ISTANBUL TECHNICAL UNIVERSITY ★ INFORMATICS INSTITUTE

VIDEO ANALYSIS BASED FISH DETECTON AND TAIL BEAT FREQUENCY ESTIMATION IN FISHWAYS

M.Sc. THESIS

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VİDEO ANALİZİ İLE BALIK GEÇİTLERİNDE BALIK TANIMA VE KUYRUK SALLAMA FREKANSI TAHMİNİ

YÜKSEK LİSANS TEZİ

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Yasin YILDIRIM, a M.Sc. student of ITU Informatics Institute student ID 704151012, successfully defended the thesis entitled "VIDEO ANALYSIS BASED FISH DETECTON AND TAIL BEAT FREQUENCY ESTIMATION IN FISHWAYS", which he/she prepared after fulfilling the requirements specified in the associated legislations, before the jury whose signatures are below.

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To my loving family,

FOREWORD

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June 2018

Yasin YILDIRIM
(Computer Engineer)

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ABBREVIATIONS

ViBe	: Visual Background Extractor
GMM	: Gaussian Mixture Model
BS	: Background Subtraction
CNN	: Convolutional Neural Networks
ELM	: Extreme Learning Machine
AMDF	: Average Magnitude Difference Function
ACF	: Autocorrelation Function
DL	: Deep Learning
MSE	: Mean Squared Error
FFT	: Fast Fourier Transform
LSTM	: Long Short-Term Memory
SOM	: Self Organizing Maps
pdf	: probability density function
$\boldsymbol{p_t}(\boldsymbol{x})$	: the value at time t of the pixel x
$\boldsymbol{f_{TB}}$	: fish tail beat frequency

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VIDEO ANALYSIS BASED FISH DETECTON AND TAIL BEAT FREQUENCY ESTIMATION IN FISHWAYS

SUMMARY

For decades, with the growth of the human population, the need for energy and water resources has been increasing. Hydroelectricity, which is the most commonly used form among the all renewable energy types, is also increasingly used by means of the hydropower plants. Hydroelectricity generated from hydropower was expected to increase about 3.1% each year for the next 25 years. Also, with a growing human population, number of dams and weirs are in increasing trend. These man-made structures have damage on the ecological stability of the aquatic animals that are living in rivers, especially fish. For instance, dams or hydropower plants can alter the flow regime of the river which directly affects both physical and biologic characteristics of the river.

A common way to remove these negative effects of the human activities on rivers is to establish a structure that allows a free passage for aquatic animals. Fish passage is a structure that facilitates the free passage of migrating fish through a dam, hydropower plant or another human-made or natural obstructions. Fish passage may be designed to facilitate passage of migrating fish in either an upstream or a downstream direction. Aim of the fish passage is to provide a free way to endemic fish species and provide equal opportunity to all components of the fish population.

Fish passage design is considered to be successful and proper if it is physically and ecologically consistent and as similar as the natural parameters of the targeted environment. For instance, it is not desired for the fish passage that predator or prey species gain advantages from the design of it. Unfortunately, not all fish passage designs are efficient. In order to achieve these goals of fish passage, extensive research on the fishway design is required to be undertaken. This thesis aims to fulfill extensive research on computer vision and signal processing based tools and techniques for fish movement analysis in order to contribute in the understanding of fish behaviors in fish passages.

Water flow speed and other parameters related to fluid dynamics and hydraulic measurements are important in the fish passage evaluation, yet they are not sufficient alone. Kinematic data of fish and other biological parameters also provides very valuable information in terms of interpreting movements of fish inside the passage. Some of the most important parameters of fish kinematics for fishway evaluation are fish swimming speed and acceleration, trajectories inside the fishway and tail beat frequency and amplitude.

In this thesis, first part of the work that is undertaken is the process of composing a dataset by labelling the data acquired from the camera setup inside fishways. Underwater images acquired inside of the fish passages are divided into regions that are meaningful in terms of interpreting the design of the fish passage. Labelling of fish tail beat frequency values is done by extracting all frames of underwater videos and

then examining each frame manually. Tail regions of fish area is cropped wide enough to contain all oscillation range of the tail considering possible loss of the performance during the estimation of fish tail beat frequency, so that masked images for the fish tail dataset are generated. After generating datasets, training of the machine learning based fish detection is performed.

