International Journal of Earth, Energy and Environmental Sciences
ISSN: 2517-942X
Vol:4, No:8, 2010

Optical Fish Tracking in Fishways using Neural Networks

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***Abstract*—**One of the main issues in Computer Vision is to extract the movement of one or several points or objects of interest in an image or video sequence to conduct any kind of study or control process. Different techniques to solve this problem have been applied in numerous areas such as surveillance systems, analysis of traffic, motion capture, image compression, navigation systems and others, where the specific characteristics of each scenario determine the approximation to the problem.

This paper puts forward a Computer Vision based algorithm to analyze fish trajectories in high turbulence conditions in artificial structures called vertical slot fishways, designed to allow the upstream migration of fish through obstructions in rivers. The suggested algorithm calculates the position of the fish at every instant starting from images recorded with a camera and using neural networks to execute fish detection on images.

Different laboratory tests have been carried out in a full scale fishway model and with living fishes, allowing the reconstruction of the fish trajectory and the measurement of velocities and accelerations of the fish. These data can provide useful information to design more effective vertical slot fishways.

***Keywords*—**Computer Vision, Neural Network, Fishway, Fish Trajectory, Tracking

I. Introduction

HUMAN activity in rivers have a big impact on fish. One of the most important effects is produced by construction of engineering works such as dams in rivers that cause the obstruction of fish migration.

Vertical slot fishways are hydraulic structures which allow the upstream migration of fish through these artificial obstacles.

The appropriate design of a vertical slot fishway depends on interplay between hydraulic and biological variables, since the hydrodynamic properties of the fishway must match the requirements of the fish species for which it is intended.

Analysis of fish behavior in fishways is made by means of direct observation or placement of sensors on the specimens [1], these techniques have important drawbacks or affect the animal behavior. Thus, fishways design usually takes in account hydraulic parameters only.

Therefore, it is necessary to develop a new technique to measure the behavior of the fish within the scale, in a less intrusive way. To this end, the techniques based on optical or acoustic monitoring are the best alternatives.

In works such as [15] acoustic scanners have been successfully used for monitoring fish stocks. More recently, different computer vision techniques for the study of the behavior applied to fish have been used in works such as [7] where imaging techniques based on color contrast and the use of fluorescent marks were used for the identification and tracking of the fish in a tank, [5] where swimming performance of a fish was studied by analyzing the water round it with a flow velocimetry of particles based on image or [9] where a new technique to perform counting fish in a tank was proposed.

The proposed technique provides a new method to study the behavior of fish in fishways based on image processing with the purpose of improve fishway design.

The algorithm calculates the position of the fish from images recorded with a camera designed for integration in fishways.

Fig. 1. Fishway model used in experiments.

This problem can be considered a particular case with high turbulence conditions of a tracking problem, which is a key problem in computer vision.

