to filter out the data points that contain edge noise. This can be accomplished through a curve evolution technique that iteratively compares all the relevance measures of the vertices on the contour [7]-[9]. A higher relevance measure means that the vertex makes a larger contribution to the overall shape of the fish, and thus is more important to retain. In each iteration, the vertex with the lowest relevance was removed and a new polygon was created that connected the remaining vertices with a straight line.

The relevance measure, K, can be calculated as shown in (1) where β is the turn angle on the vertex between line segments s_1 and s_2 and $l(s_1)$ and $l(s_2)$ are the normalized length from the vertex to the two adjacent vertices.

$$K(s_1,s_2) = \frac{|(\beta(s_1,s_2)-180)|\,l(s_1)l(s_2)}{l(s_1)+l(s_2)} \tag{1}$$

This method reduces short, straight line segments that provide little information about the overall shape of the fish. Fig. 3 (a) shows the original data set obtained from the contour extraction algorithm. Fig. 3 (b) shows the reduced data set obtained from (1). Although there is some distortion in the fish shape of Fig. 3 (b), the basic shape of the fish is still retained.

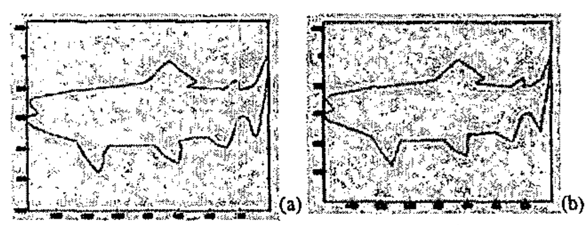

Fig. 3.(a) Original data set of Cutthroat Trout. (b) Plot of Cutthroat Trout after being processed through a data reduction algorithm.

C. *Landmark Points*

The landmark points of the fish are calculated using a curvature function analysis of the reduced data set. In the curvature function (2), the local maxima/minima of the vertex points are calculated as shown below where X_t, Y_t, and X_{tt}, Y_{tt} are the first and second derivatives of X and Y [10]-[12]. The curvature function yields a positive result for convex vertices and a negative result for concave vertices. However, only the concave vertices are retained for locating landmark points.

$$\Gamma(t) = \frac{X_t(t)Y_{tt}(t) - X_{tt}(t)Y_t(t)}{(X_t^2(t)+Y_t^2(t))^{1.5}} \tag{2}$$

These concave vertices are then run through various algorithms that determine the relative distances between them on the fish contour. Looking at relative indexing (i.e., if the current vertices is one of the first concave points or the last), threshold distances, and curvature, the landmark points are obtained according to the steps listed below.

Step 1: Normalize the distances (with respect to the total fish length with fins and tail) on the fish contour from one vertex to the next.
Step 2: Check to see if each distance is below a minimum threshold distance of 0.23.
Step 3: If the vertex distance is below the threshold, check to see if that particular point falls within a given bound of indices (i.e., it's at the beginning of the set of data points or at the end).
Step 4: If the point falls within a given set of indices, and the curvature of the point falls within a specified bound, and falls within another set of distance specifications, delete the point from the concave point array.
Step 5: Repeat Steps 3-4 for each vertex distance.

The landmark points selected were marked as red crosses as shown in Fig. 4. Therefore, once the critical points are determined, the fish polygon can be broken down to small segments for comparison.

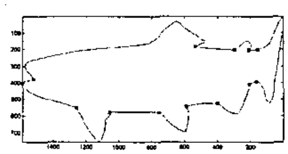

Fig. 4. Landmark points of a Cutthroat Trout.

D. *Landmark Points Statistics*

For the 22 fish images evaluated, eight landmark points were identified as essential to the fish classification process as shown below in Fig. 5. These landmark points locate Dorsal, adipose, Caudal, and Anal fins for classification.

