Detection of Abnormal Fish Trajectories Using a Clustering Based Hierarchical Classifier

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Automatic analysis of animal and insect behaviour using computer vision techniques is a growing research area with many interesting studies. The traditional way of analyzing the behaviour of animals is by visual inspection of human observers which is very time consuming and also limits the size of data that can be processed. In this study, we present a novel framework for abnormal behaviour detection and especially focus on fish trajectories. Fish behaviour analysis is a fundamental research area in marine biology as it is helpful to detect environmental changes by detecting abnormal fish patterns and to detect new behaviours of fish. Detecting abnormal trajectories is useful when the system does not have any prior knowledge about the data which especially happens in the real-world data due to the uncontrolled naturalness.

When we compare fish trajectory datasets from underwater videos with the other abnormal behaviour detection datasets (traffic surveillance, human abnormal trajectory detection etc.), there are certain differences:

- Fish in the open sea can freely move in 3 dimensions hence there are no defined rules or roads such as exist in a traffic surveillance scenario.
- Fish are not goal-oriented which produces highly complex trajectories in contrast to people or vehicles.
- Fish usually make erratic movements due to currents in the water which increases the complexity of trajectories and also makes encoding the behaviour more difficult than is in human or animal behaviour recognition.

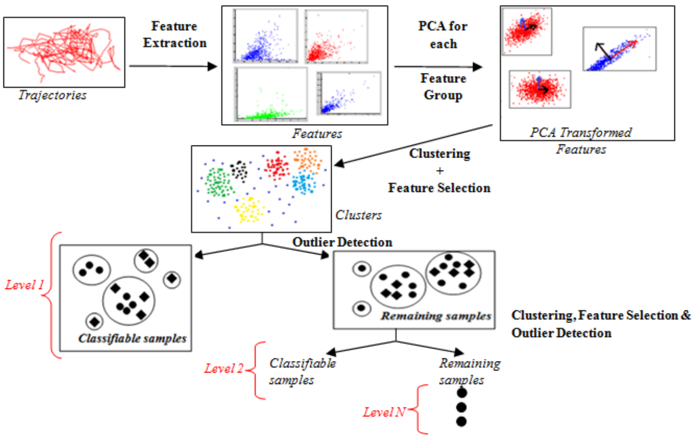

Figure 1: Overview of Proposed Method

In this study, we present an approach to detect abnormal fish trajectories using a hierarchical classifier. Normal fish trajectories are defined as the trajectories which contain frequently observed behaviours while abnormal trajectories are defined as outliers or rare trajectories. Clustered and labelled data are used together and the hierarchy is automatically built using similarity of data instead of using a taxonomy between features or classes as is common in the literature. Different than the studies which use the same feature space for classification, we use different feature sets at different levels of the hierarchy which allows more specific features to be used once the data focuses onto specific subclasses. The construction of hierarchy and new trajectory classification using the hierarchy are described in detail in the paper. Figure-1 also shows the feature extraction, hierarchy construction and the component of the proposed method which is based on clustering, feature selection and outlier detection.

Features: Curvature scale space based features [2], moment descriptors [3], velocity and acceleration based features, turn based features [4], centred distance function [2], vicinity features [5], loop features, fish pass by features (using the image segmentation given in Figure-2), features based on normalized size of bounding box, and features based on displacement on the location (using the image segmentation given in Figure-2).

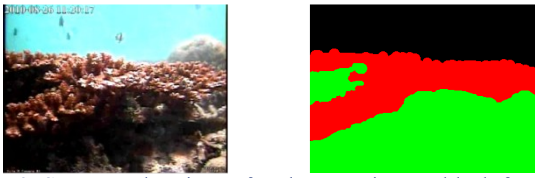

Figure 2: Segmented regions of underwater image; black for open sea, red for above the coral and green for under coral.

Altogether 776 features are obtained in the feature extraction step. As a post processing step of feature extraction, PCA is applied to the data from each feature group individually to get rid of from correlation between the features and handle the over-training. This left 179 features.

Outlier detection is similar to [6]. Present two types of abnormal (outlier) trajectories: those located in small clusters and those that exist in dense clusters but deviate from other trajectories in its cluster.

3102 trajectories (3043 normal, 59 abnormal) were used. The most usual and frequent behaviours in the dataset are freely swimming fish in open sea and hovering fish on the coral (Figure 3a-b) which represent normal behaviours. Abnormal trajectories are: i) fish suddenly (in one frame) diving under the coral, ii) fish suddenly (in one frame) changing direction (predator avoidance, Figure 3c), iii) fish diving quickly between the coral branches when frightened or to hide from predators, and iv) aggressive fish which is moving fast. A trajectory that has normal and abnormal segments is assumed as abnormal.

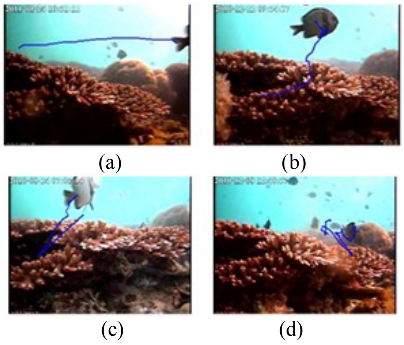

Figure 3: (a-b) Examples of normal fish trajectories, (c-d) Examples of abnormal (rare) fish trajectories.

The proposed method has highest abnormal trajectory detection rate compared to state of art methods of abnormal trajectory detection (fish and in general) while also the best method in overall. *t*-tests show that it is significantly better than all methods. Moreover, the proposed hierarchical classifier is not limited to fish trajectory analysis and is a general framework for classification of imbalanced datasets as shown on popular imbalanced datasets.

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