Image Analysis Based Fish Tail Beat Frequency Estimation for Fishway Efficiency

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***Abstract*—In this paper, we propose image analysis based methods for estimating fish tail beat frequency, which is an indicator of fish energy consumption at fish passage structures. For this purpose, average magnitude difference and autocorrelation function based periodicity detection techniques are utilized. Actual fish images are acquired using a visible range camera installed in a brush type fish pass in İkizdere River, near Rize, Turkey, which is very rich in biodiversity. Results show that image analysis based periodicity detection methods can be used for fishway efficiency evaluation purposes. To the best of authors' knowledge, this is the first study that automatically estimates fish tail beat frequency using image analysis. The findings of this study are expected to have implications for fish monitoring and fishway design.**

***Index Terms*—fish detection, fishway, frequency detection, tail beat frequency, environmental monitoring**

I. Introduction

Today, construction of man-made structures in rivers are in the increasing trend with the growth of the world population and energy consumption [1]. Flow regime and other hydraulic and physical characteristics of rivers are directly affected by these man-made structures. These physical changes like flow regime alter ecological sustainability of rivers and streams [2]. Structures like weirs or dams have negative effects on biodiversity of river ecosystem including upstream fish population.They cause the obstruction of fish migration. To overcome negative effect of dams, one common solution used is the construction of the appropriate fishways in dams. Patterns of the movements of the targeted fish species in the fishway should be matched with the natural patterns in habitat of the same species. Because of this, hydraulic and kinetic measurements for fish movement analysis is required for the evaluation of fishway. The importance of fish tail beat kinematics in swimming performance of aquatic species is shown in [3], where optimum Strouhal number is calculated for 53 different species of aquatic animals. More recently, special hydraulic and biological parameters have been used in works [4] and [5] for improving fishway design. In [5], fish tail beat kinematics, Strouhal number in particular,

$$St_{fish} = f_{TB}\frac{\lambda}{U} \tag{1}$$

is shown to be important criterion for fishway design. Here, f_{TB}, λ, and U denote fish tail beat frequency, tail beat amplitude and fish swimming speed respectively whereas the Strouhal number is denoted as St_{fish}. In spite of the recent improvements, evaluation for the true performance of the fishway is still cumbersome, due to the lack of adequate tools and data [6], [7]. In this work, we proposed signal processing based new methods for the measurement of fish behaviour for the fishway proposed in [8]. In addition to optical data from the work of brush based fishway proposed in [8], we evaluated our fish detection technique using research videos from Lauder Lab [9], [10] and analyzed tail beat frequency for the analysis of fish movement in K*á*rm*á*n vortex which is also generated in brush based fishway. View of the fishway structure studied in this work can be seen in Fig. 1. Our method can be generalized to other fishway systems by using standard 60 fps underwater cameras and proper setup in fishway. The work in [11] focused on fish motion detection and aeration detection using SURF key-points and k-nearest neighbors classifier in the videos of territorial and stationary fish. In [12], fish detection and recognition is performed using Convolutional Neural Networks (CNN) in unconstrained underwater videos. In [13], CNN based approach is used in fish foreground segmentation in order to count fish from footages collected in fishing trawlers. Texture and color based analysis of underwater videos and fish counting system is proposed in [14]. More similar works in the vision-based fishway analysis are done in [15], [16]. In [15], a system that provides fish velocities in fishway by detecting fish region with special type of Artificial Neural Networks (ANN), called Self Organizing Maps (SOM) is developed. In [17], 3D fish tracking system based on Long Short-Term

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Fig. 1. Brush based fishway model used in experiments.

Memory (LSTM) network is proposed. Another similar work is done in [18], where fishway flow field is calculated by means of Particle Image Velocimetry (PIV) and autocorrelation is used for manually detecting fish tail beat frequency in image sequences. Our contribution is to provide further investigation on measurement of fish tail beat frequency using signal processing based methods including the comparison of Average Magnitude Difference Function (AMDF) and Autocorrelation Function (ACF) based techniques.