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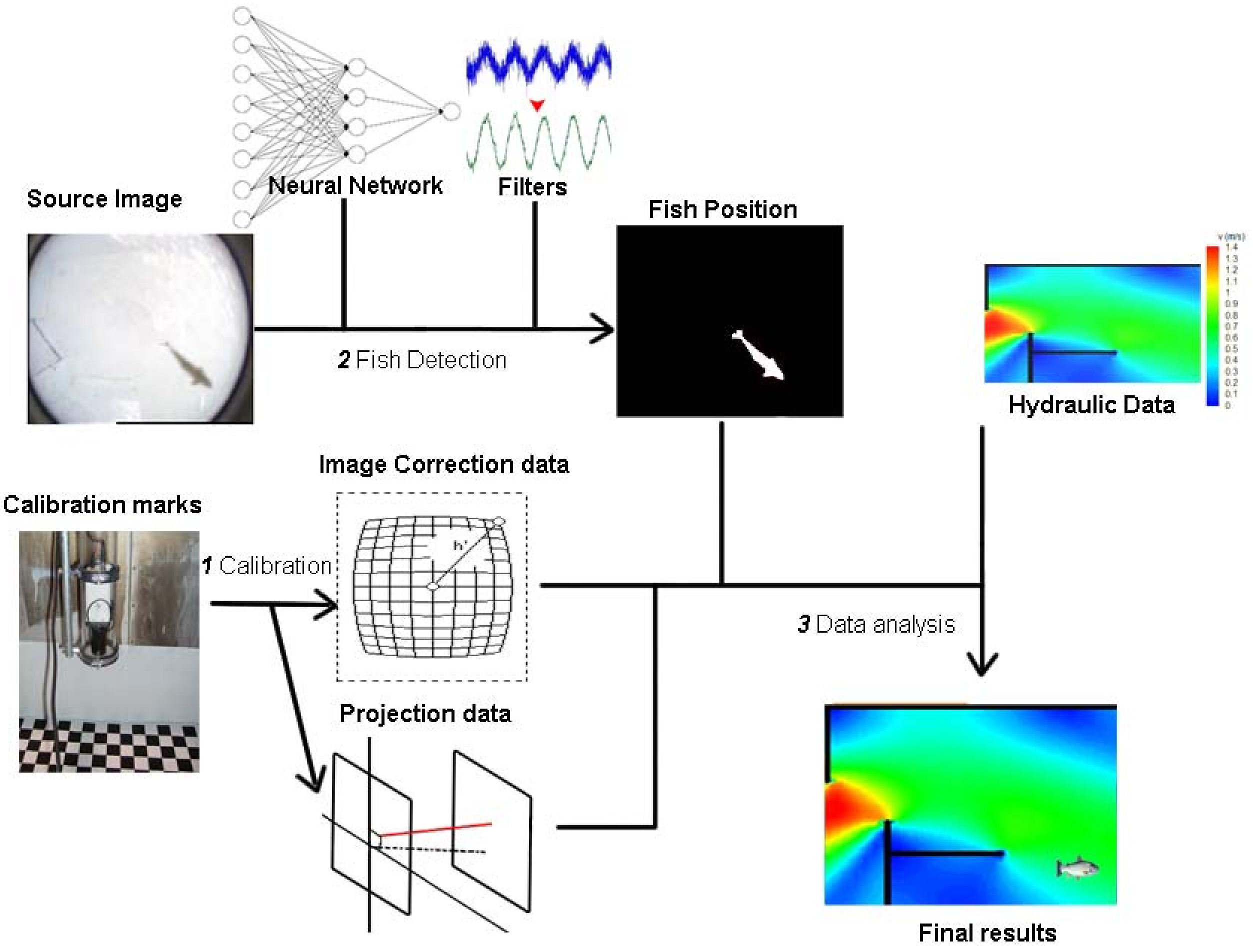

Fig. 2 Algorithm scheme

Tracking is essentially a detection and correspondence problem between entities seen in the current image and those in the previous image.

Most common schemes to face this problem are based on discriminate moving foreground objects from the background using background models [13, 4], edge-based classification by means of analyzing the discontinuities in the image [13], or on the use of color or other features of objects being tracked to perform a region-based classification by analyzing the similarity of pixels [12]. More complex approaches have been performed through fuzzy logic or artificial neural networks [3].

Finally, matching may be performed statistically in a Kalman Filter framework [18] or using a Bayesian Network approach, as in [2].

The algorithm purposed computes and eliminates distortion introduced by fish-eye camera, uses a neural network to realize image segmentation, analyzes the segmented image to detect the mass center of the fish body without probabilistic models and obtain real scale measurements of fish movement.

The functioning of the algorithm can be summarized as follows (see Fig. 2):

1) Image calibration
2) Fish detection
   a) Image segmentation using neural networks.
   b) Noise filtering
3) Data analysis

II. Image Calibration

The assays were realized in 1:1 scale model of vertical slot fishway built at Center for Studies and Experimentation of Public Works CEDEX, in Madrid.

This type of fishway is basically a channel divided into several pools separated by slots (see Fig. 2).

To record the assays, a camera equipped with fisheye lenses that provide a 180º viewing angle was installed.

With this purpose, a support structure to fix the camera to the fishway and a water protection structure have been designed.

The camera was placed in an overhead perspective and partially submerged so that surface turbulence and reflections are avoided as shown in Fig. 3.

