21st International Conference on Pattern Recognition (ICPR 2012)
November 11-15, 2012. Tsukuba, Japan

A Filtering Mechanism for Normal Fish Trajectories

Cigdem Beyan, Robert B. Fisher
IPAB, School of Informatics, University of Edinburgh, UK
C.Beyan@sms.ed.ac.uk, rbf@inf.ed.ac.uk

Abstract

Understanding fish behavior by extracting normal motion patterns and then identifying abnormal behaviors is important for understanding the effects of environmental change. In the literature, there are many studies on normal/abnormal behavior detection in the areas of human behaviour analysis, traffic surveillance, and nursing home surveillance, etc. However, the literature is very limited in terms of normal/abnormal fish behavior understanding especially when natural habitat applications are considered. In this study, we present a rule based trajectory filtering mechanism to extract normal fish trajectories which potentially helps to increase the accuracy of the abnormal fish behavior detection systems and can be used as a preliminary method especially when the number of abnormal fish behaviors are very small (e.g. 40-50 times smaller) compared to the number of normal fish behaviors and/or when the number of trajectories are huge.

1. Introduction

The study of marine life is important for understanding environmental effects such as: pollution, climate change, etc, although accessing underwater data is mostly very difficult. Fish behavior analysis is helpful to detect such environmental effects by extracting the changes in behavior patterns or finding abnormal behaviors.

The traditional way to analyze fish behavior is based on visual inspection by marine biologists [1]. However, this analysis is very time consuming and needs a huge amount of human labor. Moreover, manually analyzing the data decreases the amount of data that could be analyzed. Therefore, at this point, computer vision techniques could play an important role.

In the computer vision area, behavior understanding studies can be classified into two categories: prominent activity recognition and abnormal behavior detection [2]. Prominent activity recognition is very difficult when the number of behavior models in an uncontrolled and uncooperative real-world data is considered [2]. On the other hand, abnormal 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 abnormal behaviors are generally defined as outliers or rare events [3, 4]. In this scope, the clusters with small numbers of elements represent rare trajectories and the samples that are different from samples in the same cluster are considered as outliers [3]. Although this approach is reasonable, when the number of trajectories is huge like thousands, millions etc. and/or the number of normal trajectories are much bigger than the number of abnormal trajectories, such as 40 or 50 times bigger, normal trajectories can dominate abnormal trajectories and extracting small clusters and outlier detection might be inaccurate.

In this study, we present a rule based trajectory filtering mechanism to extract normal fish trajectories. The aim of this filtering mechanism is to reject normal trajectories as much as possible (ideally all) while not rejecting any abnormal trajectories. Altogether 21 filters (event rules) were defined. The remaining trajectories after one filter were used as the input of the following filter. Finally, the remainders of last filter were defined as abnormal trajectories. To the best of our knowledge, the literature is very limited in terms of studies of fish behavior understanding especially in the field of normal and abnormal behavior detection. The number of studies which deal

978-4-9906441-0-9 ©2012 ICPR

with live underwater environments [5, 6] is very few and these studies generally focus on analyzing fish trajectories in an aquarium [7], a tank [8] or a cage [9] which makes the analyses simpler in terms of motion patterns and also removes the effects of habitat on the behavior of fish. Additionally, the studies in the literature are also restricted in terms of the number of fish (usually 10-30 fish) and the number of fish species that they are analyzing. Our study is distinguished not only by the approach but also containing 10 fish species (which increase the behavior variety) and being tested on thousands of trajectories, which are captured in different underwater locations with different camera distances. In addition, it provides an approach to model fish movements for future work.

2. Related Work

In the literature, fish trajectory monitoring studies that utilize computer vision technology generally perform studies for water quality monitoring and toxicity identification [7, 10]. Beside this aim, studies focus on fish stress factor identification [1] or automatically abnormal trajectory understanding to help the farm operator in aquaculture sea cages [9]. Automatic fish motion pattern analysis in underwater environments in order to help marine biologists is another recently studied problem [5, 6].

Some of the research on fish behaviour understanding has focused on the trajectory of individual fish such as [10] while others have studied fish group behaviours [7, 8]. Some studies analysed only one species like [1, 8, 9].

