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Automatic Analysis of Fish Behaviors and Abnormality Detection

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Abstract

Current state-of-the-art fish monitoring systems are lack of intelligent in interpreting fishes behaviors automatically. To tackle these problems, we propose a vision-based method that automatically analyze behaviors of a group of fishes in an aquarium and detect abnormality precisely. Here we consider the problem in two steps. First, we propose a new incremental spectral clustering method to extract frequently occurred key swimming patterns of fishes. Then, we present video sequences of fishes into a trajectory through the space of these key patterns. Studying these trajectories provides a new tool to analyze fishes behaviors. Comparisons of fishes behaviors in clean water and water in the presence of chemicals provides a new tool to detect any abnormality. Experimental results illustrate that the precision value of our proposed method is above 90%.

1 Introduction

Visual analysis of animals and insects behavior is a growing research area with a number of interesting applications. For instance,

- Biological Study on genetics of certain diseases and
- Biological early warning system: monitoring behaviors of aquatic organisms such as fishes to detect various chemicals in water.

The traditional way is to first videotape the animal for a period of time and then, observe animal behaviors manually. But, this is time-consuming process and also observation results is subjective to knowledge of human observers. Therefore, automated system that could analyze the behaviors of animals and detect any abnormal behaviors is a crucial task in above discussed applications. In this paper, we present a framework for efficient animals behavior analysis.

In particular, we emphasized on behaviors analysis of fishes. Over the past decades, computer vision-based fish behavior monitoring systems have been established as a way to detect toxicity in drinking water ([1, 2, 3] [4] and the references therein). Swimming patterns and behavior of fishes are monitored by using computer vision techniques to observe changes that could be indicative of developing toxicity conditions. As observed in above literatures, more research efforts have been put on analyzing behaviors of individual fishes. Hence, most of the state-of-the-art fish behavior monitoring systems are limited with restricted environments (for example, individual fish is required to stay in a very narrow chamber with electrodes). This makes the system costly, and also put fish in stressed environment. In this work, we focus on studying group behaviors of fishes in a standard aquarium rather than individual fish in a small chamber. In our knowledge, there is one similar work which uses a standard tank in literature [5]. In their work, parameters for 15 individual fishes in a standard tank are tracked and analyzed using artificial intelligence concept. But, in reality, tracking of multiple fishes simultaneously is noisy due to occlusion and abrupt motion of fishes.

In this work, based on group activities, we propose a novel approach for automatic clustering of fishes swimming patterns and abnormal detection using spectral clustering method. The main steps and contributions are as follows:

- Key Patterns Extraction: For an input a long video sequence, we propose a new incremental spectral clustering based method to extract frequently occurred key swimming patterns of fishes. This summarizes long video sequence into a space of possible patterns.
- Trajectory Presentation: We describe video sequences of fishes into a trajectory through the space of extracted key patterns. Studying these trajectories provide a new tool to analyze fishes behaviors.
- Abnormal Detection: Comparing fishes behaviors in clean water and water in the presence of chemical, we can generate early warning signals of water quality deterioration precisely.

Experiments on long video sequences, including both normal and abnormal conditions are performed. Experiments with different chemicals such as aldicarb and chloramine are evaluated. The evaluation reports that our proposed method can detect any chemical in less than 10 minutes and precision value (correctly detected/number of images) is above 90%.

2 Discovering Key Swimming Patterns

In this section, we review spectral clustering method first and explain our proposed method in details. In addition to developing an application of spectral clustering method to *real-life* videos, we contribute in 1) developing an algorithm to compute distance measure between two images, and 2) proposing a new method to perform spectral clustering incrementally.

2.1 Basic Concepts on Spectral Clustering

This section gives a basic concepts of spectral clustering. For details, please refer to [7, 8, 9].

Given a set of data points, the first step of spectral clustering is to compute a pairwise similarity matrix W where w_{ij} represents similarity measure between data points i and j. There are a number of methods to compute similarity matrix. One of the most popular methods is to use Gaussian similarity function. Mathematically, it is defined as:

$$w_{ij} = \exp\left\{-\frac{\| d(i,j) \|^2}{2\sigma^2}\right\}, \tag{1}$$

where d_{ij} is distance measure between two data points and σ is a scaling parameter.

Then, a graph laplacian matrix is computed using the similarity matrix W. In literature on spectral clustering, a number of different laplacian matrix is being used and comparisons of these matrixes are discussed in [8]. Here, we shows only normalized graph laplacian matrix which applied in our proposed method.

$$L = I - D^{-1/2} W D^{-1/2}, \tag{2}$$

where I is identity matrix, W is similarity matrix(5) while D is diagonal matrix with values d_{ii} which is defined as:

$$d_{ii} = \sum_j w_{ij}. \tag{3}$$

Once the laplacian matrix is defined, eigen-decomposition of this matrix is performed using singular value decomposition. Finally, a grouping algorithm clusters data based on the eigenvalues and corresponding eigenvectors obtained.

