Fish Behavior Analysis

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Abstract In this chapter, we address fish behavior analysis in unconstrained underwater videos. Assessing behavior is based on unusual fish trajectory detection which tries to detect rare fish behaviors, which can help marine biologists to detect new behaviors and to detect environmental changes observed from the unusual behaviors of fish. Fish trajectories are classified as normal and unusual which are the common behaviors of fish and the behaviors that are rare respectively. We investigated three different classification methods to detect unusual fish trajectories. The first method is a filtering method to eliminate normal trajectories, the second method is based on labeled and clustered data and the third method tries to construct a hierarchy using clustered and labeled data based on similarity of data. The first two methods can be seen as preliminary works while the results are significant considering the challenges of underwater environments and highly imbalanced trajectory data that we used. In this chapter, we briefly summarized these two methods and mainly focused on the third method (hierarchial decomposition) which presented improved results and performed better than the state of art methods.

1 Introduction

The study of marine life is important especially for understanding environmental effects such as pollution, climate change etc. However, accessing underwater data is mostly very difficult. Fish behavior analysis is helpful to detect such environmental effects by detecting the changes in behavior patterns or finding unusual behaviors and detecting the behavior distinctness of different species.

The traditional way to analyze fish behavior is based on visual inspection by marine biologists [1] such as by diving to observe underwater using photography or acoustic systems [2]. However, this analysis is very time consuming and needs

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a huge amount of human labor. Moreover, manually analyzing the data implies a decrease in the amount of data that could be analyzed. Therefore, computer vision techniques and machine learning methods could play an important role to analyze the underwater videos.

In the computer vision area, behavior understanding studies can be classified into two categories: activity recognition, unusual behavior detection [3]. Activity recognition is very difficult when the number of behavior models in an uncontrolled and uncooperative real-world data is considered [3]. On the other hand, unusual behavior detection analysis has become popular in recent years. In this kind of approach, the system does not have any prior knowledge about the behaviors. The unusual behaviors are generally defined as outliers or rare events and are detected with an unsupervised fashion [4, 5].

The aim of our work is to present an unusual fish behavior detection system that uses underwater environment videos. We are using detected and tracked fish by the fish detection and tracking components mentioned in previous chapters **??**. We have two classes of trajectories: normal and unusual. Normal fish trajectories are defined as the trajectories which contain frequently observed behaviors while unusual trajectories are defined as outliers or the behaviors not frequently observed. In all of our analysis, we used the trajectories of *Dascyllus Reticulatus* since it is the most frequently detected and most accurately recognized fish in the Fish4Knowledge repository. We believe that the methods proposed in this chapter are helpful to understand the unusual behavior of fish species. Furthermore, detecting unusual behaviors can be a preliminary stage to understand specific behaviors of fish species such as feeding, predator-prey, reproduction, etc.

In the rest of this chapter, we first define the problem and give related definitions and challenges (Section 2). Following this, we present a literature review on fish behavior understanding (Section 3). In Section 4, the three methods that we proposed are presented. The first two methods are summarized very briefly as they are preliminary works but the third method is described more deeply. Experiments, data set that we used and the results are also given in this section. Finally, in Section 5, we conclude this chapter by making a summary of the chapter and by giving possible future directions.

2 Problem Description, Definitions and Challenges

In the literature, the definition of unusual behavior is a bit ambiguous. Unusual behavior can be used interchangeably with the terms abnormal, rare, outlier, suspicious, subtle, interesting, and anomaly depending on the definition of the studies. For instance, Morris and Trivedi, [6] used the words abnormal, anomaly and unusual interchangeably denoting behaviors that do not fit into the typical cluster. In most of the study, the model of normal behavior is automatically learnt. Using this model, test behavior is classified as normal or unusual. However, in real life scenarios, it is very difficult to predefine all possible normal and unusual behaviors. Therefore,

many times behavior is unusual because there are no previous occurrences of it [7]. Similarly, an event that cannot be classified by the learnt models was defined as abnormal in [8]. Xu *et al.* [9] defined unusual behavior as interesting (not expected) and rare while Varadarajan *et al.* [8] assumed that an unusual event is the one that occurs at an unusual location and an unusual time while it is fundamentally different in appearance and/or order. On the other hand, Dickinson and Hunter [10] defined unusual events as rare events and due to lack of training data, which was detected by the deviation from a model of normal behaviors. Jiang *et al.* [5] defined normal events using some rules and classified the events which do not obey the rules as anomalies. In this context, anomalies appear rarely and different from the commonality while the events with large groups are normal.

