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Assessing Water Quality by Video Monitoring Fish Swimming Behavior*

Carlos Serra-Toro[2,3], Raúl Montoliu[1,3], V. Javier Traver[2,3], Isabel M. Hurtado-Melgar[4],
Manuela Núñez-Redó[3], Pablo Cascales[5]
[1]*DICC,* [2]*DLSI &* [3]*iNIT, Universitat Jaume I, 12071 Castellón, Spain*
[4] *Aquagest Medioambiente. ETAP La Contraparada, Javali Viejo s/n, 30831 Murcia, Spain*
[5] *SEDELAM. ETAP La Contraparada, Javali Viejo s/n, 30831 Murcia, Spain*
{*cserra, montoliu, vtraver*}*@uji.es*

Abstract

Animals are known to alter their behavior in response to changes in their environments. Therefore, automatic visual monitoring of animal behavior is currently of great interest because of its many applications. In this paper, a video-based system is proposed for analyzing the swimming patterns of fishes so that the presence of toxic in the water can be inferred. This problem is challenging, among other reasons, because how fishes react when swimming in contaminated water is neither really known nor well defined. A novel use of recurrence plots is proposed, and very compact and simple descriptors based on these recurrence representation are found to be highly discriminative between videos of fishes in clean and polluted water.

1. Introduction

Water quality assessment is important since contaminated water is a source of diseases in humans and other living beings. However, since chemical tests cannot be performed at all times for all possible toxic agents, alternative procedures are called for. It is known that fishes respond to environmental conditions of the water they live in [4]. Therefore, fishes can be used as bioindicators for water assessment and, when their biological response can be perceived visually, video monitoring lends itself as an automatic procedure to characterize fish behavior and, in turn, infer water quality. In the past, some works have explored the use of video analysis, mostly to assist ethologists in understanding animal behavior [2, 1, 6].

A method to asses water quality through video monitoring fish swimming behaviors is proposed in this paper. This problem is hard for several reasons. First, there is a wide range of swimming patterns fishes can do and, as consultations with zoologists reveal, no well-defined expected behaviors that can straightforwardly tell whether the fish is swimming in clean or contaminated water. Second, there are significant individual behavioral differences and different fishes of the same species may easily respond differently to the same stimuli, which makes difficult to automatically learn common swimming patterns. Third, existing systems rely on a set of heuristically defined features which are highly domain-dependent and can hardly be applied to different problems. Typical heuristics used include average velocity or amount of movement [1], angular changes, path complexity [2], etc.

The work reported in this paper is part of an undergoing project promoted and supported by *Empresa Municipal de Aguas y Saneamiento de Murcia (EMUASA, Agbar Group)* supplying water for human consumption company, which is interested in introducing video-based monitoring for water quality control. In our current prototype, fishes are monitored isolatedly in individual tanks, since the species used here is very territorial. Each fish is detected at each video frame using a background subtraction technique. The relative motion of the fish is computed using the centroids of the detected blob in consecutive frames. A state is defined for a number of consecutive frames using a sequence of these discrete motions. A binary recurrence matrix encoding the mutual similarity of these vectors over time is defined. It was found that the recurrence matrices corresponding to videos of the two studied classes had different visual patterns. Therefore, to capture this difference, some simple descriptors were defined which successfully discriminate between videos of fishes swim-

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ming in unpolluted water from those others of fishes swimming in polluted water just using existing, general-purpose, simple statistical classifiers.

The main contribution of this paper is the exploration of a powerful tool, the recurrence plot [5], which is not much known in the computer vision and pattern recognition fields. Recurrence plots not only turned out to be very appropriate for our problem, but they are also potentially useful in other related problems.

2. Methodology

A video with a fish swimming in its tank is segmented using a background subtraction algorithm. The centroid for the foreground blob corresponding to the fish is kept at each frame. Then, the problem is to classify an input video into two categories: clean and contaminated water, by using only this crude, low-level information. The behavior of a fish swimming in polluted water is expected to change over time in a way different to that of the same fish swimming in clean water. Therefore, the states of a fish at different times could be compared in order to detect these changes.