In the first phase of the fish detection system proposed in this thesis, moving objects are detected and fish candidate regions are obtained by means of the background subtraction process. In this stage, integrity of the candidate regions are enhanced by using morphological image processing operations. Then, false candidate regions are eliminated by the trained fish detector with the proposed scheme that uses extreme learning machines (ELM) and deep learning (DL) based techniques. The proposed fish detection scheme is analyzed and tested both on the lab videos and the videos obtained from the field. Promising results are obtained when considering the challenging underwater images of this application with the cluttered, highly dynamic moving objects such as seaweed and brush and the wobble of a camera due to the force of the water flow.

Secondly, fish tail beat frequency estimation techniques are proposed. Frequency / periodicity estimation is a common task in the signal processing domain. Frequencies from the temporal data are calculated by transforming the two-dimensional image data by means of the average magnitude difference function (AMDF) and autocorrelation (ACF) function in the tail beat frequency estimation method developed in this thesis. Fish tail beat frequency is an important indicator that is associated with many parameters such as fish energy expenditure, burst speed and upstream flow speed. One typical advantage of the proposed camera sensor based system is that no physical attachment to fish is needed unlike the other methods such as RFID tagging.

In conclusion, computer vision and signal processing based techniques and schemes are proposed in this thesis in order to contribute the research on the fishway evaluation. Extensive experiments are conducted in order to show the performance of the proposed techniques. Results show that proposed system can be useful not only for an analysis of the fish passages but also for a general-purpose movement based underwater fish analysis.

VİDEO ANALİZİ İLE BALIK GEÇİTLERİNDE BALIK TANIMA VE KUYRUK SALLAMA FREKANSI TAHMİNİ

ÖZET

Küresel ekonomik büyüme, artan insan nüfusu ve enerji ihtiyacı insanların enerji, gıda ve benzeri ihtiyaçlarını karşılamak amacıyla nehir göl ve akarsular üzerindeki aktivitelerini arttırmaktadır. Bu aktivitelerin en açık örneği olarak göl ve nehirler üzerine inşa edilen baraj, hidroelektrik santraller verilebilir. Hidroelektrik enerji özellikle gelişmekte olan ülkelerde ana ekonomik aktivitelerden biridir. Nehirler üzerindeki insan yapılarının nehirdeki doğal ortam (habitat) ve yaşam formlarının çeşitliliği (biyoçeşitlilik) üzerinde oldukça olumsuz etkileri bulunmaktadır. Akarsuların devamlılığı, farklı ekolojik bölgeleri doğal yolla birbirine bağlayan yapısı sebebiyle ekolojik açıdan çok değerlidir. Nehirlere kurulan baraj ve benzeri yapılar burada yaşayan su canlılarının, özellikle balıkların geçişini ve göç yollarını engellemektedir. Balık popülasyonun devamlılığını sürdürebilmesi balıkların yaşadığı ve üreme, beslenme, hareket etme gibi biyolojik fonksiyonlarını yerine getirdiği ortamın (habitat) karakteristik özelliklerine güçlü bir şekilde bağlıdır. Nehirdeki akım örüntüsü fiziksel ortamın ana belirleyici etmeni olduğundan nehirdeki biyotik ortamın da en karar verici parametresidir. Nehirler üzerine kurulan yapılar sebebiyle akıntıların debisinde meydana gelen değişiklikler o bölgede yaşayan balık türleri üzerinde baskı yaratabilir.