II. Fish Detection

Fish detection in underwater videos of unconstrained and cluttered environment is a challenging process due to the high turbulence, overlapping objects and moving particles such as blister, bush in water as seen in Fig. 2. Because of that, proper camera setup and special constraint in background is an important factor that makes fish segmentation task easier for fishway analysis. However, these constraints should not interfere with the natural behavior of fish, as well. For this purpose, we performed fish segmentation on videos captured from fishway camera setup and other videos that includes Karman vortex street conditions acquired from Lauder Lab [9], [10].

Fig. 2. Sample image taken from camera setup in fishway.

Similar to fish detection system in [14], we investigated traditional and recent background subtraction techniques for detecting fish regions.

1) Frame Difference: First approach we analyzed was frame difference method which calculates the difference between current frame and reference frame and thresholds the result as foreground object. Adaptive form of frame difference method by using dynamic thresholding and background update method is as in the following formula [14]:

$$B_n(x, y) = (1 - \alpha)B_{n-1} + \alpha CF_n(x, y) \tag{2}$$

where B_n, CF_n is nth background image and current frame respectively and α is used as an background update factor. They combined this method with the Adaptive Gaussian Mixture Model proposed in [19] using "AND" operation for more robust segmentation [14]. However, our experiments showed that "AND" operation gives worse results because of the inability of the moving average detection method in highly unconstrained scenes. So, Adaptive GMM algorithm in single use was better in handling complex environment. In this probabilistic algorithm, mixture of Gaussians is fit to each single pixel and the needed number of components per pixel is automatically selected in the background update process.

2) ViBe Algorithm: We further investigated recent approaches since the accuracy of contour area of fish during segmentation is important when calculating tail beat frequency. We compared GMM based and other background subtraction approaches with the aid of the recent survey performed in [20]. Sample-based algorithm called Visual Background Extractor (ViBe) proposed by Barnich et al. [21] performed better in our tests and it was robust enough in the high water turbulence conditions. Therefore, we chose ViBe algorithm for fish segmentation. After applying median filter and shape based (aspect-ratio e.g.) post-processing operations to the detected foreground areas, connected component labeling operation is performed to group regions. Final result of fish detection on an ordinary underwater video [22] can be seen from the Fig. 3.

III. Fish Tail Periodicity Detection

The goal of this section is to analyze fish tail beat movement by quantifying recurrence in the tail regions from an image sequences. In our case, fish tail beat movement in a video can vary in different views and angles of fish. Therefore, rotation, translation and scale invariance is important in periodicity detection techniques. We used self-similarity based techniques as in [23], [24], since they are robust against variance in different views. In the following subsections we described 2 efficient techniques, Average Magnitude Difference Function (AMDF) and Autocorrelation respectively, for tail beat periodicity detection.

A. Average Magnitude Difference Function

Average Magnitude Difference Function is calculated by computing total difference between signal and its lagged version. AMDF mostly used in the periodicity detection of 1D

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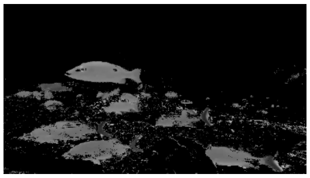
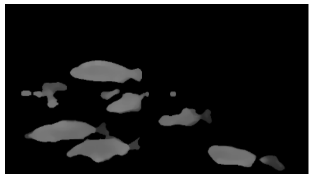
(a) Frame Difference

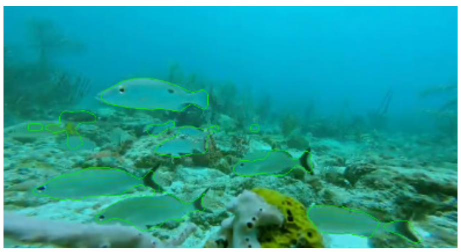
(b) Adaptive GMM



(c) ViBe



(d) Post-processing (ViBe)