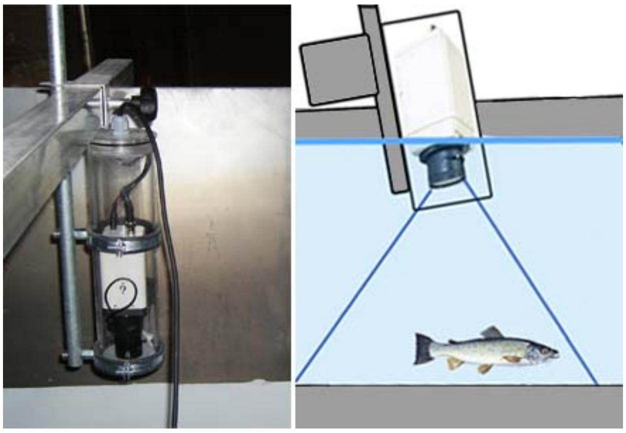

Fig. 3 Photo of camera situation and schematic representation of how camera fields of view are combined to cover the bottom of the pool and record the fish with overlapping between them.

For a real measurement of the position of the fish from the images, the transformation between pixel coordinates of each image and the coordinates on a real scale should be calculated.

With this purpose the real geometry of a calibration pattern is compared with the geometry observable by the camera using the pin-hole projective model [16], which describes how a point from the real space is projected into the image plane, together with the equation model of radial and tangential distortion (*dr* and *dt*) expressed in (1).

$$\begin{aligned} dr_x &= xk_1r^2 + xk_2r^4 \\ dr_y &= yk_1r^2 + yk_2r^4 \\ dt_x &= k_3\left(r^2 + 2x^2\right) + 2k_4xy \\ dt_y &= 2k_3xy + k_4\left(r^2 + 2y^2\right) \end{aligned} \tag{1}$$

Where x and y are spatial coordinates in the respective dimensions, r is the distance corresponding to the optical center of the lens and k_i are the distortion coefficients to be calculated.

Additionally, it must be taken in account that, when light passes from air to water, its direction changes due to a phenomenon called refraction (see Fig. 4) so the fish observed by camera is closer to the center of the image than it should be.

Thus, observed positions in the image projected to real space must be transformed again to compensate light refraction.

Refraction is corrected applying a transformation of scaling and shift showed in (2)

$$\begin{bmatrix} x_r \\ y_r \\ 1 \end{bmatrix} = M \times \begin{bmatrix} x_c \\ y_c \\ 1 \end{bmatrix} \qquad M = \begin{bmatrix} \mathrm{a} & 0 & b \\ 0 & \mathrm{c} & d \\ 0 & 0 & 1 \end{bmatrix} \tag{2}$$

Where *(Xr,Yr)* are observed point coordinates after applying distortion correction and *(Xc ,Yc)* transformed coordinates. The transformation matrix M is solved observing the position of two reference points before and after flood the fishway.

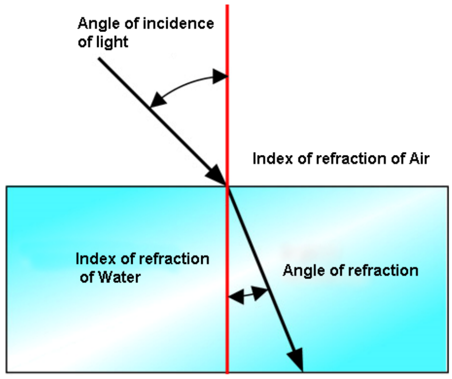

Fig. 4 Refraction of light

Finally, once obtained pixel to real scale transformation, to situate the image camera field in its corresponding position of the pool, in order to obtain the real position in the pool corresponding to real scale coordinates calculated, it is only necessary to use a reference point to obtain results according to the same coordinate system.

III. Fish Detection

A. Image Segmentation

Fish detection consists in discriminate moving fishes from the background to calculate the fish position on the image.

The main difficulties in this task are due to the fact that fish will be partially or totally occluded most of the time, and because background will be changing fast and violently due to the turbulence of the water. Additionally, the scalability of the system, being able to abstract from concrete light and focus camera variables and local luminance conditions were crucial for future developments of the system.

Finally, with the fishway conditions in the slot, the fish will be moving very fast, sometimes staying only a few seconds in the range of view of the camera.

This situation makes ineffective any typical segmentation of image such as an edge-based approximation or conventional techniques based on the analysis of the similarity of colors or textures.

In this paper, a type of Artificial Neural Network (ANN) called Self-organizing map (SOM) [10] has been used for image classification.