Balıkların yaşam alanında, hareketlerine etkileri düşünülmeden bilinçsizce tasarlanan suni değişiklikler balık popülasyonu için büyük tehdit oluşturur. Bu sebeple, balıkların santral ve baraj gibi yapılardan geçişini sağlamak amacıyla farklı çözümler sunulmuştur. Bu çözümler arasında en yaygın olanlarından birisi de baraj ve santraller içinde balıkların göçlerini tamamlaması için geçitlerin inşa edilmesi yöntemidir. Balık geçitlerinin temel amacı nehirdeki insan yapılarının sebep olduğu engeli kaldırmaktır. Geleneksel balık geçidi türleri arasında havuzlu, düşey yarıklı ve doğala benzer balık geçidi tipleri bulunmaktadır. Bunların dışında balık dostu sazlık tipi balık geçidi gibi yeni nesil tasarımlar da ortaya çıkmıştır ve bu yeni tasarımların değerlendirilmesi amacıyla yeni çalışmalara ihtiyaç duyulmaktadır. Literatüre katkı sağlamak amacıyla bu tezdeki saha ölçümleri ve deneyler sazlık tipi balık geçidi üzerinde yapılmıştır. Balık geçitlerinin verimli bir şekilde tasarlanabilmesi için biyolojik ve mühendislik yaklaşımların bütünlük içerisinde olduğu disiplinler arası bir çalışma gereklidir. Bu tezde balık geçidinin verimli biçimde tasarlamasına katkıda bulunabilecek parametrelerin hem sahada hem de laboratuvar ortamında ölçümü için sinyal işleme tabanlı yenilikçi ölçüm ve modelleme teknikleri sunulmuştur.

Balık geçitlerinin verimliliği değerlendirilirken bölgelere göre akıntı hızı ve ortamın diğer akışkan dinamikliği parametreleri ve hidrolojik ölçümler çok önemli olmakla beraber tek başına yeterli değildir. Balıkların kinematik verileri ve diğer biyolojik parametreler de balıkların geçit içindeki davranışlarını yorumlama açısından kritik öneme sahiptir. Balık yüzme hızı ve ivmesi, geçit içindeki geçiş rotaları ve kuyruk

sallama frekansları balık geçitlerinin verimliliğinin değerlendirilmesindeki başlıca önemli parametrelerden bazılarıdır.

Tüm balık türlerinin evrimsel olarak kazandığı ortak hareket örüntüleri dışında, farklı balık türleri arasındaki kinematik kabiliyetler geçirdikleri evrim sürecine göre farklılık göstermektedir. Bu sebeple, balık geçidinin tasarımı aşamasında hedeflenen endemik türlerin morfolojik ve biyolojik özelliklerinin dikkate alınması balık geçidinin verimliliği için önemlidir. Akıntıya karşı göç eden balıkların daha düşük akıntı hızına sahip bölgelere doğru yönelerek minimum enerji harcama konseptinde hareket ettiklerine dair gözlemler yapılmıştır. Belirli balık türleri bencil (bireysel) sebeplerle toplu halde harekete eder, tek bir vücut gibi tepki verirler. Böylece, avcılardan kaçarken daha az enerji harcamak, daha rahat beslenmek gibi ekolojik faydaların yanında önündeki balığın yarattığı girdabın dönme kuvvetini kullanarak akıntıya karşı dururken enerji tasarrufu yapmak gibi kinetik avantajları da kullanmayı amaçlarlar. Balıklardaki bu evrimsel davranış biçimi 'Fish Schooling' olarak adlandırılır. Balık geçitlerinde elde ettiğimiz gözlemlerde de 'Schooling' davranışı gözlemlenmiştir. Balıkların toplu davranışları ve hareket örüntülerine dair elde edilecek ölçüm yöntemleri bu bağlamda balık geçidinin verimliliğinin değerlendirilmesinde faydalı olacağı düşünülür.

Laboratuvar ortamındaki balık hareketi incelemelerinde genellikle düzenli su akımının olduğu bir ortam üzerinde ölçümler yapılır. Halbuki, nehir üzerinde hareket eden balık türlerinin doğal ortamları çoğunlukla türbülansın yoğun olduğu karmaşık akıntı dinamikleri içerir. Akıntıya karşı yönde göç eden balık türleri düzenli bir şekilde türbülans akımlarına maruz kalırlar. Su akımı silindir şeklindeki geniş ve keskin olmayan cisimlerden geçerken arakasında "girdap dökülmesi" (vortex shedding) adı verilen girdap akımları oluşturur. Üstelik *Gökkuşağı Alabalığı* gibi bazı türler akıntıya karşı hareket ederken kendi vücutlarını 'slalom' hareketi ile yönlendirip mevcut türbülans akımındaki girdapların dönme kuvvetini ve enerjisini kullanarak ve enerji tasarrufu sağlamaktadır. Bu gözlemler değerlendirildiğinde saha çalışmasının önemi ortaya çıkmaktadır.