In the unusual behavior detection area studies mostly focused on clustering based methods and did not use labeled data. This is mainly because the labeling cost is huge and very time consuming. But we claim that given a large enough data set, it is possible to find and label some unusual trajectories (although more difficult to find them compared to normal trajectories) which results in applying supervised learning techniques to obtain more normal and unusual trajectories. In our work, we present three different supervised learning methods. For all methods, we consider two classes: normal and unusual.

When we compare fish trajectory data sets from underwater videos with the other unusual behavior detection data sets (for instance traffic surveillance, human abnormal trajectory detection etc.), there are certain challenges:

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

3 Literature Review on Fish Behavior Understanding

In the literature, fish behavior monitoring studies which are utilizing computer vision technology are generally for studies on water quality monitoring and toxicity identification such as [11, 12, 13, 14]. Beside this aim, studies focusing on fish stress factor identification [1] or automatically monitoring abnormal behavior to help the farm operator in aquaculture sea cages [15] also exist. Some of the research on fish behavior understanding has focused on the behavior of individual fish such as [12, 13, 14] while others have studied fish group behaviors [11, 16]. Some studies analyzed only one species like [1, 15, 16, 17, 18]. The majority of works in this area analyze the fish trajectories in an aquarium, a tank or a cage which makes the analysis simpler, decreases the number of behavior varieties and also removes the effects of habitat on the behavior of fish. On the other hand, the number of studies using natural habitat underwater environments is very few [19, 20].

4 Proposed Methods

Our research on detection of unusual fish behaviors covers three methods: *i)* A rule based method for filtering normal fish trajectories (Section 4.1), *ii)* A method using clustered and labeled data which is also called the flat classifier (Section 4.2) and *iii)* a hierarchical decomposition method (Section 4.3).

For each method, to obtain the fish trajectories, the tracker in [21] is used and a trajectory is defined by the center (x,y) of the fish rectangular bounding boxes which tightly surrounds the detected fish in the image. For any fish i tracked through n frames the trajectory is defined as:

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

4.1 A Rule Based Method for Filtering Normal Fish Trajectories

The unusual trajectories are generally defined as outliers or rare trajectories. In this scope, the clusters with small numbers of elements are expected to represent rare trajectories and the samples that are different from samples in the same cluster are considered as outliers [4]. Although this approach is reasonable, when the number of trajectories is huge like hundred thousands, millions etc. and/or the number of normal trajectories is much bigger than the number of unusual trajectories, such as 100 times bigger (or more), normal trajectories can dominate unusual trajectories and extracting small clusters and outlier detection might be inaccurate. This might be even worse if the normal and unusual classes contain sub varieties even though they are considered as the same class [22].

The aim of this filtering mechanism is to reject normal trajectories as much as possible while not rejecting any unusual trajectories. Ideally, we should not reject any unusual trajectories while rejecting all normal trajectories. First, all fish trajectories are filtered by Filter 1. In each step, the trajectories satisfying the rule (filtered) are defined as normal trajectories (such as Normal1, Normal2 in Figure 1). The trajectories which do not satisfy the rule (not filtered) are called the remainders of the corresponding filter (Remainder1, Remainder2 in Figure 1) and are used as inputs to the following filter. This is continued until all the filters are used. At the end, the remainders of last filters are called unusual trajectories. The filtering order is independent since the rules of filters are independent. Therefore, filters can be applied in any order.

Each fish detection is in one of two categories: straight and/or cross motions and being stationary. Straight and/or cross motions includes all possible motions in all directions such as left to right, right to left, up to down, down to up. The description of straight and/or cross motions and being stationary can be found in [22].

Filters are defined as one, two and three length combinations of these motions such as moving right to left (length is one), moving right to left and then being stationary (length is two), moving left to right and then up to down (length is two),

being stationary for a while, then moving down to up and then left to right (length is three) etc. Similar trajectories like going left to right and right to left are modeled by same filter. Altogether 21 rules were used.

