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Vision-based Real-time Monitoring on the Behavior of Fish School

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Abstract

This paper introduces a technique which can automatically monitor the behavior of fish school in images in real-time. Results on the activity level, distribution and social interaction within the school are generated based on the spatial information extracted from captured images. The fish behaviors we observe here are selected based on a list of responses which fish exhibit when they are in distress. As it is a very challenging task to perform manual observations on fish, this technique creates a convenient alternative for researchers who need to study the behavior of fish. Instead, monitoring can be done effortlessly as images are translated to statistical results which can be used to describe the behavior of fish in the school. On top of this, the results can also detect any change to the water quality.

1. Introduction

Behavioral analysis of fish has been a popular approach in detecting changes in aquatic environment. Fish are observed to display variations in behavior when the environment is being modified. Some of the reaction to changes observed are avoidance behavior and change in swimming ability ([1] and [2]). Hence, the study of fish behavior is being employed in applications which perform water quality monitoring and toxicity identification.

Evaluation of the behavior changes of fish were previously done by using acoustic telemetry [3] and primitively, visual observations. These methods in general, induce a restraint on the fish being observed due to the measuring apparatus and enclosure. The fish are being deprived of the freedom to swim in a natural manner.

In contrast, our technique allows fish to swim in a less distressed environment in a standard sized tank. By monitoring a school of fish instead of an individual fish, we are able to extract more data from the images and this can ensure a more consistent and accurate detection of the reaction changes. Our goal is to provide a fully automated system which can perform analysis on some of the common behavior traits of fish school, at the same time when the images are being captured. This provides an immediate detection of any variations to the water condition.

First, we will describe the approach used to extract information from the images captured and the computation modules used to interpret fish behavior. To quantify the effects of environmental change on the fish responses, experiment is done on two different tanks, which contain 20 fish each. Both tanks are identical and are separately housed in identical enclosures. This ensures that the images captured for both tanks are not subject to different lighting and physical conditions. On top of this, all the fish in the tanks are from the same breed of Tiger Barbs.

To simulate a change in the water condition, the de-chlorination device in one of the tanks is being removed. With this, the water in this tank will be filled with water contaminated with Chlorine. This tank will be referenced as Tank B in this paper. The results obtained from this tank will then be compared with the other tank, Tank A, which acts as a control in the experiment.

2. Features Extraction

Real-time images are being captured using a camera fixed above a fish tank. To ensure constant illumination condition, the equipment is placed inside an enclosure with no or little light penetration. The fish are being detected as foreground blobs in the images using the background modeling and subtraction method in [4]. An example of the segmentation results is shown in Figure 1.

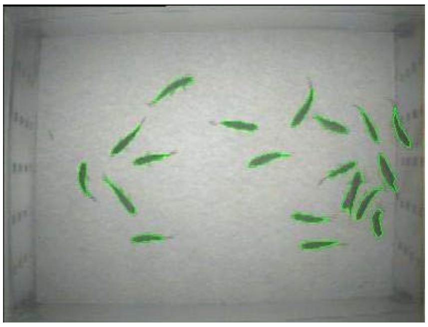


Figure 1: Result of fish detection in the image, with the contour highlighted in green

By means of linear projection of the centroid for each fish, the tracking module is then able to associate the same fish throughout the image sequence. Using the spatial information provided by its physical dimension and position mapped on the images, each fish is being represented by a set of coordinates of the pixels which it occupies.

$$F_i = \begin{Bmatrix} (x_1, y_1) \\ (x_k, y_k) \\ \ldots \\ (x_S, y_S) \end{Bmatrix}$$

This is the representation for fish i, F_i where (x_k, y_k) is the coordinate pair for the kth pixel occupied by the fish, and S the total number of pixels occupied by the fish.