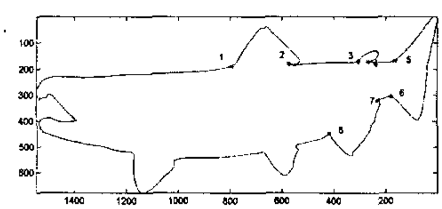

Fig. 5. Landmark points used in fish classification

The percentage breakdown of the detection of each critical landmark point is given below in Table I. The third landmark point was not detected for approximately half of the fish samples because the turn angle was too gradual or the slope was not significant enough to be kept by the landmark point algorithm. This problem is encountered again with landmark points 1, 2, 4, and 6. However, landmark points 5, 7, and 8 were found every time by the landmark algorithm. Overall, the landmark point algorithm is effective for finding all of the essential points except for landmark 3. This problem was solved by finding the largest turn angle between Point 2 and 5. The detection percentage was improved to be close to 90%.

TABLE I.
PERCENTAGE OF POINTS CALCULATED FROM LANDMARK ALGORITHM.

	1	2	3	4	5	6	7	8
% points	86	95	45	95	100	91	100	100

IV. SHAPE BASED FISH CLASSIFICATION

There are several shape characters which can be used for shape-based fish classification. By measuring the similarity of these shape features between test shape and shapes in the database, we were able to classify fish species. These shape characters include the fin shapes (especially adipose, anal, and caudal fin), fin locations (normalized distance from fish nose), tail shape (fork or not), fish body shape and length/depth ratio, etc. There may be some species sharing some of the same shape characters, such as a fork tail. By checking whether it has a fork tail or not, we will be able to separate the fish into two different groups. So a decision tree can be built based on these common characters. The number of shape characters we need to use and how to use them depends on the number of species we want to classify and also depends on what kind of species we want to classify.

Nine species of fish that have similar shape characters were chosen for study. They are the Bonneville Cisco (BC), Brook trout (Bk), Brown trout (Bn), Chinook salmon (Ci), Coho salmon (Co), Cutthroat trout (Ct), Kamloops trout (Ks), Steelhead trout (Sd) and Yellowstone Cutthroat trout (Ye). These species are found in North-West Region of US. We have total 22 fish images of nine species. Our database for testing the algorithms was built based on these 22 images. There is an individual feature vector for each species in our database and it was obtained by averaging the feature vector of each fish of the same species. The classification was done by calculating the distance between the feature vector of the test fish and the feature vectors in the database. The test fish was classified to be the species which has the smallest distance.

A. *Curve Segments of Interest*

Shape contour needs to be pre-processed before the classification process. Fig. 6 shows the typical edge image of a Chinook salmon and a Steelhead trout from the edge detector output. The edge data contained noise edges and redundant points which had to be removed before further processing.

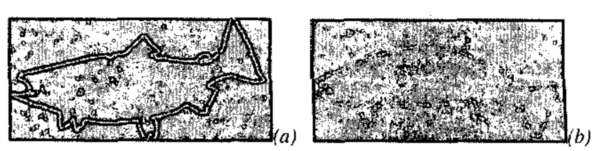

Fig.6. Edge points of (a) Chinook salmon and (b) Steelhead trout.

Fig. 7 shows the plots of shape contours of three of the nine species under study. The original number of contour points range from 290 to 384 but are reduced to 120 for all nine species using the new data reduction algorithm discussed in Section 3.B. As shown in Figs. 3 and 7, the shapes still maintained detail shape features for locating shape landmarks after data point reduction process. All the landmark points were successfully selected and were highlighted with red circles, except the anterior portion of the fish which was affected by the opening of the fish's mouth. This problem was solved by detecting the fish's moving direction and by comparing the overall fish shape.

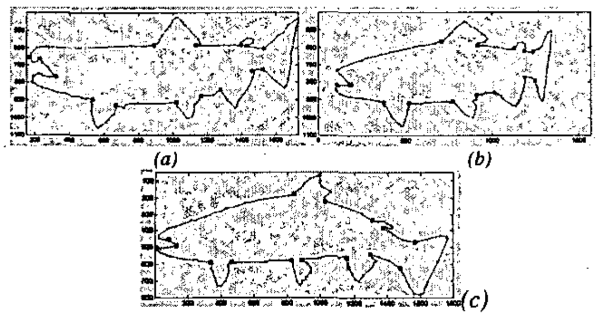

Fig. 7. Shape contours and landmarks.