2.2 Feature Extraction And Representation

In this paper, we propose to use shape feature and represent shapes of fishes using a signed-distance function. After extracting contours(shape) of fishes using fast level set method [6], we represent contours as follows:

$$\phi(x,y) = \begin{cases} d((x,y),C), & \text{(x,y) lies outside C;} \\ 0, & \text{(x,y) lies on the contour, C;} \\ -d((x,y),C), & \text{(x,y) lies inside C.} \end{cases} \tag{4}$$

where $d((x,y),C)$ is Euclidean distance between pixel (x,y) and contour C.

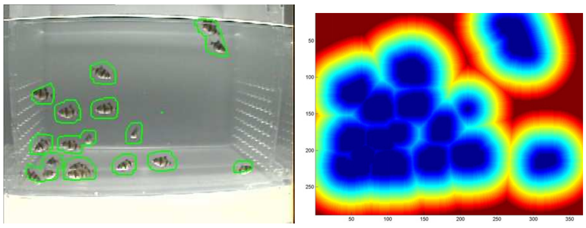

Figure 1: Swimming Pattern and its Representation Under Abnormal Condition.

Figure 1 shows contours of fishes and its representation using signed distance function. Darker color to lighter color represents values of ϕ increasing from negative to positive. This representation has been one of popular choices in shape representation due to its flexibility in topological changes. This is particulary useful in our application as it provides parameters such as location of fishes (darker regions), swimming direction (movement of darker regions) and area occupied by fishes (clustering of fishes) and many more.

2.3 Distance Measure

The success of spectral clustering depends heavily on the choice of similarity or affinity matrix. In our proposed method, similarity matrix, W is defined based on local scaling instead of fixed scaling. Mathematically, each entry of the matrix, W, is defined as

$$w_{ij} = \exp\left\{-\frac{d_{ij}^2}{2\sigma_i\sigma_j}\right\}, \tag{5}$$

where $\sigma_i = d_{ik}$ and k is the neighbor of data point i. In this work, we propose a new distance measure, d_{ij} based on our shape representations:

$$d_{ij}^2 = \frac{1}{2}\oint_\Omega (\phi_i - \phi_j)^2 (h(\phi_i) + h(\phi_j)) dxdy, \tag{6}$$

where $h(\phi_i)$ is defined as:

$$h(\phi_i) = \frac{H(\phi_i)}{\oint_\Omega H(\phi_i)}, \tag{7}$$

and

$$H(\phi_i) = \begin{cases} 1, & \text{if}(\phi < 5); \\ 0, & \text{otherwise.} \end{cases} \tag{8}$$

Please note that we give higher weight to the objects inside. Table 1 compares two distance measures, Euclidean and our proposed Pseudo-distance for images shown in Figure 2. As shown, test image 1 and test image 2 are significantly difference apparently. But, Euclidean distance measure does not show significant discrepancy while our proposed measure does.

2.4 Clustering Similar Shapes with our Incremental Approach

Knowing the pairwise distances between all frames, we can segment the sequence into clusters of similar

Table 1: Comparisons between two distance measures.

	Proposed Dist	Euclidean Dist
Ref. vs Test Img 1	0.2	0.8
Ref. vs Test Img 2	1.25	0.95

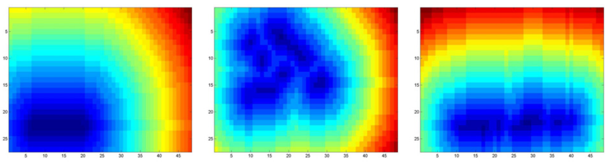

Figure 2: Two test images and reference image are shown (left to right).

shapes. But, when dealing with large amount of data, 1) constructing large similarity matrix and 2) computing eigenvalues of large matrix become challenges. To overcome these limitations, a few methods [10, 11, 12] have been proposed in literature. One of the possible solutions is to use Nystorm extension [10] which is an extrapolating method to compute eigenvalues of large matrix. This extension provides a way to extrapolate eigenvectors of large matrix based on the eigenvalues computed on a portion of entire similarity matrix, W. However, Nystorm extension will not be accurate if this portion does not include samples from small clusters. As a result, this method is not suitable if all entries in the matrix W are not available at the same time. Another possible solution is to perform spectral clustering incrementally [12]. Our proposed method belongs to the second approach. In this paper, we propose a new incremental method to cluster shapes from a large data set. We perform our algorithm in three steps.