In the training phase, for each filter the best parameters: search area for straight and/or cross motions, search area for being stationary and combinations of filters are found. Those parameters and filters are used to classify testing trajectories. When finding the best parameter values those which do not filter out any unusual trajectories are chosen using the labels of the training data. In the case of having more than one parameter set which do not filter out any unusual trajectories, the one that filtered the most normal trajectories is selected for use in testing.

4.1.1 Conclusions for Filtering Normal Fish Trajectories

The proposed rule based filtering method is successful to filter out large amounts of trajectories with a very low time complexity. This method has been used as a preliminary method to collect ground truth data (especially unusual trajectories) thanks to being fast and having low false positive and false negative detections. This method can be combined with any unusual fish trajectory detection system which might lead to increase the detection performance. It can be applied especially when the number of normal fish trajectories is much bigger than the number of unusual fish trajectories and/or when the number of trajectories is very huge.

4.2 Detecting Unusual Fish Trajectories Using Clustered and Labeled Data: Flat Classifier

In this section, we present an approach to detect unusual fish trajectories using multiple features. The presented method is mainly based on clustering. To find the unusual trajectories, an outlier detection method which is based on the sample size of
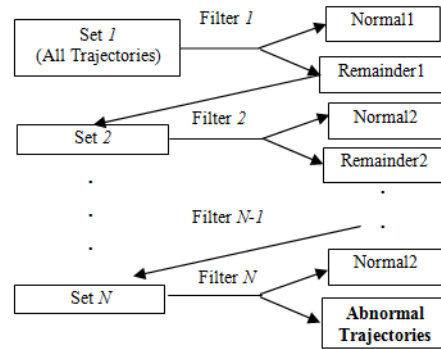
Fig. 1 The block diagram of the rule based normal fish trajectory filtering method [22]

clusters and a distance function is used. Clustered and labeled data are used together to select the best feature set (the feature set that provides the best performance) using a training set [23]. This method contains four steps: *i)* feature extraction, *ii)* clustering, *iii)* outlier detection and *iv)* feature selection (Figure 2) and includes the basics of the hierarchical method given in Section 4.3.

4.2.1 Feature Extraction

The challenges of fish detection and tracking in the underwater environment sometimes cause gaps in the fish trajectory . To handle this, before extracting features, all trajectories are linearly interpolated. 10 groups of features are extracted. In total, 776 features are obtained in the feature extraction step. These features are generally correlated with each other. Therefore to prevent a possible over-training Principal Component Analysis (PCA) is applied to each group of features individually. While applying PCA, to obtain a useful set of components the smallest number of components that represent 90% of the sum of all eigenvectors is used. As a result of this step, 179 features are obtained as feature set. Some of the extracted features are as follows (for all of them please refer to [24]):

Curvature Scale Space (CSS) Based Features
Trajectories are first represented using CSS description [25]. CSS is calculated using the curvature at every point on the curve by the formula given in Eq. 2. This trajectory description is shaped based and rotation and translation invariant.

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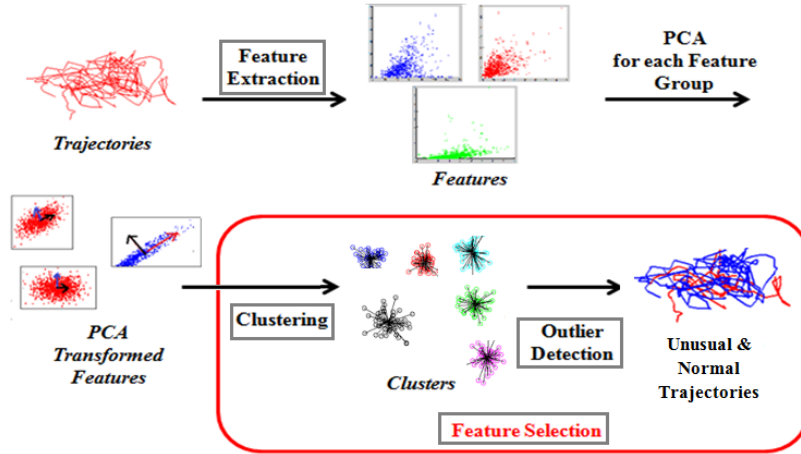

Fig. 2 Overview of the flat classifier see [23] for the description of the process

To find the scale position of the CSS, a Gaussian kernel is used. At each level of space the standard deviation of the Gaussian kernel is increased and the curvature at that level is found. The CSS is represented with a CSS image. As features, statistical properties such as mean and variance of length of curves, number of zero crossings for each standard deviation etc. which are extracted from the CSS image are used. Additionally, for each standard deviation value, statistical features of absolute curvature are extracted. In total 580 features are obtained [23].

