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DETECTING ABNORMAL FISH TRAJECTORIES USING CLUSTERED AND LABELED DATA

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ABSTRACT

We propose an approach for the analysis of fish trajectories in unconstrained underwater videos. Trajectories are classified into two classes: normal trajectories which contain the usual behavior of fish and abnormal trajectories which indicate the behaviors that are not as common as the normal class. The paper presents two innovations: 1) a novel approach to abnormal trajectory detection and 2) improved performance on video based abnormal trajectory analysis of fish in unconstrained conditions. First we extract a set of features from trajectories and apply PCA. We then perform clustering on a subset of features. Based on the clustering, outlier detection is applied to each cluster. Improved results are obtained which is significant considering the challenges of underwater environments, low video quality, and erratic movement of fish.

***Index Terms*—** Fish Behavior, Clustered and Labeled Data, Feature Selection, Abnormal Trajectory, Outlier Detection

1. INTRODUCTION

Fish behavior analysis is a fundamental research area in marine biology as it is helpful for detecting environmental changes by detecting abnormal fish patterns. However, the traditional way of analyzing fish behavior (human visual inspection) makes this task time consuming and limits the number of processed videos. Therefore, there is a need for automatic algorithms to identify fish behaviors which can be done by using computer vision and machine learning techniques.

The literature is rich in terms of behavior analysis, especially in human activity recognition, unusual behavior detection in traffic and nursing home surveillance, etc. However, it is very limited in terms of normal/ abnormal fish behavior understanding especially when unconstrained underwater videos are considered. Fish trajectory analysis has been studied for different purposes such as water quality monitoring and toxicity detection [1, 2, 3], fish stress factor identification [4], fish school monitoring [5] and abnormal trajectory detection in aquaculture sea cages [6]. However, those researches were performed in constrained places like an aquarium, a tank, or a cage which makes the analysis simpler and also removes the effect of habitat on the behavior of fish. On the other hand, in recent years unconstrained underwater studies have become popular [7, 8, 9, 10]. Although they do not directly consider abnormal fish trajectory detection they contribute to fish behavior analysis.

When we compare our dataset with other abnormal behavior detection studies, there are some differences. For instance; fish in the open sea can freely move in 3 dimensions through the open sea (there are no defined roads or rules for abnormal patterns such as in a traffic surveillance scenario), fish usually make erratic movements because of currents in the water (which makes it difficult to encode the behavior in terms of certain sequence of actions which is done in human and animal behavior recognition [9]), fish mostly are not moving goal-oriented as for instance, people or vehicles do, which cause highly complex trajectories.

In this study, we propose an approach to detect abnormal fish trajectories using multiple features. In this scope, normal trajectories are defined as the trajectories which contain the frequent (usual) behaviors of fish while abnormal trajectories are defined as outliers (rare events). To find the abnormal trajectories (rare events), an outlier detection method which is based on cluster cardinalities and a distance function is used. Moreover, we use clustered and labeled data together to select feature sets which perform best on training set. To sum up, we present a novel approach to abnormal behavior detection and demonstrate improved performance on abnormal trajectory analysis of fish in unconstrained conditions.

2. PROPOSED METHOD

To obtain the fish trajectories, the tracker in [11] is used and a trajectory is defined by the center of fish bounding boxes. For any fish i tracked through n frames the trajectory is:

$$T_i=\{(x_1, y_1),(x_2, y_2),\ldots(x_n, y_n)\} \quad (1)$$

The proposed method (Fig. 1) has four steps. Those are; 1) feature extraction (includes the pre-processing of trajectory and Principal Component Analysis (PCA) of extracted features), 2) clustering, 3) outlier detection and 4) feature selection which are based on clustered and labeled data.

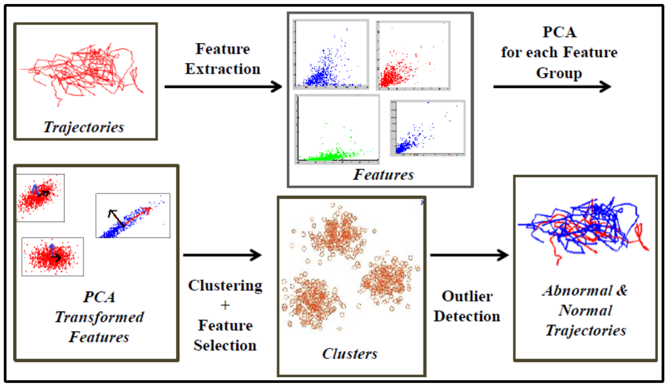

Fig. 1. Overview of the Proposed Method

2.1. Feature Extraction

Due to the challenges of tracking fish in the underwater environment, sometimes there might be gaps in the trajectory. Therefore, before extracting features, trajectories are first linearly interpolated. To classify trajectories as normal or abnormal the following features are used:

2.1.1. Curvature Scale Space (CSS) Based Features
The CSS was introduced in [12] as a trajectory representation method. It is based on curvature formula given in Eq. 2 which is rotation and translation invariant and helpful to distinguished trajectories by their convexity and concavity.

$$K_i = \frac{x_i{'}y_i{''} - y_i{'}x_i{''}}{(x_i{'}^2 + y_i{'}^2)^{3/2}} \tag{2}$$

To find the CSS, at each level the standard deviation (σ) of Gaussian kernel is increased and the curvature of that level is found. As σ increases, the trajectory shrinks, becomes smoother and the number of zero crossing points on it decreases. Finally, the trajectory becomes a convex curve with no zero crossing [13]. The location of zero crossings of every trajectory is determined and the result is represented as a binary image called the CSS image (a more detailed description can be found in [12]).

In this study, statistical properties (such as mean and variance) of length of curves, number of zero crossings for each σ, total number of curves, σ in peak points which are extracted from the CSS image are used. Also, for each σ, statistical features of absolute curvature are extracted. In total 580 features are obtained.

2.1.2. Moment Descriptors Based Features
Moment invariants are well known, successful descriptors for recognizing deformed object and patterns and can be used to distinguish trajectories. We utilize the affine moment invariants proposed in [14] in addition to moments, central moments and translation and scale invariant moments. In total 55 features are extracted from those moment descriptors.

2.1.3. Velocity and Acceleration Based Features
Velocity and acceleration are useful to differentiate the behavior of fish in terms of their rate of position and speed change because a fish trajectory could be spatially similar but its velocity and/or acceleration may be abnormal. We extract statistical properties: mean, standard deviation, minimum, maximum, # of zero crossings, # of local minima and maxima from velocity and acceleration in 3 dimensions (since fish can swim in 3 dimensions). To describe the 3D fish trajectories, in addition to the representation given in Eq. 1, the width (w) and height (h) of fish blob in each detection can be combined ($z=1/\sqrt{wh}$) to estimate the displacements of objects in z. In total 42 features are obtained.

2.1.4. Turn Based Features
Trajectory turn gives an idea about the shape of fish trajectory and is calculated as given in [15] (Eq. 3). The same statistical properties as velocity and acceleration features are extracted from the angles of each trajectory. In total 7 features are extracted from turn of trajectory.

$$\theta_i = \frac{y_{i+1} - y_i}{x_{i+1} - x_i} \tag{3}$$

2.1.5. Centroid Distance Function (CDF)
CDF is an invariant shape descriptor that gives the distance of each point in a trajectory from the center of the trajectory [12]. The mean, maximum, minimum, standard deviation, number of mean crossings, # of local minima and maxima, skewness and kurtosis of 3 dimensional and 2 dimensional CDFs are used to differentiate the trajectories. In total 18 features are extracted from CDF.

2.1.6. Features of the Vicinity

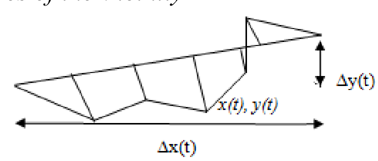

Fig. 2. Features of the Vicinity [16]

Features extracted from the trajectory vicinity (Fig. 2) were introduced in [16] for handwriting recognition but to the best of our knowledge they were never used to represent trajectories. Three groups of features: aspects of vicinity given in Eq. 4, vicinity curliness (the length of trajectory in the vicinity divided by maximum ($\Delta x(t)$,$\Delta y(t)$)) and vicinity linearity (the average square distance of each point in the vicinity to the straight line from the last and first vicinity point). In total 40 features are extracted.

$$\begin{gathered} \textit{Type1: } (\Delta y(t)-\Delta x(t))/ (\Delta y(t)+\Delta x(t)) \\ \textit{Type2: } \Delta y(t)/\Delta x(t) \end{gathered} \tag{4}$$

2.1.7. Loop Features
As we mentioned before, due to the erratic motion of fish, the trajectory can be complex and might contain loops.

(a) Underwater Image (b) Segmented Image

Fig. 3. Segmented regions of underwater image; black for open sea, red for above the coral and green for under coral

Therefore, extraction of loop based features such as the number of loops, maximum, minimum, median of number of points in a loop etc. can be used as shape descriptors. In this context, the existence of a loop in a trajectory can be determined as reaching the same point from any point to the final point of trajectory and from the same point to the starting point of trajectory. In total, 4 features are extracted.