Thida et al. [7] proposed a system which analyses behaviors of a group of fish in an aquarium using a shape feature based signed function and incremental clustering and detects abnormal swimming patterns in the presence of a chemical in the water. Chew et al. [8] presented a fish school behavior monitoring system where the activity of the fish school is determined using the overall speed of fish and the complexity of the path. The trajectories of fish which are extracted from live videos are first sub-sampled using the Douglas-Peucker algorithm and then clustered using the I-kMeans algorithm in [5]. In this study, small clusters are identified as interesting events. In [11], fish trajectory states were represented as no movement, up, down, left and right using the center of fish bounding boxes and the recurrence plot is used to analyze these trajectories. Differently, study [9] presents an analysis of fish movement in aquaculture

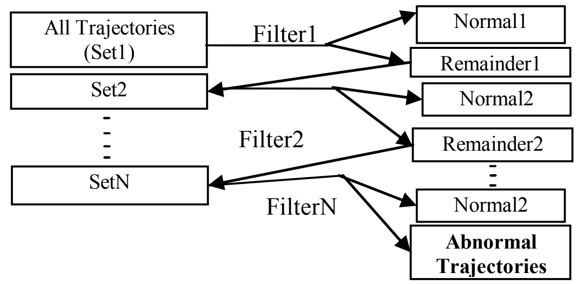

Figure 1. The block diagram of the proposed method

sea cages to inform operators about unusual fish behavior throughout the day. The system selects 30 random objects to analyze their average swimming speed and direction. Using these features and a set of thresholds the normal and abnormal behaviors are classified. Amer et al. [6] classifies underwater videos of fish using the speed, direction, periodicity and escape response time. Using three sea depths, six behaviour patterns of fish are defined and a new video is identified. A Random Forest method is used to identify the distinct fish motion patterns and a linear Support Vector Machine is applied to learn the six behaviours.

3. Proposed Method

The tracker [12] gives the trajectories for fish moving across the image. For any fish *i* tracked through *n* frames, a trajectory can be defined as the center of fish bounding boxes as given in Eq. 1.

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

In Figure 1, the block diagram of the filtering mechanism is given. The mechanism of our method is processing like a cascade classifier such as [13]. First, all fish trajectories are filtered by filter1 (event rule 1). In each step, the trajectories satisfying the rule are defined as normal trajectories (such as Normal1, Normal2…). The trajectories which do not satisfy the rule are called the remainders of the corresponding filter and are used as inputs to the following filter. This is continued until all the filters are used. At the end, the remainders of all filters are called abnormal trajectories (which is a set with many fewer normal trajectories). At this point we should state that the filtering order is independent since the rules of filters are independent. Therefore, filters can be applied in any order.

3.1. Definition of Filters (Event Rules)

Primitive motions are defined in two categories as *straight and/or cross movements* containing all the

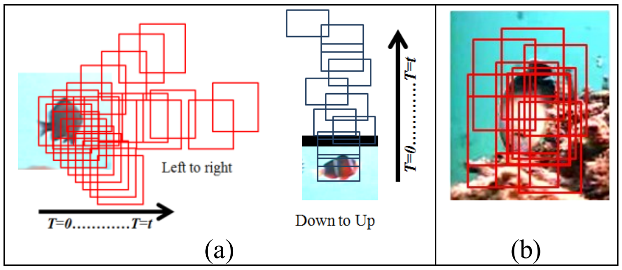

Figure 2. (a) Example straight and/or cross movements, (b) Example being stationary.

movements in all directions (such as; left to right, up to down etc.) and *being stationary*.

Straight and/or cross movements are defined in three ways: 1) the center of fish bounding boxes over the whole trajectory is inside an area (search area) which is determined by the first detection's bounding box boundary while the fish is going only one direction such as left to right, right to left, up to down and down to up, 2) the center of the fish bounding box in frame $f+i$ is inside an area which is determined by the detection bounding box in frame $f+i-1$ for $i=1$ to N (N represents trajectory lengths) while the fish is going only one direction such as left to right, right to left, up to down and down to up, 3) the center of the fish bounding boxes over whole trajectory are inside an area which is determined by the first and last detection's bounding box boundaries while fish is going only one direction such as left to right, right to left, up to down and down to up. This state covers all the horizontal, vertical and diagonal motions and is defined assuming that straight or cross movement in any location of the open sea is a normal behavior which should corresponds to freely swimming fish.