Bu tez kapsamında, ilk aşamada balık geçidi altına kurulan kamera sistemi ile elde edilen görüntüler üzerinde veri etiketleme ile veri seti oluşturulması işlemi üzerinde çalışılmıştır. Balık geçidi içindeki su altı görüntülerinden balık bölgeleri bölütlenerek maske görüntüleri oluşturulmuştur. Balıkların kuyruk sallama frekansları video görüntülerinin çerçevelere ayrılması ve her çerçevenin manuel olarak incelenmesi ile etiketlenmiştir. Balıkların kuyruk frekanslarının tespit edilmesinde balığın kameraya göre poz açısından kaynaklanan olası performans kaybı etkileri de düşünülerek balıkların kuyruk bölgeleri kuyruk hareketinin genliğini kapsayacak kadar geniş kırpılmış, böylece balık kuyruğu bölütlemesini sağlayan maske resimleri oluşturulmuştur. Bu maske resimlerinin çıkarılarak balık bölütleme etiketlerinin elde edilmesi işlemi elle yapılmıştır. Daha sonra, balıkların lokal ve zamansal balık hareket örüntülerini hareketli nesne tanıma ve derin öğrenme (DL) ile özellik çıkarma yöntemleriyle balıkların yerini tespit eden yöntem geliştirilmiştir. İlk önce giriş su altı görüntülerinin gamma düzeltme yöntemi ile kontrast ve parlaklık ayarı önişleme adımında düzenlenmiştir. Daha sonra, oluşturulan balık veri seti ile derin öğrenme tabanlı yaklaşımın yüksek temsil edici yapısı kullanılarak özellik öğrenmesi işlemi gerçekleştirilmiştir. Sistemin çalışma zamanı verimliliği de düşünülerek eğitim aşamasında Aşırı Öğrenme Makineleri (ELM) yöntemi ile sığ (tek katmanlı) yapay sinir ağından yararlanılmıştır.

Kamera görüntüleri üzerinde hareketli objeleri tanımlamak bir çok uygulamada fayda sağladığından, bilgisayarla görü alanında araştırmaların yoğun olduğu problemlerden biridir. Arka planı belirlemek uygulama alanına göre genellikle farklılık gösterir. Bu tezdeki uygulamadan örnek vermek gerekirse, kamera görüntüleri üzerinden balıkların sayımının yapılması deniz bilimciler için önemli verilerden birini teşkil etmektedir. Bu uygulamada su altı görüntülerdeki balık haricindeki her nesne arka planı oluşturmaktadır. Arka plan çıkarma aşamasında çerçeve farkı, Gauss karışım modelleri (GMM) ve ViBe yöntemleri karşılaştırılmıştır. Farklı yöntemlerin sonuçlarını birleştiren çözümler de denenmiştir.

Bu tezde sunulan balık tanıma sisteminin ilk aşamasında hareket eden objeler arka plan çıkarma yöntemleri ile bulunarak aday bölgeler hesaplanır. Bu aşamada morfolojik görüntü işleme yöntemleri ile aday bölgeler arasındaki bütünlük dengesi arttırılır. Daha sonra derin öğrenme ve ELM yöntemleri ile eğitilen balık bulucu modülü ile aday bölgeler filtrelenerek balık tanıma gerçekleştirilmiştir. Bu yöntem hem saha görüntüleri hem de laboratuvar ortamındaki sazlık tipi balık geçidi su altı görüntülerinde analiz edilmiştir. Önerilen balık tanıma sistemi üzerinde yapılan deneylerde balık geçidi içindeki kameradan alınan su altı görüntülerindeki bulanıklık, sudaki dalgalardan ve akımdan kaynaklanan aydınlanmadaki değişimler ve hareketli gölgeler, sazlık ve yosun gibi dinamik objelerin yanı sıra akıntının kuvvetinden dolayı su altı kamerasının sallanması gibi birçok parametre düşünüldüğünde bu karmaşık bilgisayarla görü probleminde umut vadedici sonuçlar alınmıştır.