2.1.8. Fish Pass By Features

Fish behavior can change from location to location and is also affected by the underwater geographical properties. Therefore, while finding normal and abnormal trajectories those properties can be useful to consider. In this context, we label the video scene as open sea, under coral and above coral (Fig. 3) and extract some descriptors using them and the trajectory of fish. As descriptors, the frequencies of being in different locations, frequency of crossings from one location to another are considered. In total 12 features are obtained.

2.1.9. Displacement on the Location Based Features

Lastly, statistical properties such as maximum, minimum and median etc. of average displacement in different locations described in section 2.1.8 are also used to distinguished trajectories and in total 15 features are obtained.

As a result of the feature extraction step, altogether 773 features are obtained. Some of those features are correlated which might cause over-training of data in case of being selected by feature selection. Dimensionality reduction can reduce the curse of dimensionality and other undesired effects of high dimensional spaces [17]. Therefore, before applying clustering we apply PCA to each feature group individually. To obtain the optimum number of components the smallest number of component that represent 90% of the sum of all eigenvectors are used. This leaves {76, 13, 12, 3, 8, 13, 2, 6 and 5}=138 feature for each of the 9 groups respectively.

2.2. Clustering

Affinity propagation [18], which measures the similarity between pairs of data points (in our case; in terms of negative Euclidean distance) and determines cluster centers from the data points themselves, is applied. Beside its fast processing speed, being non parametric, not requiring initializations, not being depending on sample order and scalability properties, it can produce smaller clusters compared to traditional clustering methods (such as k-means) and can produce uneven sized clusters by minimum error rate [18] which is useful given our assumptions for outlier detection.

2.3. Outlier Detection

An abnormal (outlier) trajectory can be defined as one that deviates from other trajectories in its cluster. In this study, we adapted the outlier detection method from [19] and proposed two types of abnormal trajectories: those located in small clusters and those that exist in dense clusters but are far from the common behavior. For the first type of outlier, it is assumed that small clusters are those which have less data samples than A% (such as 10%) of the median cardinality or a cluster that has only one instance. Otherwise it is classified as a dense cluster. For the second type of outlier, the Euclidean distance between the data point and corresponding cluster's centre is calculated. A trajectory that has a distance bigger than a threshold ($\tau=\mu+w\sigma$) based on the mean (μ), weight (w) and standard deviation (σ) of all distances in the cluster is defined as an outlier.

2.4. Feature Selection

Feature selection is embedded in clustering and outlier detection to prevent over fitting, get rid of irrelevant, redundant features and even features that might misguide clustering. In this step, forward sequential feature selection is used and class labels which are found by clustering-outlier detection and ground truth labels are used to calculate the feature selection criteria which is average class accuracies (to handle the disadvantage of highly imbalanced data). In detail, given the current set of features, an additional feature is added one by one, clustering and outlier detection are performed with the extended feature set. The class accuracies are found using the ground-truth labels at each iteration. Feature selection stops when the average class accuracy on the training set decreases compared to previous iteration.

To classify new trajectories (testing), features, outlier detection parameters (A and w) and the number of clusters that are found during training (which makes the testing fully unsupervised) are used.

3. DATA SET AND RESULTS

The proposed method was applied to 683 trajectories (652 normal, 31 abnormal) from 15 hours of video (320x240 resolution, 5 frames per second) which belong to *Dascyllus reticulatus* in the Taiwanese coral reef in the morning (a single species and time period is used because behavior varies by species and time of day). The normal and abnormal behaviors are determined by visual inspection. Freely swimming fish (Fig. 4a-b) were considered as normal behavior since this is a most frequent behavior of that

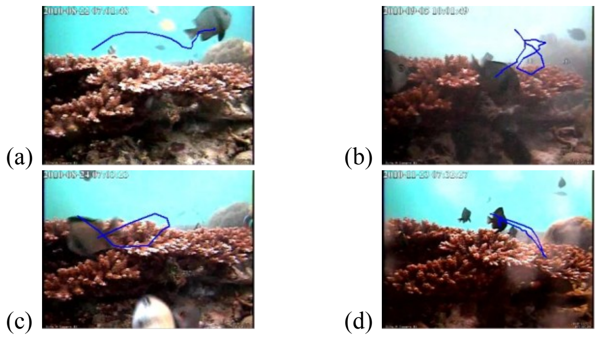

Fig. 4. (a-b) Examples of normal fish trajectories, (c-d) Examples of abnormal (rare) fish trajectories.

species. On the other hand, abnormal trajectories are rare trajectories which are not observed as frequently as normal trajectories such as: fish suddenly (in one frame) changing direction (predator avoidance, Fig. 4c), interaction with coral (Fig. 4d), aggressive movements of fish (sometimes due to another fish or because of being frightened) are considered.