Two features are needed to learn the behavior of fish in images and they can be easily computed from the coordinate information we have extracted. These features are:

1) Position, (P_x, P_y) : A pair of coordinates of centroid of each fish in the image

2) Size, S: The total number of pixels being occupied by each fish in the image

3. Behavior Analysis

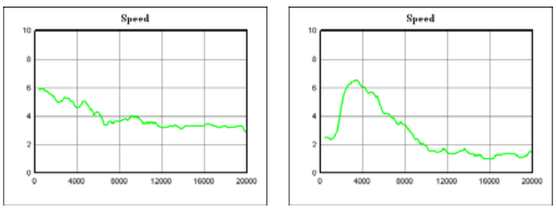
3.1 Activity Level

The activity level of the fish school can be determined by how fast they swim and the complexity of their swimming path. We calculate the speed of each fish in the tank by taking the displacement of its position between two consecutive frames. The overall school speed can be computed by:

$$v = \sum \sqrt{(P_x(t) - (P_x(t-1))^2 + (P_y(t) - P_y(t-1))^2}$$

where $P_x(t)$ and $P_y(t)$ represent the x and y coordinates of the position of a fish at Frame t, $P_x(t\text{-}1)$ and $P_y(t\text{-}1)$ the x and y coordinates of the position of the same fish at Frame $t\text{-}1$.

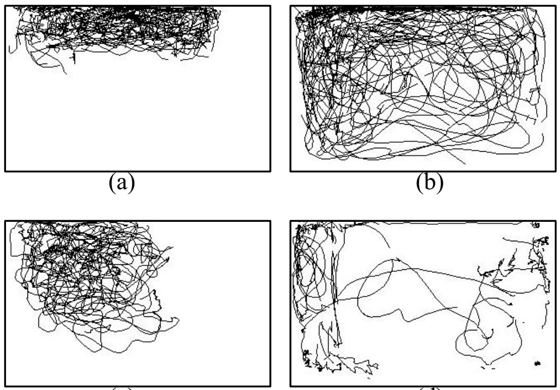
Figure 2 shows the plot of the overall school speed for Tank A and Tank B over 20,000 frames. Fish are put into the water at Frame 0. It can be seen that the speed for Tank A becomes constant after the fish has settled down at around Frame 6000. This is different from the results for Tank B where the fish shows hyperactivity after being placed into the tank and started to swim more lethargically after a while. A lower speed indicates difficulties in swimming imposed by the chemical contamination in the water.



(a) (b)

Figure 2: Overall school speed for (a) Tank A and (b) Tank B

We can verify the results by looking at the motion trajectory of the fish, as shown in Figure 3. The plots display the swimming path of the 20 fish over 250 frames for the two tanks at two instances. The messy and complex trajectory in Tank B shows an erratic behavior, which corresponds to the rise in speed between Frame 2,001 and Frame 2,250. As the fish start to swim slower between Frame 19,751 and 20,000, we can see a less dense trajectory which mostly occupies the sides of the tank. On the other hand, the fish in Tank A are seen to swim in a more controlled and regular manner.



(a) (b) (c) (d)

Figure 3: (a) and (b) are the motion trajectory for Tank A and Tank B respectively between Frame 2,001 and Frame 2,250. (c) and (d) are the motion trajectory for Tank A and Tank B respectively between Frame 19,751 and Frame 20,000.

3.2 School Distribution

The distribution of a fish school is determined by the population of fish in different parts of the tank. First, we split the tank into more than one region. This is followed by the calculation of the occupancy, Q in each region, which is represented by the percentage of the size of fish in that region:

$$Q = \frac{\sum_{j=1}^{r} S_j}{\sum_{i=1}^{n} S_i} \times 100\%$$

where S_j is the size of fish j located in the region, and r the number of fish located in the same region, while S_i is the size of fish i and n the total number of fish in the tank

Avoidance behavior has been observed in fish where the tank is being contaminated. Hence, we can make use of Q to determine if there is any region in the tank where the fish are trying to swim away from or attracted to.