Formally, let S_i and S_j represent the states of the fish at times i and j, respectively. A recurrence plot R can then be defined as:

$$R_{i,j} = H(\epsilon - d(S_i, S_j)), \tag{1}$$

where d is a similarity measure, ϵ is a threshold on this similarity, and $H(x) = 1$ iff $x \geq 0$ and $H(x) = 0$ otherwise. The recurrence plot (RP) is therefore a symmetric binary matrix R encoding whether any pair of given states S_i and S_j are similar ($R_{i,j} = 1$) or not ($R_{i,j} = 0$); by definition, $R_{i,i} = 1$. While a simple visual inspection of a RP can provide insight into the behavior of a dynamical system, measures based on the RP can be defined for an automatic analysis [5]. When displaying a RP, $R_{1,1}$ will correspond to its top-left corner. The rest of this section describes the states (Sect. 2.1) and the similarity measures d required for our novel use of the recurrence plots (Sect. 2.2), as well as the RP-based descriptors (Sect. 2.3) considered for our problem of water classification. The full experimental setup is described in Sect. 3 and results in Sect. 4.

2.1. Fish behavior state definitions

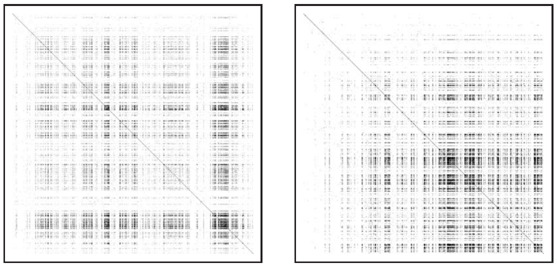
Each video is split into a number of fragments of a fixed number of consecutive frames, F. For each frame within a fragment, the centroid of the fish is estimated. The movements of the fish at every frame are discretized into a 5-code movement: N (no movement), U (up), D (down), L (left), R (right), using the centroids at consecutive frames. The sequence of $F - 1$ of these discrete movements corresponding to a video fragment defines the state of the fish for that fragment. This state definition will be later referred to as *S-state*. To prevent subtle fish movements from being considered as non-stop movements (U, D, L, R), a threshold τ on the motion was experimentally set (Sect. 3).

A second alternative to define the state is a compressed version of the former definition so that consecutive equal motions are replaced by a single one. For instance, for $F = 7$, “UUNRRR” would be a possible S-state, which would be compressed as “UNR” according to the second definition, which we name *Z-state*.

2.2. Measuring similarity between states

Once the states are defined and computed, a similarity measure is required to set the entries of the RP. Since the states are defined as sequences of symbols, they can be coded as constant-length strings (the length is always $F - 1$) for S-states, or as variable-length strings (whose length varies between 1 and $F - 1$) for Z-states. To be able to compare these strings, two well-known string comparison algorithms are tested [7]: the Levenshtein distance for strings of arbitrary lengths, and the faster Hamming distance for strings of the same length.

Fig. 1 shows two examples of RPs computed from the same fish swimming in clean and polluted water, using S-states with $\epsilon = 12$. It is worth noticing the different distribution of black entries (those which correspond to states similar enough) in these two RPs. In general, the plots corresponding to contaminated fishes tend to have more black entries in the bottom-right part of the plot, which is the area corresponding to the last periods of the observation time. This fact is used below (Sect. 2.3) for guiding the definition of descriptors over the RPs.



(a) Clean water (b) Contaminated water

Figure 1. RPs corresponding to the same fish swimming in different water

2.3. RP-based descriptors

The aim is to obtain a feature vector v describing each RP (and, therefore, each video). Four different descriptors are proposed, based on the observation made in Sect. 2.2 regarding the distribution of marked entries in the RPs. All of the explored descriptors consider M to be the total number of frames in a video, so that the size of a RP is $L \times L$, with $L = \lceil M/F \rceil$.