(e) Detections with ViBe

Fig. 3. Comparisons of detected fish regions with different techniques.

signals such as pitch detection of audio signals [25]. AMDF is used in the work of Gunay et al. [24] for detecting frequency of fire in order to eliminate artificial flashing lights and reduce false alarms in video based wildfire detection. We described scheme of AMDF based periodicity detection in Algorithm 1. Since periodicity of the signal lies between the cut points of AMDF magnitudes, we calculated second derivatives of AMDF magnitudes in order to find cut points as discussed in Section IV.

Algorithm 1 Detect periodicity using AMDF

procedure AMDF($ImageBuffer$, $BufferSize$)
  $k = BufferSize$
  initialize array $amdfMagnitudes \leftarrow 0$
  for each integer l in k **do**
    initialize matrix $SumMatrix \leftarrow 0$
    for each integer n from 0 to $k - l$ **do**
      $SumMatrix \leftarrow SumMatrix + ImageBuffer[n+l] - ImageBuffer[n]$
    end for
    $amdfMagnitudes[l] = mean(SumMatrix)$
  end for
  Return $max(secondDerivative(amdfMagnitudes))$
end procedure

B. Autocorrelation Function

Autocorrelation is a function that identifies correlation of signal with its lagged version. Autocorrelation function is useful for identifying an appropriate time series model of a signal. For a 2D discrete signal $x(m,n)$, Autocorrelation Function (ACF) is calculated using eq. (3) where M and N correspond to dimensions of the signal and $\overline{x}(m,n)$ is its complex conjugate.

$$ACF(i,j) = \frac{1}{M}\frac{1}{N}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} x_{m,n}\overline{x}_{m+i,n+j} \tag{3}$$

The value of $ACF(i,j)$ increases when $x(m,n)$ gets similar to $x(m+i,n+j)$, and it will have peaks at periods of $x(m,n)$. ACF calculation has quadratic time complexity in time domain when eq. (3) is used. Similar to convolution, ACF can be calculated in more efficient way with dot product in frequency domain using Fast Fourier transform (FFT). For input signal $x(n)$, ACF is computed with FFT as follows:

$$\begin{aligned} \mathcal{F}_R(f) &= \mathcal{FFT}(x(n)) \\ \mathcal{S}_R &= \mathcal{F}_R(f)\mathcal{F}_R^*(f) \\ ACF() &= \mathcal{IFFT}(\mathcal{S}_R) \end{aligned} \tag{4}$$

F^* denotes complex conjugate of F and $IFFT$ denotes Inverse Fast Fourier transform. We used eq. (4) in our approach for reducing complexity of ACF to $O(nlog(n))$ time.

IV. Experiments

We performed several preliminary tests on fish segmentation techniques discussed in Section II, since false alarms in tail segments directly affect the success of the tail frequency detection. Therefore, we used manually collected fish segmentation masks for highly unconstrained videos obtained from cameras in fishway when accuracy of fish detection algorithm is insufficient. In order to evaluate the performance of our tail beat frequency detection system we collected ground truth from videos by inspection. Fish tail oscillation between the opposite end points from time t_0 to t_1 is shown in Fig.4. We evaluate tail periodicity as a time difference between two opposite end points denoted by T as shown in Fig.4. Tail beat frequency f_{TB} can be denoted as inverse of periodicity:

$$\begin{aligned} T &= |t_1 - t_0| \\ f_{TB} &= 1/2T \end{aligned} \tag{5}$$

We first compute tail beat periodicities with proposed methods. Then, using sampling rate of video we derive frequency using eq. 6, where f_{TB}, fps and $Fr_{interval}$ denotes fish tail beat frequency, video frame rate and frame interval (periodicity) computed by AMDF or ACF, respectively.