Being stationary is defined as the state that the center of the fish bounding box is inside an area which is defined in terms of first detection's bounding box. This state is defined considering the fact that fish cannot stay at the same point in most of the cases due to the sea currents. Some examples of straight-cross movements and being stationary are given in Figure 2.

Filters are defined as one, two and three length combinations of these primitive motions such as moving left to right (length is one), moving left to right and then being stationary (length is two), moving right to left and then down to up (length is two), being stationary for a while, then moving up to down and then right to left (length is three) etc. Similar behaviors like going left to right and right to left are modeled by same filter and altogether 21 rules were used.

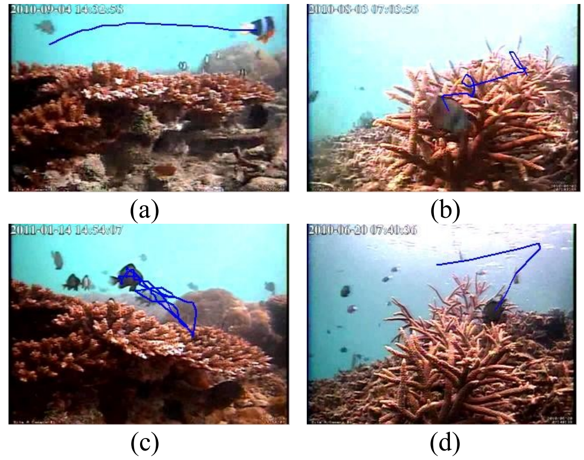

Figure 3. (a-b) Examples of normal fish trajectories which are filtered out by the proposed method, (c-d) Examples of abnormal (rare) fish trajectories.

4. Data Set

To test the proposed method 271 sample underwater videos including 4 different locations and 2486 trajectories (46 abnormal, 2440 normal) belonging to 10 different species were used. The normal and abnormal (rare) behaviors are determined based on visual inspection. In this context, freely swimming fish were considered as normal behavior since this is the most frequent behavior in the dataset. The abnormal or rare behaviors were: i) Stationary fish for a long time (compared to detection length) inside of coral: this kind of a behavior assumed to be an eating behavior hence differentiated from swimming, ii) Biting at coral (Figure 3c), iii) Fish suddenly (mostly in one frame) diving (Figure 3d), iv) Fish suddenly (mostly in one frame) changing direction, v) Fish turning around in an area like a predator.

5. Results

To evaluate the proposed filtering mechanism a 9 fold cross validation test was performed. Train and test sets were constituted randomly while the normal and abnormal trajectories were distributed equally. In the training phase, for each filter the best parameters (search area for straight and/or cross movements, search area for being stationary and using only definition 1, 2, 3, definitions 1 and 2 together, 2 and 3 together, 1, 2 and 3 together (see subsection 3.1) etc.) were found and those were used in the test phase. When finding the best parameter values those which did not filter out any abnormal trajectories were chosen. In the case of having more than one parameter set which did not filter out any abnormal trajectories, the one that filtered the most normal trajectories was selected. The overall performance is given in Table 1.

Table 1. Performance of Proposed Method

		Result of Method		
		Filtered	Maintained	Total
Actual Label	Normal	916	1524	2440
	Abnormal	6	40	46
	Total	922	1564	2486

As result, 38% of normal trajectories were detected by the filtering mechanism while 13% of the abnormal trajectories were also detected and filtered out as normal trajectories.

The proposed method is also compared with the method [5] (since it is the most applicable/similar study that can be compared) based on false positive rate and the results are given in Table 2. As is it seen from the table our method presents much better results compared to [5].