An ANN is a processing element based on brain functioning whereas the SOM model is aimed at establishing a correlation between the number patterns supplied as an input and a two-dimensional output space (Topological map); thus, the input data with common features activate areas close to the map. This characteristic can be applied to image segmentation, also giving the following advantages: Adaptive Learning based on a training phase using input examples, generalization ability, error tolerance, highly operable in parallel and integrable into the existing technology [10].

Thus, works like those carried out by [19, 6] have successfully applied the SOM networks to image segmentation.

To test the proposed approach, different tests were realized with different SOM architectures, and using different combinations of features for classification, such as color and grey values, local average, local standard deviation or local entropy.

Additionally, to avoid dependence from luminance factors, as well to deal with pool features such as corners, irregularities on the painting of the bottom or the presence of strange objects; background modeling was introduced to the ANN, adding features based on differences from current frame with a selected one as background model.

Obtained results were very good, being many of these ANN capable of detecting the fish position with low noise as shown in Fig. 5

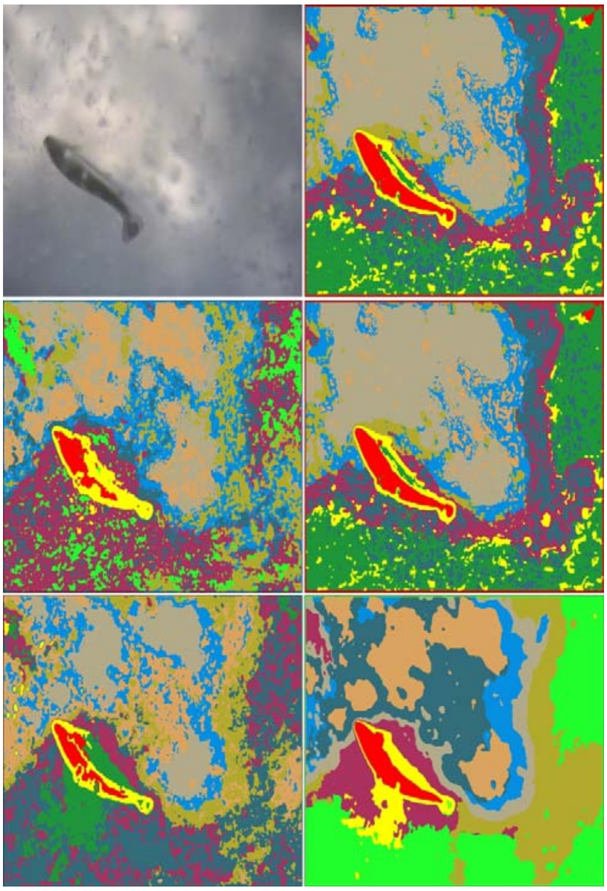

Fig. 5 A real image taken from an assay and results obtained segmenting this image with different ANNs. The ANN in the bottom right corner was the one used in the final system.

The selected ANN uses statistical features based on local averages extracted from the RGB color space and includes background information.

In this way, input numerical values to the ANN are less sensitive to factors such as changes in light or specific conditions the camera.

Hence, we have chosen a three-layer topology with 3 processing elements (neurons) in each layer, and the input data for the pixel (i, j) have been defined as two vectors of parameters defined in (3) and (4)

$$E_{i,j} = \{V_{a,b} \quad W_{a,b}\}_{(a,b)=\left[\left(i-\frac{N}{2}, j-\frac{N}{2}\right),\left(i+\frac{N}{2}, j+\frac{N}{2}\right)\right]}$$

$$V_{a,b} = \frac{\mu_{a,b}}{\mu_I} \quad W_{a,b} = \frac{\mu_{a,b}}{\mu_I} - \frac{\mu_{a,b}'}{\mu_I'}$$

$$\mu_{i,j} = \frac{\sum_{x,y}^{N_2} I(x,y)}{N_2} \quad \mu_{i,j}' = \frac{\sum_{x,y}^{N} I'(x,y)}{N} \tag{3}$$

$$(x,y) = \left[\left(i-\frac{N_2}{2}, j-\frac{N_2}{2}\right),\left(i+\frac{N_2}{2}, j+\frac{N_2}{2}\right)\right] \tag{4}$$

Where *Va,b* and *Wa,b* are calculated for each *(a, b)* pixel adjoining *(i, j)*. This measurements are calculated using the average local intensity and the average global intensity of the image I where the analysis is performed and of a reference image I' , of the same camera which recorded no fish.