To evaluate the proposed method 5-fold cross validation was performed. Training and test sets were constituted randomly with the normal and abnormal trajectories distributed equally in each set. During training, for the desired performance of the proposed method (given below) different features are selected in each fold. However, in 4 of 5 folds, the same feature from loop features category (Sec. 2.1.7) was selected as the first feature. The class average accuracies while features were adding one by one including the value that ends feature selection is given in Table 1.

Table-1: Average of class accuracies after the corresponding feature (section of feature group is given in the parenthesis) is added. Best feature selection criteria value is shown as bold.

Fold	Average of class accuracies							
1	**0.65 (2.1.7)**	0.61 (2.1.6)						
2	0.60 (2.1.6)	0.65 (2.1.6)	0.69 (2.1.2)	0.71 (2.1.2)	**0.73 (2.1.8)**	0.70 (2.1.3)		
3	0.57 (2.1.7)	0.65 (2.1.2)	0.69 (2.1.2)	0.72 (2.1.2)	0.78 (2.1.9)	0.82 (2.1.2)	**0.84 (2.1.6)**	0.82 (2.1.1)
4	0.57 (2.1.7)	0.59 (2.1.6)	0.62 (2.1.9)	0.68 (2.1.2)	**0.75 (2.1.2)**	0.74 (2.1.2)		
5	**0.59 (2.1.7)**	0.58 (2.1.6)						

The overall performance in terms of false positive rate and false negative rate (detection error tradeoff graph) is given in Fig. 5 where the positive class is the normal and the negative class is the abnormal trajectories. The equal error rate is approximately 0.31 (Fig. 5), but considering we are more interested in abnormal trajectories, for the tradeoff between class accuracies we selected 64% accuracy for normal, and 78% accuracy for abnormal trajectory detection as the method's desired performance.

The proposed method was also compared with method [10] (most similar study that can be compared) which tries to filter out normal fish trajectories while not filtering any abnormal trajectories (Table-2) in terms of average of normal class accuracy, abnormal class accuracy and class average accuracy for 5 folds. For each evaluation metric, the standard deviation considering folds is given after ± sign. The desired performance of the proposed method is obtained when A is 10 and w is 3. As shown, our method presented better results especially for detecting abnormal trajectories.

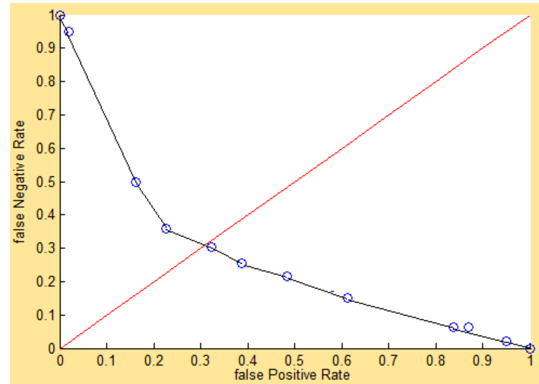

Fig. 5. The overall performance in terms of false positive and false negative rate (Outlier detection parameters: A={10, 20} and w={-1, -0.3, 0, 0.3, 0.6, 0.9, 1, 2, 3, 6})

Table-2: Comparison with other methods

	Normal Class Accuracy	Abnormal Class Accuracy	Class Average Accuracy
Method [10]	0.61±0.02	0.65±0.19	0.63±0.10
Proposed Method	0.64±0.10	**0.78±0.08**	**0.71±0.07**

4. CONCLUSIONS

In this study, an abnormal fish trajectory detection method in underwater videos is presented. To represent fish trajectories novel descriptors which were not used previously for fish behavior analysis purposes are used. Clustered and labeled data are used together to select the best feature set and classify trajectories.

As a result, 71% accuracy is obtained as average of class accuracies which is the best in this area that we know, especially considering the challenges of underwater environments, low video quality, noisy data and erratic movement of fish. Normal class accuracy is also promising to help the marine biologist by eliminating many normal trajectories with a relatively low error rate. This allows the biologists to focus on data that is potentially abnormal which is valuable especially considering the amount of data that they might have had to consider. Additionally the proposed method helps to detect rare trajectories which might help marine biologist to detect more interesting behaviors (may be even behavior changes for a specific species). As a future work, we propose to investigate hierarchical classification methods.

5. ACKNOWLEDGEMENTS

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