Automated Techniques for Detection and Recognition of Fishes using Computer Vision Algorithms

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Introduction

Automated recognition and classification of fish and other organisms is beneficial to efforts of counting fish for population assessments, for describing associations between fish and habitats, or monitoring ecosystems. In this work, we summarize current efforts to automate the process of fish detection and recognition from a video or still camera source using computer vision algorithms. In order to recognize a fish from video source, there are two steps involved. First is the fish detection process, in which the fish is detected and separated from background. The detected fish image from previous stage is then passed to a recognition algorithm to identify the species of the fish. The latter is known as the recognition or identification stage.

Fish Detection Methodologies

The detection process consists of identifying fish locations in an image frame (i.e., its x,y pixel coordinates), fish extent (width, height), followed by a clear segmentation of fish from background. The outcome is an image that only contains fish targets, with the background masked out, and individual non-overlapping fish targets separately labeled. The Viola and Jones (VJ) object detection algorithm based on haar-like features(Viola and Jones 2004) was evaluated for identifying fish. First, a training image set was assembled consisting of positive (with fish) and negative images (without fish). Then this training set was used to identify test sets of images to determine the effectiveness of the method. The detection of two fish species, the Scythe butterfly fish (*Prognathodes falcifer*) and flag rockfish (*Sebastes rubrivinctus*) from images was tested using this approach. Images of butterfly fish in an aquarium collected by Benson et al. (2009) and rockfish images collected *in situ* by an ROV were provided by J. Butler, NOAA SWFSC Benthic Resources Group (Fig. 1).

Fish Identification Methodologies

The recognition of fish is the process of identifying fish targets to species based on similarity to images of representative specimens (testing sets of images of know species). Following is a brief description of PCA (principal component analysis) and SIFT (shift invariant feature transform) algorithms used for the recognition process.

- **PCA (Principal Component Analysis)** Turk and Pentland (1991) introduced an algorithm for face recognition based on PCA. It is the simplest and most widely used face recognition algorithm, and is quite effective. The PCA recognition algorithm has two stages. As in the fish identification stage the first step consisted of assembling the test sets, and in the second stage this test set was compared to unknown fish targets.
- **SIFT (Scale Invariant Feature Transform** Introduced by Lowe (2004), the scale invariant feature transform (SIFT) can be used for matching images or for object recognition. The main objective of SIFT is to find important key points in two images and match those points against other images. The main focus of SIFT is to find these points by dimensionality reduction. The SIFT approach is robust to variations in scale, rotation, and illumination in test set images. We used the VLFeat software tool for training the SIFT process and for validation of the results. For further information see http://www.vlfeat.org/.

Fish Detection Results

An example of the application of the VJ algorithm to identify fish targets is presented below. Table 1 summarizes results for six different test cases in detecting butterfly fish. The first three test cases use 1,000 positive images and 3,000 negative images as the training set and the second three test cases use 2,689 positive images and 3,000 negative images.

Table 1. VJ fish detection algorithm results. P/N indicates positive and negative image ratio in the training set. TS indicates test set size. Hits indicate the number of and percentage of correctly detected fishes. Missed indicates the number missed fishes. The “False” column indicates false positives.

#Test	P/N	TS	Hits	Missed	False
1	1000/3000	112 R	94 (83%)	18	23
2		112 L	68 (60%)	44	48
3		224 LR	162 (72%)	62	71
4	2689/3000	112 R	101 (90%)	11	16
5		112 L	91 (81%)	21	19
6		224 LR	192 (85%)	32	35

S. constellatus | *S. levis* | *S. miniatus* | *S. rubrivinctus (flag rockfish)* | *Scythe butterflyfish*

Figure 1. Training set for principal components analysis (PCA).

Table 2. Flag rockfish detection with Viola and Jones (2004) algorithm.

#Test	P/N	TS	Hits	Missed	False	#Stages	#Weak Classifiers
1	3100/3000	1272 LR	245 (19%)	916	138	3	3
2	3800/3000	1272 LR	615 (49%)	546	196	6	11

Using test image set of known fish targets for validation consisting of 112 right side, 112 left side, 224 left and right side fish images, we got 83%, 68%, 72% hit rates for first three test cases and 90%, 81%, 85% hit rates for the second three test cases. The results show that larger training image sets result in higher hit rates.

This analysis was repeated on images of flag rockfish. The first test consisted of a training set of 3,100 positive images and 3,000 negative images (Table 2.). Flag rockfishes were less successfully detected with a 19% hit rate for a test set which contains 1,272 left and right side images. In the second test the positive images were increased to 3800, improving the hit rate to 49%.

Fish Recognition Using PCA

PCA approach was used with four species of rockfish (genus *Sebastes*) and one species of butterfly fish. The images used in this experiment are shown in Figure 1. Seven images of each species were used as a training set. In order to produce high quality training data, training images were normalized for position and had similar illumination. The result of applying the PCA resulted in 100% successful clustering for every case. This result may be unrealistic, as it was limited by the number of high quality training images, and should be further evaluated with larger image sets, and with fish in different positions and varying illumination. However, as a preliminary assessment, the PCA shows promising results.

There are also modular PCA (MPCA) and weighted modular PCA (WMPCA) which are reported to be more robust than normal PCA (Gottumukkal and Asari 2004) and could further improve performance over the PCA approach.

SIFT Results

The SIFT approach was applied using the VLFEAT tool for four different test cases (Table 3). Using five positive images of butterfly fish and flag rockfish resulted in a 50% recognition rate. With an increase in the number of positive images to 10, a 100% hit rate (#Test = 2) was achieved. Performance seem to have decreased when more potential classes were added to the analysis. As with the PCA, these results are limited by the number of training images. As a result, the SIFT approach will be further evaluated with more images in the future. Current studies showed that SIFT works well when images vary in scale, illumination and pose. Therefore, we think SIFT may be more suitable than PCA for underwater fish recognition.

Conclusions and Future Direction

We tested different detection and recognition algorithms in this project. Our main conclusion is that with a larger training set, we obtain better results. In order to evaluate existing classical object detection and recognition algorithms, we need more robust training data set. In the future, first we will move towards preparing a standardized training and testing database, which will allows us to 1) make a direct comparison between different algorithms for fish detection and identification, 2) identify the most promising fish classification/detection algorithms, 3) assess the state of the art algorithms for fish detection/recognition, 4) to identify future directions of research for fish detection/identification, and 5) advance the state of the art in fish detection and identification. In addition, we plan to test emerging object detection and recognition algorithms with standardized data set. For example, we will test combining computer vision with human effort for fish recognition following a method introduced by Branson et al. (2010).

Table 3. Scale invariant feature transform (SIFT) results.

#Test	Used Images	P / Test Set	Hits
1	*P. falcifer* (butterfly fish) and *S. rubrivinctus (flag rockfish)*	5/5	50%
2		10/10	100%
3	*S. miniatus*, *S. constellatus*, and *S. levis*	4/4	33%
4	*P. falcifer* and *S. rubrivinctus* *S. miniatus*, *S. constellatus*, and *S. levis*	10/10 4/4	40%

Citations

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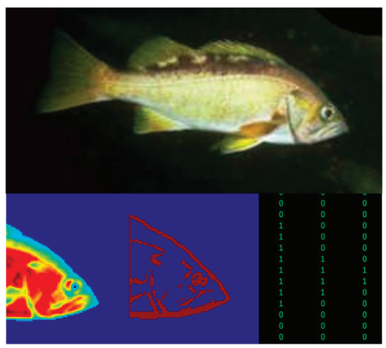

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