Sonraki aşamada, balıkların kuyruk sallama frekansını sunulan sinyal işleme tabanlı yöntemler ile hesaplayan sistem anlatılmıştır. Balığın kuyruk sallama frekansı balığın harcadığı enerji, itme hızı (burst speed) ve ters yöndeki akıntının kuvveti gibi birçok parametre ile doğrudan ilişkili olan oldukça önemli bir parametredir. Kameralar aracılıyla kuyruk sallama frekansının çıkarılmasının balıklara RFID etiketi takılarak yapılan ölçüme göre belirli avantajları vardır. Örneğin, RFID sisteminde takılan etiketin balığın hareketini nasıl etkileyeceğine dair kestirimde bulunmak zordur ve takılan etiket balığın hareketini kısıtlayıp ölçümde hatalara yol açabilir. Oysaki, kamera tabanlı analizde balığa fiziksel bir müdahale yoktur. Frekans ve periyodiklik tahmini sinyal işleme uygulamalarında sıklıkla rastlanan bir işlemlerden biridir. Bu tezde geliştirilen kuyruk frekansı hesaplama yönteminde ortalama büyüklük farkı fonksiyonu (AMDF) ve otokorelasyon fonksiyonu (ACF) ile iki boyutlu görüntü verisi üzerinde hesaplama yapılmıştır. Ayrıca iki yöntemin sonuçları farklı ortamlardan ve kamera açılarından elde edilen su altı görüntülerinde karşılaştırılmıştır.

Yapılan deneyler sonucunda balık geçidi verimliliği için önemli olan parametrelerin hesaplanması için ilk adımları atacak veriler yorumlanmıştır. ELM yöntemindeki aktivasyon fonksiyonu için farklı parametreler test edilmiştir. Ayrıca, gizli katmandaki nöron sayısının eğitim aşamasında systemin performansına olan etkileri test edilmiştir. Balığın kuyruk frekansını hesaplamak için geliştirilen yöntemler üzerinde yapılan testler, balıkların farklı poz ve kamera açılarına sahip görüntülerindeki sonuçların tümünü içerir. Balık tanıma sistemi ile balıkların balık geçidinin farklı bölgelerine göre dağılımını veren ısı grafiğini çıkarmak gibi faydalı analizlerin yapılmasının önü açılmıştır. Burada balığın önden çekilen görüntüsünde kuyruğun balığın baş kısmı tarafından gizlenebileceğini ve kısmi olarak görünebileceğini belirtmek gerekir. Ayrıca, balığın profilden (yan) alınan görüntülerde kuyruğun simetrik olarak sallanma durumları kısmi olarak gözlenir. Bu görüntülerde diğer pozlara kıyasla kuyruk frekansı hesaplama yönteminin performansının daha düşük olduğu gözlenmiştir. Sistemin tahmin hassasiyetini değerlendirmede ortalama kareli hata (MSE) metriğinden yararlanılmıştır.