Moment Descriptors Based Features

The Shape of fish trajectories can be distinguished by using moment descriptors. We utilize affine moment invariants as proposed in [26] in addition to moment, central moment and translation and scale invariant moments. In total 55 features are extracted using those moment descriptors.

Velocity and Acceleration Based Features Statistical properties: mean, standard deviation, minimum, maximum, number of zero crossings, number of local minima and maxima etc. of velocity and acceleration are extracted in three dimensions considering the fact that fish can swim in three dimensions in an open sea. However, since the trajectory description in our data repository is in two dimensions, we estimated the third dimension using the width (w) and height (h) of fish detection bounding box ($1/\sqrt{wh}$). In total 42 features are obtained.

Fish Pass by Features

Fish trajectories are affected by the geographical properties of the underwater environment and their trajectories can be different in different locations. In this study, we divide the underwater environment into three: open sea, under the coral and above the coral (3). We manually segmented each video scene once and utilize them to obtain the features corresponds to all fish trajectories of a video. As features the frequencies of being in different locations and frequency of crossings from one location to another location is extracted. In total 12 features are obtained.

Fig. 3 Segmented regions of underwater image; black for open sea, red for above the coral and green for under coral [23]

4.2.2 Clustering

We used affinity propagation (AP) [27] as the clustering method. AP was used by many studies for different purposes including anomaly detections. AP can produce smaller clusters and produce uneven sized clusters which make it compatible with the outlier detection strategy that we use. Furthermore, it is fast, non-parametric, does not depend on sample order and does not need initialization.

4.2.3 Outlier Detection

Outlier detection is used to detect unusual trajectories. In this study, we adapted the outlier detection given in [4]. Basically, there are two types of unusual trajectories: *i)* those located in small clusters, *ii)* those in dense clusters but far from cluster centers.

The samples in small clusters are classified as outliers which makes them unusual trajectories. For the samples belonging to dense clusters, an unusual trajectory is detected using the Euclidean distance between the sample and the cluster exemplar. A data sample which is far away compared to threshold $\tau = \mu + w\sigma$ (with mean (μ), weight (w) and standard deviation (σ) of all distances between all samples and the cluster center) is defined as an outlier (unusual trajectory) . As can be inferred this threshold is different for each cluster and calculated using the specific cluster.

4.2.4 Feature Selection

For feature selection, Sequential Forward Feature Selection [28] is applied together with clustering and outlier detection. Feature selection provides the proper feature sets which also decreases the chance of over-fitting. It eliminates irrelevant and redundant features. Moreover, it might filter out the features which might misguide the clustering. Feature selection is applied as given in [23, 24].

In the testing phase the new trajectories are classified using outlier detection parameter *w* and the number of clusters that are found during training. In detail, first clustering is applied to the testing trajectories using the same number of clusters that are found in training and outlier detection is applied with the selected *w* parameter from the training.

4.2.5 Conclusions for Flat Classifier

In this section, we represented fish trajectories with novel descriptors which were never used before for fish behavior analysis. Clustered and labeled data were used together to select the best feature set and classify trajectories as normal or unusual. The flat classifier improved performance of unusual fish detection compared to the filtering mechanism (given in Section 4.1) where results are given in Section 4.4. The performance of the flat classifier is successful especially considering the

challenges of underwater environments, low video quality, noisy data and erratic movement of fish. Additionally, it is good at detecting normal trajectories as well which is promising to help marine biologist by eliminating many normal trajectories with relatively low error rate.