The results obtained by the ANN are shown in Fig. 6.

B. Noise Filtering

Once the image segmentation is obtained with the SOM network by the cameras, part or the totally mass of the fish has been separated from the background in one or multiple regions together with some noise artifacts due to presence of shadows, bubbles and reflections, where each region can be expressed like possible fish detection.

With this purpose, each detected region was reduced to its mass center coordinates by calculating the average position of the detected pixels.

In this point, we have obtained a position estimation system subject to random perturbations and external noise.

A standard approximation to face this problem consists in applying a recursive predictive filter such as the Kalman filter [18] so, using the previous position of the fish, the filter can obtain a prediction of current position, allowing to reduce the search area for ANN, decreasing computational cost and noise.

Additionally, predicted position can be used to discriminate from multiple measurements from the ANN.

However, uncertainty in noise distribution and movement of fish, convergence time from these filters, and the fact that fish will only be present in a small fraction of images analyzed, make this approximation impractical. Especially when analyzing short and fast sequences of high interest for fishway design, like sequences of the fish crossing from one pool to another through a slot, where water speed reach the maximum.

Thus, a combination of simple filtering processes, using empirically adjusted thresholds, has been chosen:

1) Application of temporal and spatial filters to eliminate isolated detections.
2) Application of a bi-dimensional Gaussian filter to smooth the results, reducing the variability due differences in deep of the fish or camera perspective.