Initial Step The first step performs traditional spectral clustering on a subset S_1 of large data set S where $S_1 \subset S$.

- Compute distance measure between all images within S_1 using the proposed distance measure (6).
- Obtain Laplacian matrix by equation (2).
- Compute eigenvalues of Laplacian matrix, and extract the first K smallest eigenvalues and corresponding eigenvectors.
- Perform $K-$means clustering algorithm on the extracted eigenvectors to group the shapes into K clusters.
- Extract representative swimming pattern which has minimum distance from any other images within the same cluster.

Incremental Step This step brings most of our contribution. We first compute distance between new image from data set to representative images obtained in the first step. We require that its minimum distance from the current clusters must not far away from the current cluster representatives. If it is, we must perform a new clustering. Hence, for every new image from complement set of S_1,

- Compute distance measures (6) between new image and cluster representatives and select the minimum distance.
- When the new images are far away from the current representatives, we put the image into a set of cluster-to-be.
- In contrast to other incremental spectral clustering approaches [12], we perform spectral clustering (step one) only when the set of cluster-to-be has sufficient amount of data. This reduces computational cost significantly. Then, new cluster representatives are augmented into the previous cluster lists.

Refine Step This final step refines the results obtained. The tightness of each cluster is computed by calculating the maximum distance of any two images within the cluster. If the maximum distance is greater than a threshold, we re-perform spectral clustering on that particular cluster.

2.4.1 Choice of Parameter K

In spectral clustering, one of the most important parameter is the number of clusters, K. In our proposed method, we define K based on matrix perturbation theory [13]. This theory states that the number of clusters in a data set depends on the stability of eigenvalues which is determined by the gap δ_e between two consecutive eigenvalues. Based on this theory, we define the number K by finding for the maximum gap δ_e over a set of eigenvalues:

$$K = \arg\max_{i} \mid \lambda_i - \lambda_{i-1} \mid, \tag{9}$$

where λ_i and λ_{i-1} are two consecutive eigenvalues.

3 Interpreting Fishes Behaviors

Having key swimming patterns, we can describe a sequence of video frames as a trajectory through these patterns. Figure (3) shows extracted key swimming patterns in $2D$ space. These swimming patterns are obtained from video of fishes swimming in clean water (no chemical involved) using our proposed method explained in the above section.

Given a sequence of images, we can generate a trajectory through extracted key swimming patterns. By studying these trajectories, we can analyze behaviors of fishes. Figure (4) shows the trajectory of video of fishes in clean water (five hour long video sequence, total images 110730). The different swimming behaviors is clearly visible in its trajectory. The first one and half-hour (shown in green color) illustrates *repeated* bottom-swimming behaviors while the second part (shown in black color) demonstrates more complex fish behaviors.

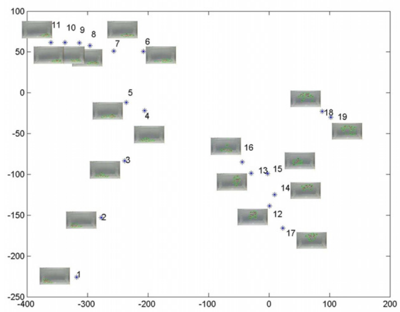

Figure 3: Projection of key swimming patterns in 2D space by using Principal component Analysis(PCA).

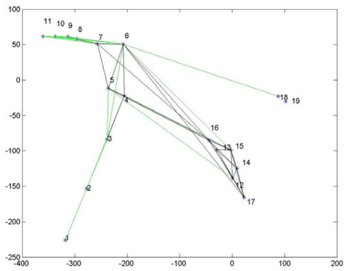

Figure 4: Video trajectory of fishes swimming in clean water(no chemical involved).

4 Abnormal Behaviors Detection

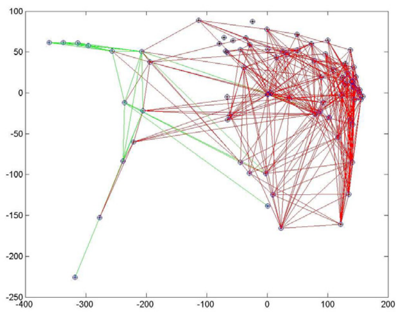

Figure 5: Video trajectory of fishes in clean water(green) and toxicity water (red).

Based on comparisons of fishes behaviors in clean water and water in the presence of chemical, we can generate early warning signals of water quality deterioration. In order to detect abnormality, we first extract key patterns from two video sequences: one is video of fishes in clear water and another is video of fishes in water with chemical. Projection of these key patterns into $2D$ space are shown with circle in Figure (5). Video trajectories of fishes in clean water (green) and fishes in the water with chemical (red) clearly illustrates different behaviors of fishes in clean water and toxicity water.