Table 2. Comparison with method [5]

	False Positive Rate
Proposed Method	0.1304
Method [5]	0.9130

6. Conclusion

In this study, a rule based trajectory filtering mechanism to detect normal fish trajectories in open sea is presented. The results show that the proposed method can filter out more than one of the four of normal trajectories with 99% precision, but also filters out one in ten of the abnormal behaviors which ideally should be zero. However, we believe that this is still a good result since the fish species which cause variation in the fish behavior and the location variants which affect the fish behavior were not considered while defining the filters. Additionally, filters and parameters are defined without considering the type of abnormalities to propose a general mechanism which is independent to data and five different types of abnormalities were considered as the same.

In conclusion, this work presents first algorithm for filtering normal fish behavior in an unconstrained open sea environment. This method can be used as a preliminary step to increase the accuracy of an abnormal behavior detection system, especially when the number of normal fish trajectories is much bigger than the number of abnormal fish trajectories and/or when the number of trajectories is very huge (like millions etc.). As a future work, improved/additional rules (such as based on velocity, orientation etc.) will be defined to decrease the false filtering. The authors will also focus on automatically labeling fish behaviors to construct a ground truth dataset which is currently constructed manually.

7. Acknowledgements

This research was funded by European Commission FP7 grant 257024, in the Fish4Knowledge project (www.fish4knowledge.eu).

References

[1] V. M. Papadakis, I. E. Papadakis, F. Lamprianidou, A. Glaroulos, and M. Kentouri, A computer vision system and methodology for the analysis of fish behaviour, *Aquacultural Engineering*, 46:53-59, 2012.

[2] C. Piciarelli, C. Micheloni and G. L. Foresti, Trajectory-based Anomalous Event Detection, *IEEE Trans. Circuits Syst. Video Technol.*, 18(11):1544-1554, November 2008.

[3] N. Anjum, and A. Cavallaro, Multifeature Object Trajectory Clustering for Video Analysis, *IEEE Trans. Circuits Syst. Video Technol.*, 18(11):1555-1564, 2008.

[4] F. Jiang, J. Yuan, S. A. Tsaftaris and A. K. Katsaggelous, Video Anomaly Detection in Spatiotemporal Context, *IEEE ICIP,* pp: 705-708, 2010.

[5] C. Spampinato, D. Giordano, R. D. Salvo, Y. Chen-Burger, R. B. Fisher, G. Nadarajan, Automatic Fish Classification for Underwater Species Behavior Understanding, *First ACM ARTEMIS*, 45-50, 2010.

[6] M. Amer, E. Bilgazyev, S. Todorovic, S. Shah, I. Kakadiaris, and L. Ciannelli, Fine-grained Categorization of Fish Motion Patterns in Underwater Videos, *IEEE ICCV Workshop*, 1488-1495, 2011.

[7] M. Thida, H. Eng and B. Fong Chew, Automatic Analysis of Fish Behaviors and Abnormality Detection, *In Proc. of IAPR MVA*, 8-18, 2009.

[8] B. F. Chew, H. L. Eng, M. Thida, Vision-based Real-time Monitoring on the Behavior of Fish School, *IAPR MVA,* 3-16, 2009.

[9] T. H. Pinkiewicz, G. J. Purser, R. N. Williams, A Computer Vision System to Analyse the Swimming Behaviour of Farmed Fish in Commercial Aquaculture Facilities: A case study using cage-held Atlantic salmon, *Aquacultural Engineering*, 45:20- 27, 2011.

[10] W. H. van der Schalie, T. R. Shedd, P. L. Knechtges, and M. W. Widder, Using Higher Organisms in Biological Early Warning Systems for Real-time Toxicity Detection, *Biosensors and Bioelectronics*, 16:457–465, 2001.

[11] C. Serra-Toro, R. Montoliu, V. J. Traver, and I. M. Hurtado-Melgar, Assessing Water Quality by Video Monitoring Fish Swimming Behaviour, *IEEE ICPR,* 428-431, 2010.

[12] C. Spampinato, S. Palazzo, D. Giordano, I. Kavasidis, F-P Lin, Y-T Lin, Covariance Based Fish Tracking In Real-Life Underwater Environment, *VISAPP*, 2012.

[13] M. J. Saberian and N. Vasconcelos, Boosting classifier cascades, NIPS, 2010.