4.3 Detecting unusual fish trajectories using a hierarchical decomposition

In this section, we present a novel type of hierarchical decomposition method to detect unusual fish trajectories. The basics of the proposed hierarchical decomposition method are the same as the method presented in Section 4.2. Clustering of data based on selected features without initially using the known labels is the key to partitioning the data into separable subsets. To automatically generate the hierarchy during training, clustered and labeled trajectories are used together. Different from the traditional way which uses the same feature set for every level of hierarchy or from a flat classifier (Section 4.2), we use different feature sets at different levels of the hierarchy, which allows selecting more specific features [24]. The main contribution of this part is presenting a novel approach for unusual behavior detection which constructs a feature or class taxonomy independent hierarchy.

4.3.1 Hierarchy Construction

Training of the proposed method includes hierarchy construction. At each level of hierarchy, data is first clustered using the best feature subset found using feature selection (Section 4.2.4). After clustering, outlier detection is applied to each cluster and outliers (unusual trajectories) for a specific level of the hierarchy are found. Then, for each cluster, the number of false positives (positive class represents the unusual trajectories) and false negatives (negative class represents the normal trajectories) are found. The clusters which do not have any false positives and false negatives are fixed for that level (shown as classifiable samples which belong to perfectly classified clusters in Figure 4). The hierarchy construction recurses similarly with all samples of clusters that have false negatives or false positives (shown as remaining samples which belong to any misclassified clusters in Figure 4). That tree is extended by repeating the clustering, feature selection and outlier detection until there is no cluster which is perfectly classifiable or all the training samples are perfectly classified [24]. The leaf nodes of the hierarchy can be either: perfectly classified clusters (which contain classifiable samples) which can be observed mostly at the upper levels or misclassified clusters (which contain remaining samples). These occur only in the leaf nodes belonging to last level of hierarchy.

Perfectly classified clusters can be either:

- Perfectly classified mixed cluster: Includes unusual and normal trajectories which are correctly classified using the outlier detection.
- Perfectly classified pure normal cluster: Includes only normal trajectories which are correctly classified using the outlier detection threshold.
- Perfectly classified pure unusual cluster: Includes only unusual trajectories which are correctly classified due to being in a small cluster where we assume that samples of small clusters are unusual trajectories.

Misclassified classified clusters can be either:

- Misclassified mixed cluster: Includes both unusual and normal trajectories with at least one sample wrongly classified using the outlier detection threshold.
- Misclassified pure normal cluster: Includes only normal trajectories with at least one trajectory classified as an unusual trajectory using the outlier detection threshold or includes only normal trajectories which are wrongly classified as unusual trajectories due to being in a small cluster.
- Misclassified pure unusual cluster: Includes unusual trajectories where at least one trajectory is classified as a normal trajectory using the outlier detection threshold.

4.3.2 New Trajectory Classification Using the Hierarchy

To classify a new trajectory in the testing, the built hierarchy is used, using all perfectly classified clusters and misclassified clusters of each level, the selected feature subsets for each level and the outlier detection threshold for each cluster are used. Testing is based on finding the closest cluster at each level of hierarchy. The closest
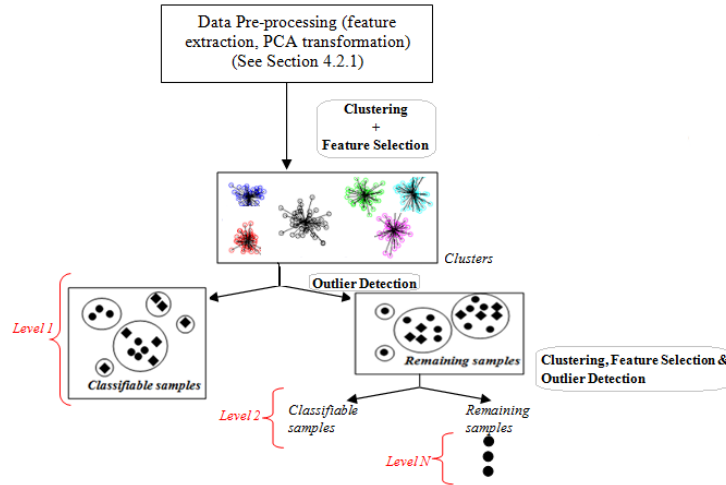
Fig. 4 Hierarchy Construction [24]

cluster is found by the Euclidean distance between the new trajectory (in terms of the features selected at the current level) and the cluster examples (including misclassified clusters) at each level of the hierarchy.