For any test video, we first segment video into N overlapping segments where n^{th} video segment contains M number of images. Then, we compute probability of observing any abnormality as follows:

1. First, we assign every image of video segment, v_n, into one of key patterns extracted from two video sequences. Hence, video trajectory for segment becomes $v_n = \{k_1, k_2, ..., k_M\}$ where M is number of frames and k is given as:

$$k = \arg\max_k [\exp(-\frac{d_{xk}^2}{2\sigma_k^2})], \tag{10}$$

where d_{xk} is the distance measure (6) between new image and representative image of cluster k and σ_k is variance of the cluster.

2. Second, we compute normality score of fishes behaviors as follows:

$$P_{nor} = \frac{1}{M}\sum_{i=1}^{M}\left[1 - \frac{1}{1+\exp(v_n^i - K)}\right], \tag{11}$$

where K is parameter estimated using the set of video trajectories of fishes swimming in clear water.

3. Finally, we assign an image as abnormal if

$$P_{nor} < k_{th}, \tag{12}$$

where k_{th} is threshold defined empirically.

Table 2: Abnormal Detection Summary Results.

	Video 1 (clean water)	Video 2 (Chlora)	Video 3 (Aldicarb)
Num of Images	110730	77324	92567
Correctly Detected	101995	73689	87250
Falsely Detected	8735	3635	5317
Precision (%)	92.11	95.30	94.26

5 Conclusion

In this paper, we have proposed a vision-based animals behaviors analysis system. Though we emphasized on studying fishes behaviors, our proposed method can be successfully applied to other animals such as ants, bees and mice due to its robust feature extraction and representation. Our proposed incremental method provides a tool to project long video sequence into a space of possible patterns. Experimental results illustrates that our proposed method provides abnormal detection signal in less than 5 minutes while precision value is maintained above 90%.

References

[1] S. Anitei, “Fishes used against terrorist attacks,” September 2006, http://news.softpedia.com/news/Fishes-Used-Against-Terrorist-Attacks-36818.shtml.

[2] “Small fish detect big problems: Environmental scientists use fish behavior to monitor water quality,” Science Video, March 2007, http://www.sciencedaily.com/videos/2007/0303-small-fish-detect-big-problems.htm.

[3] S. Nogita, K. Baba, H. Yahagi, S. Watanabe, and S. Mori, “Acute toxicant warning system based on a fish movement analysis by use of AI concept.” in *Proceedings of the International Workshop: Artificial Intelligence for Industrial Applications*, Hitachi, Japan, 1988, pp. 273–276.

[4] 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*, vol. 16, no. 7-8, pp. 457–465, Spetember 2001.

[5] J.-y. Xu, X.-w. Miao, Y. C. Liu, and Shao-rong, “Behavioral response of tilapia (oreochromis niloticus) to acute ammonia stress monitored by computer vision,” *Journal of Zhejiang University Science*, vol. 6B, no. 8, pp. 812–816, May 2005.

[6] Y. Shi, , and W. C. Karl, “Real-time tracking using level sets,” *Computer Vision and Pattern Recognition*, vol. 2, pp. 34–41, June 2005.

[7] J. Shi and J. Malik, “Normalized cuts and image segmentation,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 22, no. 8, pp. 888–905, 2000.

[8] U. von Luxburg, “A tutorial on spectral clustering,” Max Planck Institute for Biological Cybernetics, Spemannstr. 38, 72076 Tbingen, Germany, Tech. Rep. TR-149, August 2006.

[9] A. Y. Ng, M. Jordan, and Y. Weiss, “On spectral clustering: Analysis and an algorithm,” in *Advances in Neural Information Processing Systems*, vol. 14, British Columbia, Canada, December 2002, pp. 849–856.

[10] C. Fowlkes, S. Belongie, F. Chung, and J. Malik, “Spectral grouping using the nystörm method,” *IEEE Transactions on Pattern Analysis and Machine Intelligence*, vol. 26, no. 2, pp. 214–225, February 2004.

[11] M. M. Naeini, G. Dutton, K. Rothley, and G. Mori, “Action recognition of insects using spectral clustering,” in *IAPR conference on Machine Vision Applications*, Tokyo, Japan, 2007, pp. 1–4.

[12] L. A. Valgren Christoffer and, Duckett Tom and, “Incremental spectral clustering and its application to topological mapping,” in *IEEE International Conference on Robotics and Automation*, Roma, Italy, April 2007, pp. 4283–4288.

[13] X. Zheng and X. Lin, “Automatic determination of intrinsic cluster number family in spectral clustering using random walk on graph,” in *International Conference on Image Processing, ICIP*, vol. 5, no. 3471-3174, 2004.