Fish are observed to swim along the sides of the tank when there is an alteration in the water condition in some cases. Hence, in our experiment, we pre-define the regions by splitting the tank into the centre and side region. Figure 4 shows the boundary between these regions and the number stated in the centre is the occupancy in the centre region. In this case, 8% of the total fish size is detected in the centre. For each frame, this value is being compared to a threshold, T which determines if the probability of avoidance behavior, $Pb(t)$ should increase.

$$Pb(t) = \begin{cases} (1-\alpha)Pb(t-1) + \alpha & ,Q < T \\ (1-\alpha)Pb(t-1) & ,Q \geq T \end{cases}$$

where α is the weight of each frame and, *Pb(t)* and *Pb(t-1)* are the computed probability at Frame *t* and *t-1* respectively.

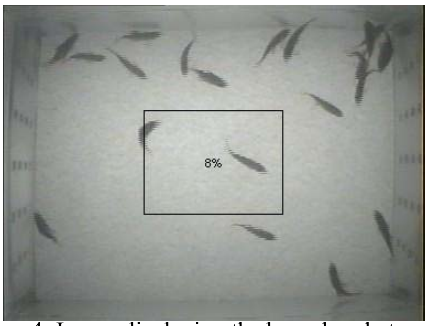
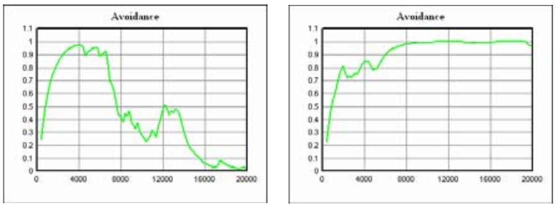


Figure 4: Image displaying the boundary between centre and side region with the occupancy stated in the middle

If most of the school is swimming along the sides of the tank, the probability of avoidance from the centre region will increase as *Q* in the centre is lesser than *T*. Figure 5 shows the probability computed over 20,000 frames. There is a significant difference in the results obtained from the two tanks. The probability of avoidance behavior in Tank B remains high even when the fish in Tank A seem to be settled down in the new environment. This indicates that the contaminant in Tank B affects the distribution of the fish school within the tank as the fish seem to be swimming away from the centre region.



(a) (b)

Figure 5: The probability of avoidance behavior for (a) Tank A and (b) Tank B

3.3 Social Interaction Within a School

Interaction among the fish is another response that we want to observe using the features we have extracted. In this part of the analysis, we determine the level of proximity the fish are swimming to one another and if sub-groups are being formed within the tank. This is then followed by the detection of leaders in the school.

Hierarchical k-means clustering is applied to the image captured. This process makes use of the coordinates we obtained from the position of the fish. When any fish is too far from the centre of the school, a cluster is formed to split the school into two. This process iterates until the one of the following conditions is met:

1) if the distance between every fish and its nearest cluster centre, *N* is smaller than T_C

$$\sqrt{(P_x - N_x)^2 + (P_y - N_y)^2} < T_C$$

2) if the density of any cluster is greater than α

$$D = \frac{\sum_{i=1}^{c} S_i}{A} > \alpha$$

where *A* is the area of the convex hull representing a cluster, *c* the number of fish belonging to the same cluster, and T_C and α are the pre-defined thresholds.

The second condition is included to prevent over-splitting of dense clusters with large area. An example of this type of cluster is shown in Figure 6. The distance of the fish at the boundary of the cluster and the cluster centre is large. According to condition 1, another cluster should be added to the image. However, this is prevented by condition 2 whereby the convex hull formed by the fish in the cluster is largely occupied.

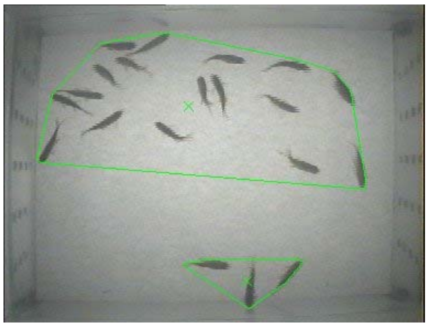
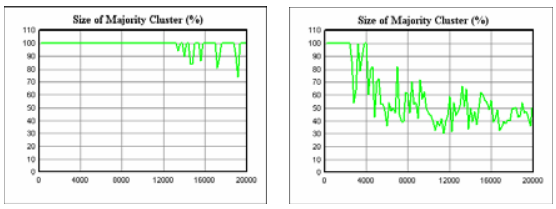