As illustrated in Fig. 8 of a steelhead trout, it shows each of the separated curve segments and reconnected overall body shape for classification. The separation of these curves of interest was achieved by removing the curve segments between each pair of landmark points and reconnecting them with a straight line (red solid line).

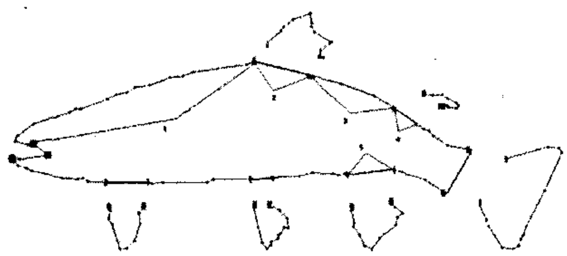

Fig. 8. Curve segments of interest.

B. Feature Vector and Classification

Feature vector is formed based on the landmark points or the curve segments of interest. But, some fins are not reliable to be a feature for classification. As shown in Figure 2, the pectoral fin and pelvic fin are not reliable because the fish has these fins in both sides, which changes the fish contour when we take the picture only from one side. The fins we used were Dorsal fin, Adipose fin and Anal fin. The perimeter of the fish is calculated by excluding all the fins and the tail (Caudal fin), which is just the closed curve by connecting all the landmark points as shown in Fig. 8. The feature vector is basically the length percentage vector. The percentage of five segments of the fish was calculated. The five segments are the length from the mouth to the Dorsal fin, the width of the Dorsal fin, the length between Dorsal fin and Adipose fin, the width of the Adipose fin and the width of the Anal fin. They are also shown and numbered in Fig. 8. The feature vector can be expressed in a vector form as follows:

Feature Vector = [Per. 1, Per. 2, Per. 3, Per. 4, Per. 5].

There are nine different feature vectors for all nine species under study in our database. When performing the classification, the distance between the feature vector of the test fish and those vectors in the database was calculated respectively using l_2 norm. Table II shows how the classification worked. The smallest distances in each line are highlighted. The fish is classified as the species with which it has the smallest distance. For example, the first column means the fish we are trying to classify is Bn. Then we calculate the distance between the feature vector of the testing fish and all of the nine feature vectors in our database. The smallest distance (0.2) lies between the testing fish and Bn. The testing fish was classified correctly. Similarly, the second column shows that Ci was classified correctly with the smallest distance (1.3). Using the 22 samples, it has shown that the classification algorithm worked very accurately.

TABLE II

FISH RECOGNITION RESULTS

	Bn	Ci	Ci	Co	Ct	Sd	Ye
BC	5.2	3.3	3.4	5.9	5.8	2.6	6.8
Bk	3.7	2.5	2.8	4.4	3.7	4.8	5.4
Bn	**0.2**	3.7	3.6	2.0	1.5	4.9	3.0
Ci	2.8	**1.3**	**1.5**	2.7	3.0	3.6	4.6
Co	2.0	3.4	3.0	**0.8**	2.2	4.7	3.0
Ct	1.3	3.3	3.7	1.5	**0.4**	5.2	3.2
Ks	3.0	3.3	3.6	3.8	3.9	4.1	5.4
Sd	5.1	4.1	3.3	5.5	5.8	**0.5**	5.4
Ye	3.5	5.6	5.1	3.6	3.6	5.2	**0.5**

More features may be needed if there are more species to be classified. Comparison of the width of the dorsal fin and the length between dorsal fin and adipose fin are also potential features to be considered because the relationship of these two varies for different species.

V. Conclusions and Future Work

Commercial tape reviewing software for fish counting exists. Another system uses arrays of photo diodes and detectors assembled into a submersed site-specific dimension to count and determine the size of fish migrating though the array. Similar to the tape reviewing software, it does not have fish classification capability and its size measurement accuracy is affected by the fish moving speed. According to the review of current work and feedbacks from biologists studying fish behavior and migration patterns, this research is the first in the field focusing on fish classification for different species.

The results presented in this paper have clearly shown that the building of the FIRM system is feasible. Future work includes testing the algorithms on a large number of live images acquired on site in Seattle, Washington from the machine vision system that is being constructed and refining the shape-based fish classification algorithms.

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