At each level in the hierarchy, the closest cluster can be one of the six possible cluster types: *i)* perfectly classified pure unusual, *ii)* perfectly classified pure normal, *iii)* perfectly classified mixed, *iv)* misclassified pure normal, *v)* misclassified pure unusual, and *vi)* misclassified mixed. At each level in the hierarchy, for the new trajectory, three types of class decisions are possible: unusual trajectory , candidate normal trajectory and no effect on the decision.

The decision is based on one of these six cases:

- The closest cluster is a perfectly classified pure unusual cluster which makes the new trajectory an unusual trajectory and classification stops (there is no need to look at any other level of the hierarchy).
- The closest cluster is a perfectly classified mixed cluster and the new trajectory is further than the outlier detection threshold of that cluster which makes the new trajectory an unusual trajectory and classification stops (there is no need to look at any other level of the hierarchy).
- The closest cluster is a perfectly classified pure normal cluster and the new trajectory is further than the outlier detection threshold of that cluster. This makes the new trajectory an unusual trajectory and classification stops (there is no need to look at any other level of the hierarchy).
- The closest cluster is a perfectly classified pure normal cluster and the distance between the new trajectory and the corresponding cluster's center is smaller than the outlier detection threshold of that cluster. This makes the new trajectory a candidate normal trajectory . The new trajectory does to next level of the hierarchy.
- The closest cluster is a perfectly classified mixed cluster and the distance between the new trajectory and cluster center is smaller than the threshold. The new trajectory is a candidate normal trajectory . The new trajectory goes to the next hierarchy level.
- The closest cluster is a misclassified cluster (pure or mixed). The new trajectory proceeds to the next level. This does not have any effect on the classification of the new trajectory unless the closest clusters at each level are misclassified clusters.

Those rules are illustrated in Figure 5.

In summary, even a single level's decision as unusual trajectory is enough to classify the new trajectory as an unusual trajectory regardless of the level of the hierarchy. On the other hand, if there is no decision as unusual trajectory from any level and if the decision of at least one level is candidate normal then the class of the new trajectory is declared to be normal. However, it is possible that the closest cluster at each level of the hierarchy is a misclassified cluster. In this case, we use the ground-truth labels of the training trajectories and apply the following rules, starting from the top of the hierarchy:

- The closest cluster at the current level contains all normal trajectories by looking at the ground-truth class labels: If the new trajectory is further than the rest of the samples in that cluster this makes it an unusual trajectory and classification stops here. Otherwise the data goes to the next hierarchy level.
- The closest cluster contains all unusual training trajectories by the ground-truth: The new trajectory is classified as an unusual trajectory and classification stops here.
- The closest cluster contains both normal and unusual training trajectories. In this case, we apply the nearest neighbor rule which makes the class of the new trajectory the same as the closest training sample's class. If the class is an unusual class then classification stops. Otherwise, the data goes to the next level to apply above rules.
- If the new trajectory reaches the last level and could not be classified yet, then it is classified as a normal trajectory .

Those rules are illustrated in Figure 6.

4.3.3 Conclusions for Hierarchical Decomposition Method

In this section, we presented a hierarchical decomposition method to detect unusual fish trajectories. Considering all three proposed methods in this chapter, hierarchical decomposition method performed the best. Additionally, the comparison between the state of the art methods and the proposed hierarchical method showed that the hierarchical method performs better in overall (see Section 4.4.2). Besides, this method is also efficient at classifying new tracks as it is only based on distance