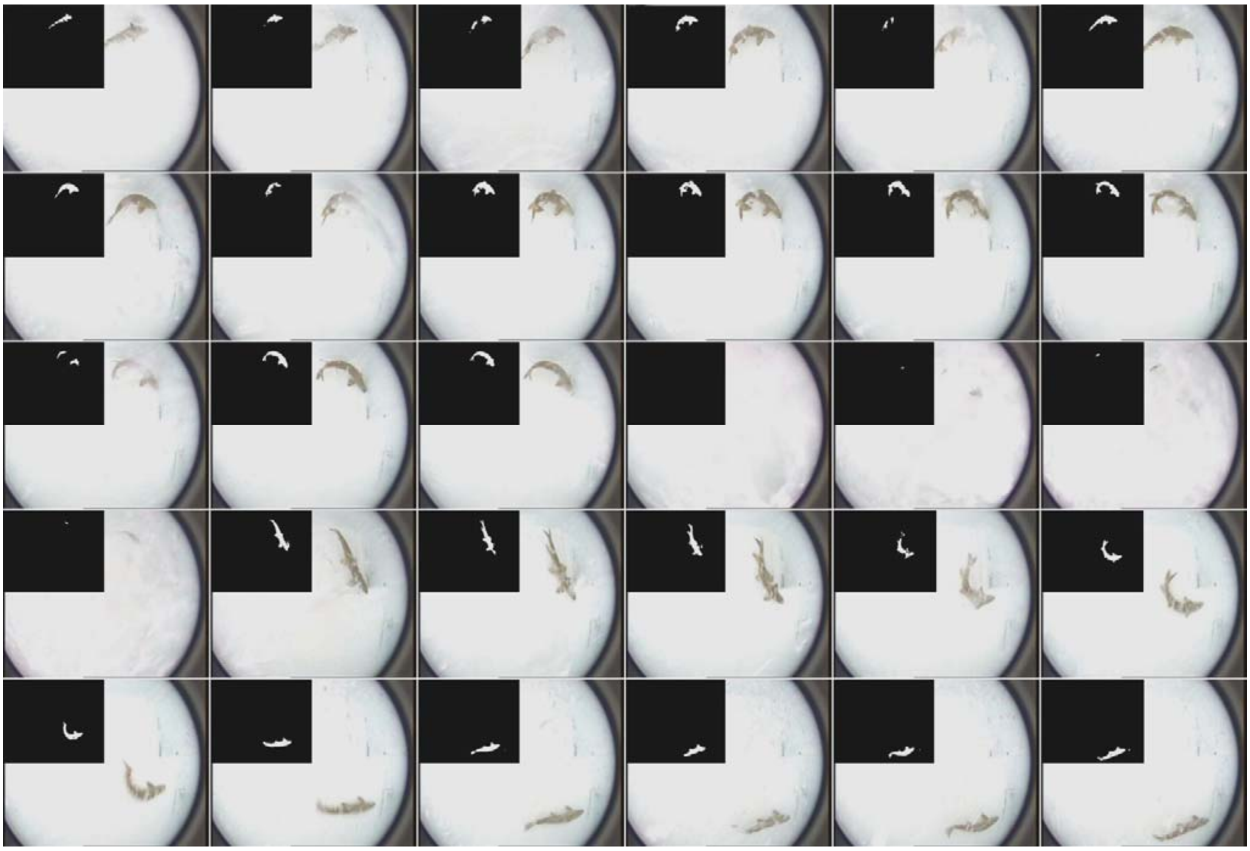

Fig. 6 ANN segmentation results for one of the sequences analyzed in preliminary assays. The fish shown is a barb from cyprinids family.

IV. Data Analysis

The result of the previous process is a vector of the positions in the image. These measurements are transformed using the previously calculated projection and image correction data to obtain the real coordinates (x_i, y_i, t_i) of the fish on the scale over time.

In this point, apparent instant velocity (V_{iA}) of the fish can be calculated from fish spatiotemporal position using (5)

$$V_{iA} = \frac{\sqrt{\left(x_{t_{i+1}} - x_{t_{i-1}}\right)^2 + \left(y_{t_{i+1}} - y_{t_{i-1}}\right)^2}}{t_{i+1} - t_{i-1}} \quad (5)$$

True fish velocities can be obtained from apparent velocities by subtracting water velocity, and water velocity on the scale can be calculated by using experimental studies or numerical models. [20, 11, 17].

Thus, velocity field of water in the fishway used in experimental assays has been calculated using a 2D depth averaged numerical model. Obtained results are showed in Fig. 7.

Instantaneous acceleration of fish can be calculated from fish velocities using (6).

$$A_i = \frac{V_{i+1} - V_{i-1}}{t_{i+1} - t_{i-1}} \quad (6)$$

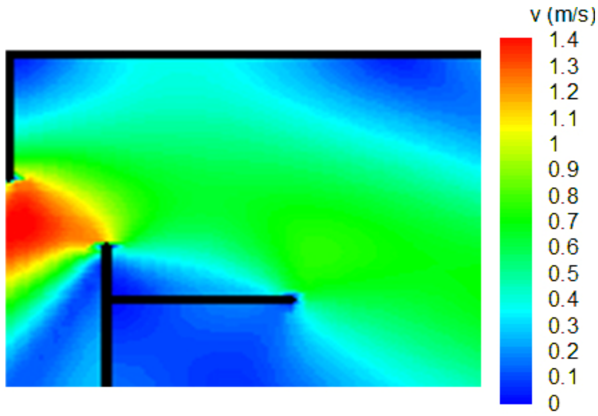

Fig. 7 Velocity field of water calculated for the camera field zone in the vertical slot fishway built at CEDEX.

V. Experimental Results

Several preliminary assays have been carried out using fishes of different species in the vertical slot fishway full scale model which is located in the Center for Studies and Experimentation of Public Works, Madrid.

Fish trajectories and numerical velocities and accelerations have been obtained from short sequences where the fish is crossing through the slots between two pools using the technique presented in this work.

In these assays a medium sized trout from salmonid family has been used (Graphic shown in Fig. 11 corresponds to a numerical model of the autonomy and velocity of this specie and size of fish).

Presented results correspond to different pools of the fishway, although they are presented together for comparing reasons.

Obtained results are showed in Fig. 8, Fig. 9 and Fig. 10.

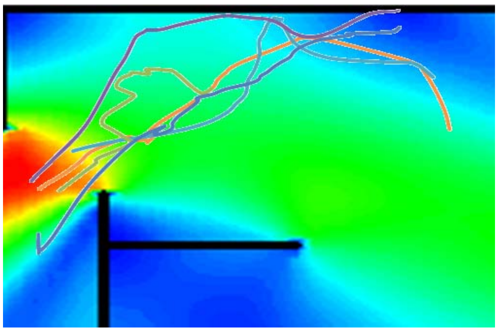

Fig. 8 Projection of the measured trajectories of the fish over the velocity map of water in the fishway.