Sonuç olarak, bu tezde balık geçitlerinin verimliliğinin değerlendirilmesinde literatüre katkıda bulunacak bilgisayarla görme ve sinyal işleme tabanlı analiz yöntemleri geliştirilmiştir. Yapılan deneyler ile sistemin performansı değerlendirildiğinde, önerilen balık tanıma ve balık kuyruğu hesaplama yöntemlerinin hem balık geçitlerinin hem de genel amaçlı su altı balık görüntülerin analizinde faydalı olabileceği görülmektedir. Balık geçitlerinin doğru bir şekilde tasarlanması biyolojik, hidrolik ve kinematik birçok parametreyi içeren analizler gerektiren kompleks bir süreçtir. Tasarlanan balık geçitlerinin ve su kanallarının çoğunun balıkların geçişini sağlamada yeterince verimli olmamaktadır. Bunun en büyük sebeplerinden biri de balık geçitlerinin verimliliğinin analiz edilmesinde yeterli verilerin ve ölçüm tekniklerinin olmamasıdır. Bu durum, bu tezdeki çalışmanın önemini doğrulamaktadır. Gelecekteki çalışmada üç boyutlu çıktı üretecek çoklu kamera sistemi tasarlanıp kalibrasyonunun yapılması ve derinlik bilgisini de kullanan bir ölçüm sisteminin geliştirilmesi hedeflenmektedir. Bu sistem ile üç boyutlu balık göç rotalarının çıkarılması ve ısı grafiğinin elde edilmesi sağlanabilir. Resimler üzerinde balıkların yerlerinin tespit edilmesi işlemi de aynı şekilde derinlik bilgisini hesaba katacak şekilde güncellenebilir.

1. INTRODUCTION

With the increasing human population and need for energy resources, human activity in rivers is also in increasing trend [1]. Hydroelectricity, which is a way of generating energy using hydropower, is one of the main energy production methods that is widely used, especially in developing countries. Human-made structures in rivers (e.g. dams, hydroelectric power plants) cause obstacle in fish movement and interfere with natural lifecycle of fish and that alteration of longitudinal connectivity in fish migrations causes a major threat for the ecological sustainability of fish. Flow regime and other hydraulic and physical characteristics of rivers are directly affected by these man-made structures. These physical changes like flow regime alters ecological sustainability of rivers and streams [2].

Fishways (also called as 'fish ladder', 'fish passage' or 'fish pass') are critical structures that provide passage and serve as a gate in the upstream and downstream movements of fish. However, most of the established fishways and culverts are inefficient due to the improper design caused by the lack of adequate tools and techniques [3], [19]. In [3], it is shown that majority of the culverts are categorized as having high level of barrier risk for upstream migration.

Fish have complex characteristics in flow, and fish movement patterns can differ from species to species. Fish locomotion patterns include not only undulating motion of fish bodies in steady flow environment but also other special actions in various conditions. For instance, fish performs brief, sudden acceleration patterns during predator–prey encounters. This highly dynamic and energetic swimming pattern is called fast-start swimming [4].

Fish consumes a significant amount of energy while producing undulatory propulsion during steady, continuous swimming. It is known that some fish species (e.g. rainbow trout) exploit vortices in water flow to reduce muscle activity and save their own energy by benefiting from nearby water vortices [5]. Vortices are swirls of water that can be produced by internal flow dynamics or from moving objects. Some fish species, rainbow trout for instance, alter their body shapes and perform a ‘slalom’ movement between vortices in order to take advantages of vortex energy. Successful fish passage design should consider all of these complicated fish movement patterns in different circumstances.

The concept of the fish passage efficiency is related to both qualitative and quantitative evaluations. The efficiency of a fish passage is considered as a qualitative concept, which involves checking whether the system provides satisfactory passage for the target species, under the flow conditions observed during the migratory period [42], [43]. Quantitative assessments of efficiency take into account the percentage of fish present in one side of the passage that are able to move through the fish passage [43], [44]. Hence, the fish passage efficiency, E, is defined as a ratio of the number of individuals that were passed through the structure, FP_{ex}, to the number of individuals that were detected at the fishway entrance, FP_{en}. The fish passage efficiency of the structure is calculated from:

$$E = \frac{FP_{ex}}{FP_{en}} \ x \ 100 \tag{1.1}$$

From the standpoint of image based analysis, detecting, counting and tracking fish in underwater image frames are necessary in order to measure E accurately, which was the original goal of this thesis. While this project did not end up happening (fish detection framework is developed only), this goal drove many decisions relating to the development of techniques and algorithms.