Fig. 5 New trajectory classification using the hierarchy
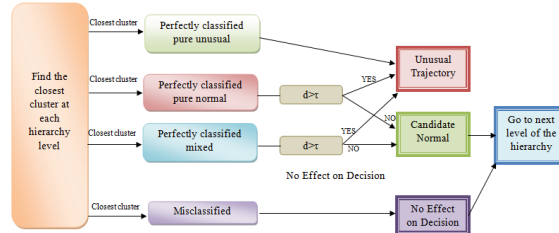
Fig. 6 New trajectory classification when the decisions of all levels are "no effect on decision".
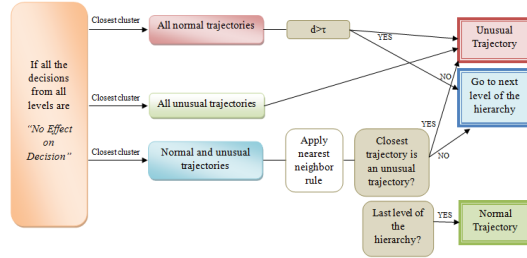
calculations between the new trajectory and the cluster centers of each level of the hierarchy. The main contributions of this section are: *i)* presenting a novel approach for unusual behavior detection which builds a feature or class taxonomy independent hierarchy, *ii)* showing that using different feature spaces in the classification at different levels can improve the performance.

4.4 Experiments and Results

In this section, the data set and the state of art classification algorithms to compare their performance with the proposed methods are given. The results are evaluated in terms of *TPrate* (Eq. 3), *TNrate* (Eq. 4) and geometric mean of *TPrate* and *TNrate* (Eq. 5).

$$TPrate = TP/(TP+FN) \text{ unusual trajectory class accuracy} \quad (3)$$

$$TNrate = TN/(TN+FP) \text{ normal trajectory class accuracy} \quad (4)$$

$$\text{Geometric Mean of TPrate and TNrate (GeoMean)} = \sqrt{TPrate \, TNrate} \quad (5)$$

where *TP* is the number of correctly classified unusual trajectories, *TN* is the number of correctly classified normal trajectories, *FN* is the number of misclassified unusual trajectories and *FP* is the number of misclassified normal trajectories.

4.4.1 Data Set

The proposed methods and all the states of art methods (such as Random Forest [29], Spectral Clustering [30], and LOF [31]) were applied to 3102 trajectories (3043 normal, 59 unusual trajectories). To the best of our knowledge, this data set is the largest fish trajectory data set in the underwater environment and the largest labeled data set in general. Data includes a single fish species which is *Dascyllus reticulatus* living in the Taiwanese coral reef. Data was collected from 93 different videos having 320x240 resolutions, 5 frames per second. Considering that the fish behavior can change during the time of the day and *Dascyllus reticulatus* is more active in the morning we used the videos that were captured in the morning.

The normal and unusual behaviors are determined by visual inspection and also examined by the marine biologists. The most usual and frequent behaviors in the data set are hovering over the coral and freely swimming fish in open sea (Figure 7a-b) which represent normal behaviors. On the other hand, unusual trajectories are such as fish suddenly (in one frame) changing direction (predator avoidance, Figure 7c), fish biting at coral (also interaction with plankton, Figure 7d) and so forth. A trajectory that has normal and unusual segments is assumed as unusual.

4.4.2 Results

The proposed methods were compared with several of art classification methods and other popular trajectory analysis methods (see Table 1). 9-fold cross validation was performed. Training, validation and test sets were constituted randomly and the normal and unusual trajectories are distributed equally in each set.

Table 2 shows the best results in terms of *TPrate*, *TNrate* and average of geometric mean (*GeoMean*) of *TPrate* and *TNrate*. For each evaluation metric the standard deviation (considering cross validation folds) is also given after ± sign. The best results in terms of each evaluation metric are emphasized in bold-face.

The results show that the hierarchical decomposition method has highest unusual fish trajectory detection rate (*TPrate*) and is the best method in overall. On the other hand, the flat classifier (Section 4.1) and filtering method (Section 4.2) are as good as SVM in terms of unusual fish trajectory detection but worse than SVM in terms of normal trajectory detection (*TNrate*). The KNN algorithm has the best *TNrate*, but this is at a considerable miss classification that produces lowest *TNrate* and *GeoMean*.