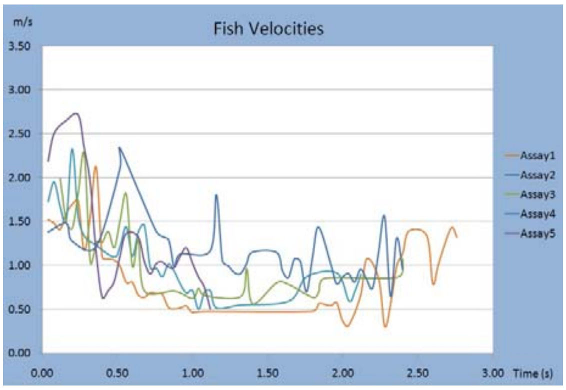

Fig. 9 Measured velocities of the fish.

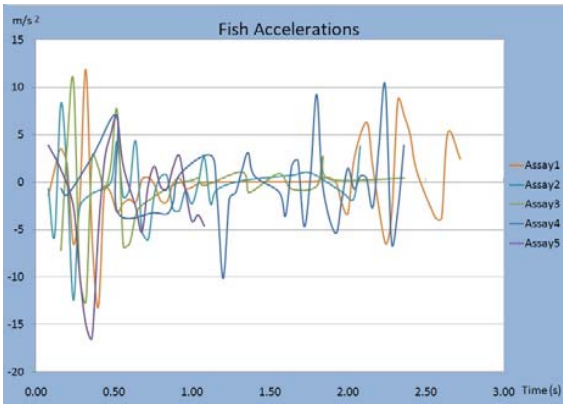

Fig. 10 Measured accelerations of the fish

To validate obtained results we compared measured velocity with theoretical velocities for the fish used in experimental assays.

With these purpose, we used numerical models carried out in works such as [8] of the relationship between autonomy and velocity for fishes.

Fig. 11 shows numerical model calculated, which is consistent with measured velocities.

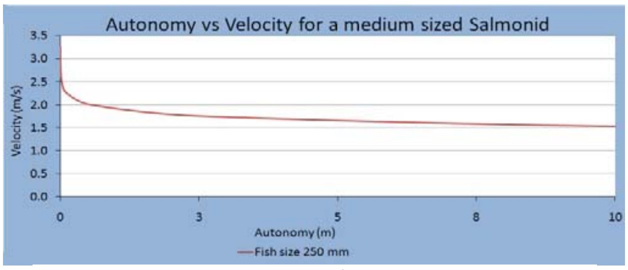

Fig. 11 Graphical representation of relation between swimming velocity and autonomy for salmonids using numerical models.

VI. Conclusions and Future Work

A Computer Vision system based on Artificial Neural Networks has been designed for automatic analysis of biological tests in full scale fishways models.

This system allows the observation and monitoring of experiments in an accurate and effective way, obtaining the fish position starting from recorded images of the experiment.

This new method for analyzing fish behavior in fishways is non-invasive and can provide useful information about how these structures can be modified to enhance fish passage.

Preliminary laboratory tests have been conducted with living fishes obtaining very promising results, as they allowed the measurement of fish positions, velocities and accelerations.

In future stages of this work, the system will be adapted to use several cameras simultaneously to cover the entire area of the fishway, allowing the fish tracking during all its displacement through the fishway.

Thus, further assays will be carried out and the system will be improved to manage longer sequences, multiple fish situations and to reduce computational costs.

Additionally, a Computer Vision algorithm will be carried out to improve obtained results using a fish model to manage the detection of separated parts of the fish and to discard detection of image regions with a shape not corresponding to a fish body.

We will also perform studies to determine the fish biological parameters that are relevant to the fishway design. Therefore, it is expected that the conclusions drawn from these studies will contribute to the construction of more effective fish passes.

Acknowledgment

This work was partially supported by the General Directorate of Research, Development and Innovation (Dirección Xeral de Investigacíon, Desenvolvemento e Innovación) of the Xunta de Galicia (Ref. 08TMT005CT , Ref. 07TMT011CT and Ref. 08MDS003CT).

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