$$f_{TB} = fps/Fr_{interval} \tag{6}$$

Test results of detected frequencies in AMDF and ACF methods are given in Table I. Strouhal number is calculated with respect to eq. (1). Among the test videos, 'rize1.mp4' video contains the lowest tail beat amplitude and highest tail beat

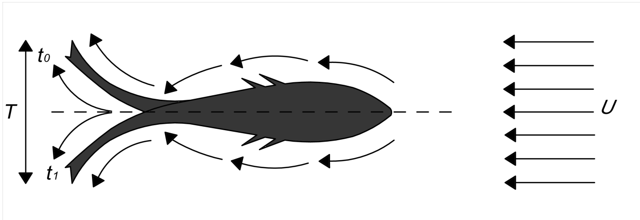
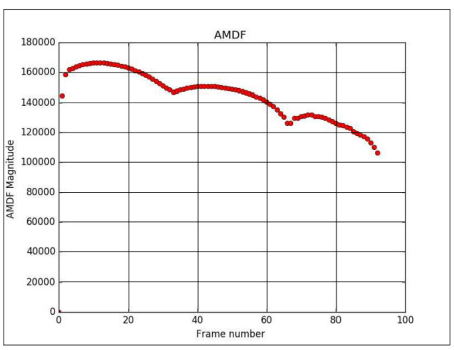
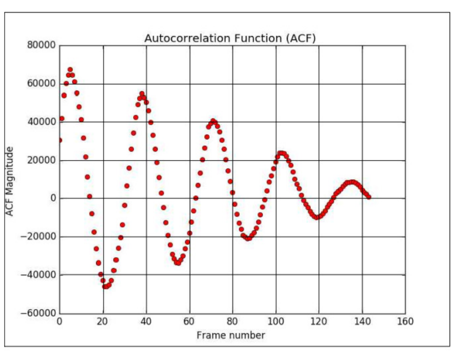


Fig. 4. Tail beat time points (t_0 and t_1) for determining the tail beat periodicity. Here, U represents flow speed.

frequency movements. Estimation in the lower tail amplitude movement is a harder case due to the smaller temporal difference in video sequences. It can be seen from the results of the 'rize1.mp4' video which has the lower accuracy for both methods compared to other samples. Temporal distribution of AMDF and ACF magnitudes computed from fish tail regions in video named 'troutfs.avi' can be seen in Fig. 5. Interval between the cut points in AMDF graph indicates periodicity of fish tails. Similarly, periodicity can be seen intuitively between the peaks of ACF magnitudes. Comparison of the two methods



(a)



(b)

Fig. 5. Plots corresponding to AMDF (a) and ACF values (b) in fish tail regions.

by means of the mean squared error is given in Table II.

V. Conclusion

Efficient fishway design has become increasingly important with the growing human activity at global scale in river

TABLE I
EXPERIMENTS OF FISH TAIL BEAT FREQUENCY DETECTION.

Videos	Troutfs.avi	rize1.mp4	uvs-012.avi
Frame Rate (fps)	30	60	25
Number of Frames	159	660	450
Strouhal Number	0.042	0.3	1.1
AMDF (Hz)	**0.882**	2.35	**1.398**
ACF (Hz)	0.87	**2.5**	1.471
Ground Truth (Hz)	0.943	3	1.428

TABLE II
MEAN SQUARED ERROR OF AMDF AND ACF METHODS.

Method	**Total Number of Frames**	**MSE**
AMDF	1269	0.142
ACF	1269	0.086

ecosystem. Lack of adequate data and tools for identifying biological, hydraulic, and other physical parameters is the main challenge in fish passage design.

In this paper, we proposed image analysis based methods for fish tail beat frequency estimation. Tail beat frequency is an indicator of fish energy expenditure and swimming speed, and it is a parameter of the Strouhal number. Experiments suggest that proposed image processing based fish tail beat frequency estimation approach may be utilized for fish passage analysis.

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