5 Concluding Remarks

In this chapter, we addressed fish behaviors with a unusual fish trajectory detection schema using underwater environment videos. We distinguished the fish trajectories as normal and usual trajectories. All the analysis in this chapter were applied to the trajectories of *Dascyllus Reticulatus* from the Taiwanese coral reef during morning time. We presented three different classification methods to detect unusual fish trajectories. The first method (filtering method) is more specific to eliminating normal trajectories. The other methods (flat method and hierarchical decomposition
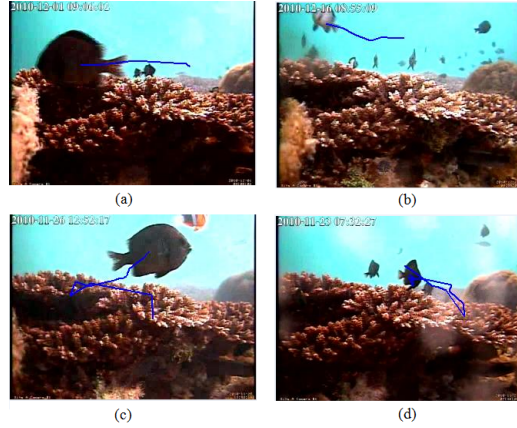
Fig. 7 (a-b) Normal fish trajectory examples, (c-d) Unusual fish trajectory examples [23, 24].

Table 1 The used state of the art classification methods, popular trajectory analysis methods and the proposed methods.

Method	Parameters	Abbreviation
k-Nearest Neighbors	$k=\{1, 2, 3, 4, 5, 10, 15, 25\}$ were used as the common parameters. Sequential forward feature selection was applied as given in Section 4.2.4.	kNN
SVM	As the kernel function, radial basis function with varying kernel parameters was used. Hyperplanes were separated by Sequential Minimal Optimization. Sequential forward feature selection was applied as given in Section 4.2.4.	SVM
Random Forest with Balanced Training	A number of trees $\{10, 30, 50, 70, 100, 120, 150, 200, 500, 1000\}$ were tested and the trees are grown without pruning. For node splitting, the Gini index was used.	RF BT
Spectral clustering based method	Normalized Cuts spectral clustering was applied to unusual and normal trajectories individually and each cluster of behavior was modeled as a mixture of Gaussians in the spectral embedding space. A new track is classified by projecting it into the spectral embedding space for normal and unusual classes and based on the likelihood the new track is classified as a normal or unusual trajectory. Different sigma values such as $\{1, 10, 20$ etc.$\}$ and different cluster size $\{10, 15, 20, 30, 40, 50, 60, 80, 90\}$ for normal and unusual clusters were tested.	Spec
LOF	LOF is a density based method which considers a sample to be an outlier if its surrounding space contains few samples. It does not use any clustering technique. Training is performed only using normal classes. During validation normal and usual class trajectories are used and the best feature set is selected using sequential forward feature selection. Neighborhood is defined with a parameter called k. k was taken as $\{1, 3, 5, 10, 15, 20$ and $25\}$.	LOF
Filtering Method	Pixels $\{2, 4, 8, 16, 20\}$ were taken to define the search area.	Proposed M1
Flat Classifier	Outlier detection parameter w was taken as $\{-1, -0.3, 0, 0.3, 0.6, 0.9, 1, 2, 3, 6\}$	Proposed M2
Hierarchical Decomposition	Outlier detection parameter w was taken as $\{0, 0.3$ and $1\}$	Proposed M3

Table 2 Results of each method in terms of average of *TPrate*, *TNrate* and *GeoMean*. The best results are emphasized in bold-face.

	TPrate	TNrate	GeoMean
KNN	0.37±0.28	**0.99±0.01**	0.55±0.27
SVM	0.81±0.16	0.93±0.03	0.86±0.09
RF BT	0.88±0.01	0.91±0.10	0.89±0.05
Spec	0.57±0.20	0.85±0.11	0.66±0.04
LOF	0.62±0.17	0.97±0.01	0.77±0.08
Proposed M1	0.80±0.20	0.77±0.04	0.78±0.09
Proposed M2	0.81±0.17	0.76±0.02	0.78±0.09
Proposed M3	**0.94±0.10**	0.88±0.02	**0.91±0.05**

) aimed at detection of unusual fish trajectories and performed better than filtering mechanism. The results show that the proposed method and especially the hierarchical decomposition method is good at detecting unusual fish trajectories while it is the best method overall compared to the state of art methods. As a future work, the proposed methods can be applied to larger fish data sets and may be also other fish species.

Index

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