The proposed RP-based descriptors are defined as follows:

- **Density of two sections** (*DTS*): The recurrence plot is split into two by the diagonal going from the top-right corner to the bottom-left, resulting in two triangular sections of equal size. The feature vector is then the ratio between the density of these two triangular sections:

$$v_{DTS} = \left(\frac{\sum_{i=1}^{L} \sum_{j=1}^{L-i+1} R_{i,j}}{\sum_{i=1}^{L} \sum_{j=L-i+1}^{L} R_{i,j}} \right). \qquad (2)$$

- **Center of mass** (*CM*): The center of mass of the RP is computed. Since every plot is symmetric by its top-left to bottom-right diagonal, the center of mass lies always over this diagonal at $R_{i,i}$ for some i, as follows:

$$v_{CM} = \left(\frac{\sum_{i=1}^{L} \sum_{j=1}^{L} i \cdot R_{i,j}}{\sum_{i=1}^{L} \sum_{j=1}^{L} R_{i,j}} \right). \qquad (3)$$

- **Density of quadrants** (*DQ*): The RP is split into four quadrants with two orthogonal axes, parallel to the sides of the plot and whose intersection is in the middle of it. The density of the top-left, top-right (or bottom-left, since they are equal) and bottom-right quadrants are considered resulting in a three-feature vector:

$$v_{DQ} = \frac{1}{A} \begin{pmatrix} \sum_{i=1}^{L/2} \sum_{j=1}^{L/2} R_{i,j}, \\ \sum_{i=1}^{L/2} \sum_{j=L/2+1}^{L} R_{i,j}, \\ \sum_{i=L/2+1}^{L} \sum_{j=L/2+1}^{L} R_{i,j} \end{pmatrix}, \qquad (4)$$

  with $A = \frac{L^2}{4}$ being the area of each quadrant.

- **Density of expanded squares** (*DES*): The plot is split into P squares, each of them including the previous one, growing from the bottom-right corner to the top-left corner of the plot. The side of each square is $\frac{L}{P}$ entries bigger than the previous one. The resulting P-feature vector is:

$$v_{DES}(p) = \frac{\sum_{i=1+(p-1)\frac{L}{P}}^{L} \sum_{j=1+(p-1)\frac{L}{P}}^{L} R_{i,j}}{\left(L - \left((p-1)\frac{L}{P}\right)\right)^2} \qquad (5)$$

  where $1 \leq p \leq P$.

3. Experiments

In order to evaluate our proposal, we use a collection of videos provided by EMUASA company. In our prototypes, fishes belonging to *Lepomis gibbosus* species are used since they are widely available in the local area the final system is intended to operate. Up to 14 fishes swimming in individual 30-liter tanks were recorded (in April 2009) for 3 hours in two consecutive days. The water used in the first day was clean, while a contaminant, *chlorpyrifos* (using a concentration of 0.075mg/l), was used in the second day. It is important to remark that fishes are the same in both days, so that the changes in the behavior of each fish can be studied. The duration of the video recording was set to 3 hours since, with that high toxic concentration, fishes are bound to die after that long. Before starting the experiments, fishes were quietly left to live in their tanks for 30 days so that they got acclimated to their new environment and, hence, removing their new living conditions as an stressful factor. The same fishes were used in both days and the capture process was carefully made to be similar so that the absence/presence of the contaminant was likely to be the only independent variable.

Each video with a fish swimming in its tank was segmented with a background subtraction algorithm [3]. The threshold τ under which small fish movements are considered as no-movement, is species-dependent, and was chosen empirically as $\tau = 5$ pixels by considering the sizes of the fish and its fins. The number of frames within a video fragment was $F = 30$.

As it has been explained, two videos were recorded for each of the 14 fishes: one video of the fish swimming in clean water and one in polluted water; thus, there are 28 videos (prototypes). For each video, the four RP-based descriptors (Sect. 2.3) were extracted for both S- and Z-states (Sect. 2.1) using their corresponding measures (Sect. 2.2). Then, a leave-one-out error estimation procedure was performed (one for each kind of feature vector) in order to find out the discriminative power of each of the four proposed descriptors. Several classifiers have been tested such as the *1-Nearest Neighbor*, the *Linear Normal Bayes*, etc. All of these experiments were repeated for all the possible values of the threshold ϵ in (1) for both S- and Z-states.