Figure 6: The fish school is split into two clusters using hierarchical k-means clustering; the green lines represent the outline of the convex hull formed by the fish in the same cluster

Next, we identify the majority cluster in the school. This is done by computing the size of every cluster, which is equivalent to the sum of *S* of the fish that belong to the same cluster. The one with the largest size is then labeled as the majority. The size of the majority is then plotted as a percentage of the total school size over a period of 20,000 frames for Tank A and Tank B, as shown in Figure 7. What we can deduce from the graphs is that the fish school in contaminated water tends to be more scattered as compared to that in a normal water condition.

After splitting the school into clusters and identifying the majority in the school, the process continues to detect the fish that appears to act as a leader. Since the leader is defined as the one which guides others, we make use of the features that have been extracted to determine the fish that is followed by the majority.



(a) (b)

Figure 7: (a) Percentage of the size of the majority cluster for (a) Tank A and (b) Tank B

We assume that the fish that is swimming away from the majority is the one that is leading the school. Hence, we measure the distance between the majority cluster centre, (M_x, M_y) and every fish that is not swimming within the majority cluster. The distance, d is then compared between two consecutive frames. If the value, *d* from the current frame is greater than that from the previous frame, that fish is identified as a leader.

$$d = \sqrt{(P_x - M_x)^2 + (P_y - M_y)^2}$$

An example is shown in Figure 8, where the green line encompasses the majority and the letters "L" and "F" on the fish indicate whether a fish is a leader or follower.

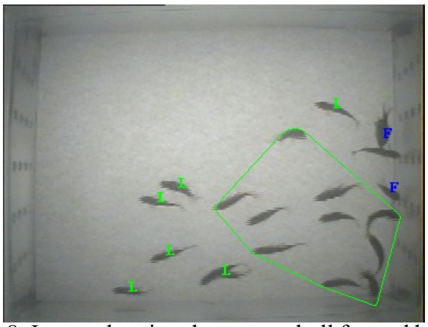


Figure 8: Image showing the convex hull formed by the majority group and the leaders (L) and followers (F) detected

4. Conclusion

We have presented a technique which can automatically monitor the change in behavioral response of fish to contaminants in the water at real-time. The disparity in the experimental results shows that the system is sensitive to the effects of water condition changes. Besides being able to describe the swimming patterns and movements of the fish school, the system can also act as a tool for water quality monitoring. The activity level indicates that the fish are lethargic when the value is low and that they are behaving erratically when the value shoots above the normal value. The detection of avoidance behavior in a school can help to indicate any possibility of contaminant in the water. On top of this, we can show the dominance characteristic of the fish school and the level of interaction of fish with a school. Further work will be done to include the other behaviors which have was previously observed. This includes loss of equilibrium and irregular turnings. Images showing the side views will also be tested to expand the range of activities that can be observed.

Acknowledgement

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References

[1] Kane, AS, Salierno, JD, and Brewer, SK.: "Fish models in behavioral toxicology: Automated techniques, updates, and perspectives" *Techniques in Aquatic Toxicology*, 559-590, 2005.

[2] Kane, A.S., Salierno, J.D., Gipson, G.T., Molteno, T.C.A., Hunter, C. "A video-based movement analysis system to quantify behavioral stress responses of fish" *Water Res.*, 38(18):3993-4001, 2004.

[3] Eisenhardt, E.P.: "Acoustic Telemetry of Rocky Reef Fish Home Range to Evaluate Marine Protected Area Size", 2003.

[4] H.-L. Eng, J. Wang, A. H. Kam and W.-Y. Yau: "Robust Human Detection Within a Highly Dynamic Aquatic Environment in Real Time", *IEEE Trans. Image Processing*, 15(6):1583-1600, 2006.