Table 1. Best results (%) of overall accuracy (Acc.), true positive rate (TPR), and false positive rate (FPR), obtained for each combination of descriptor and state definition

	DTS			CM			DES (with $P = 8$)			DQ		
	Acc.	TPR	FPR	Acc.	TPR	FPR	Acc.	TPR	FPR	Acc.	TPR	FPR
S-state	**100**	**100**	**0**	**100**	**100**	**0**	92.9	92.9	7.1	92.9	92.9	7.1
Z-state	96.4	100	7.1	**100**	**100**	**0**	82.1	71.4	7.1	89.3	85.7	7.1

4. Results

The final system must satisfy two requirements. First, it must minimize the false positive rate (FPR), i.e. how frequently clean water is wrongly classified as contaminated, for economic reasons, since stopping the water plant to do manual analysis is expensive; and second, and most importantly, the system must maximize the true positive rate (TPR), i.e., considering polluted water as such, for obvious health reasons. Overall accuracy and these two important rates are summarized in Table 1 for the best threshold under each of the 8 combinations of state definition (S or Z) and descriptors. It is worth noticing how compact (just 1, 3 or 8 real values) and discriminative these simple descriptors are. In particular, the single-value descriptors, *CM* and *DTS* give the best results: 100% accuracy.

On the other hand, S-states are more discriminative than Z-states. This suggests that it is important to consider for how long the fish moves following some orientation (or how long it is stopped), and not only the compressed represenation of these discrete movements.

Among the tested classifiers, the *Linear Normal Bayes* was the most appropriate one for the *CM* and *DTS* descriptors. Fig. 2 shows, for this classifier, the evolution with increasing threshold values of the TPR and the FPR for the *CM* descriptor and S-states. Interestingly, there is a range of threshold values ($\epsilon \in [17, 20]$) in which both TPR and FPR have optimum values. The plot for *DTS* is similar, then it is not shown.

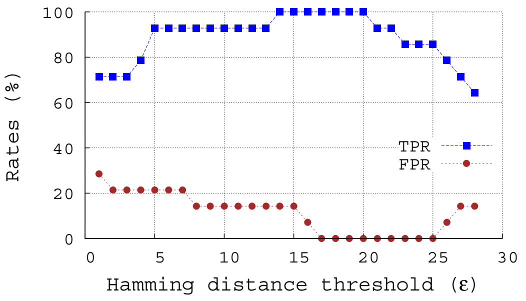


Figure 2. TPR and FPR using the *CM* descriptor and S-states

5. Conclusions

Fishes swimming in individual tanks have been video-recorded with clean and contaminated water in controlled conditions as an initial prototype for a video-based water quality assessment. Simple definitions for the state of a swimming fish have allowed to make a novel use of recurrence plots as a powerful tool to capturing the similarity between these states over time. Then, simple descriptors derived from the recurrence plots have been shown to be highly discriminative between videos of fishes in clean or contaminated water. Furthermore, this discriminative power is achieved very compactly with a few features for the considered 3-hour-long videos. Further work is aimed at performing tests with more fishes under a variety of conditions, as well as exploring alternative ways to represent states and similarity measures for recurrence plots. A final interesting issue is the analysis of short-term recurrence plots, instead of the current video-wise ones, as an step towards actual on-line water-quality monitoring.

References

[1] J. Cazenave et al. Changes in the swimming activity and the glutathione s-transferase activity of *Jenynsia multidentata* fed with microcystin-rr. *Water Research*, 42(4–5):1299–1307, 2008.

[2] A. S. Kane et al. A video-based movement analysis system to quantify behavioral stress responses of fish. *Water Research*, 38:3993–4001, 2004.

[3] K. Kim et al. Real-time foreground-background segmentation using codebook model. *Real-Time Imaging*, 11(3):172–185, 2005.

[4] E. E. Little and S. E. Finger. Swimming behavior as an indicator of subletal toxicity in fish. *Environment Toxicology and Chemestry*, 9:13–19, 1990.

[5] N. Marwan, M. C. Romano, M. Thiel, and J. Kurths. Recurrence plots for the analysis of complex systems. *Physics Reports*, 438(5–6):237–329, 2007.

[6] J. Salierno, G. Gipson, and A. Kane. Quantitative movement analysis of social behavior in mummichog, fundulus heteroclitus. *Journal of Ethology*, 26(1):35–42, January 2008.

[7] S. Theodoridis and K. Koutroumbas. *Pattern Recognition*. Acta Press, Fourth edition, 2009.