Also, fish swimming speed, tail beat frequency and amplitude measurements are important quantities that are informative about the way fish move and swim in a fish passage. To evaluate the swimming performances of aquatic animals, one of the important dimensionless quantities is the Strouhal number. Strouhal number calculation for fish can be specified as:

$$St_{fish} = \ f_{TB} \, {}^{\lambda}\!/_{U} \tag{1.2}$$

where f_{TB} is the tail beat frequency, λ is the peak-to-peak amplitude at the tail tip and U is the flow speed. Eloy addressed determining optimal Strouhal number for swimming animals, stating that aquatic animals are likely evolved swimming in certain range of Strouhal number [6].

Fish passage designers consider parameters of fish kinematics such as swimming ability and patterns, peak flow rates and time of migration in different flow field conditions while designing proper fishway. These previous studies show that fish have gained complex locomotion ability during the evolution. Successful fishway design should also provide passage for all species in local environment that it is setup. Moreover, 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. Although the recent improvements, evaluation for the true performance of the fishway is still cumbersome, due to the lack of adequate tools and data [7], [8].

While conducting experiments, images captured from both on the lab and the field are used in this thesis. Fish species detected from the field are given in Figure 1.1. Field work is done in brush fish pass in İkizdere River which is very rich in terms of biodiversity [9]. Body length of different fish species is also measured during the field work.

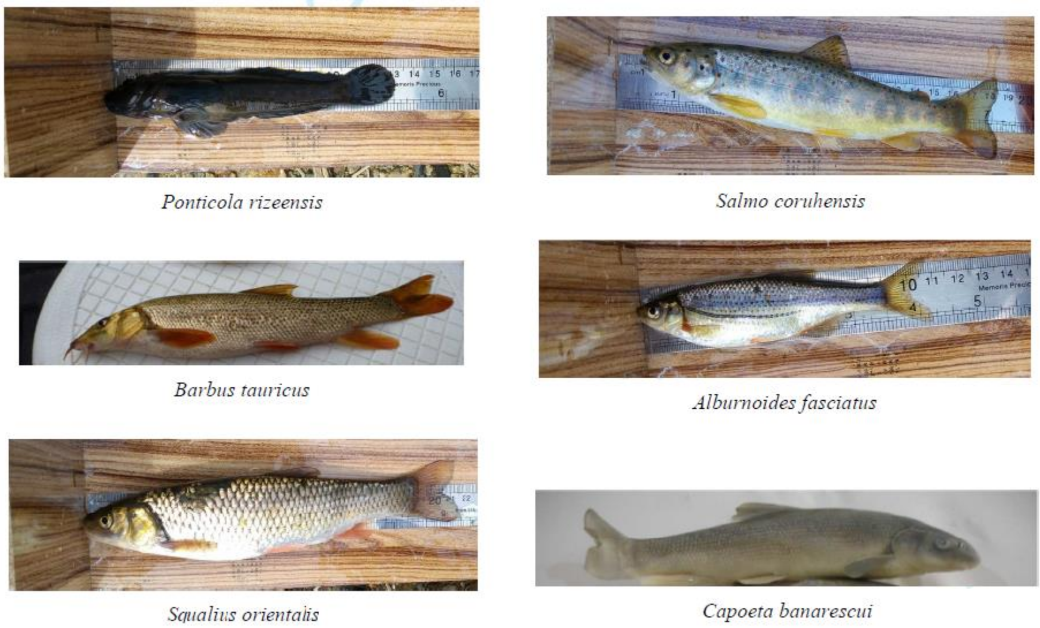


Figure 1.1 : Fish species in the project area.

Images captured from camera in the underwater environment consist of a lot of variety in scene conditions. The motion patterns of objects, possible occlusion of multiple moving objects, illumination changes and dynamic background due to the water flow are among these varieties in underwater videos. Such an example of underwater fish image captured inside the fish passage field (İkizdere River) is given in Figure 1.2.

Figure 1.2 : Sample image taken from the camera setup inside a fishway.

1.1 Purpose of Thesis

Hydro Power Plants (HPP) can block the passage of fish migrating up and down-streams or may cause delays. This situation causes a decrease in the population of fish. On the other hand, the European Union Water Framework Directive is required to ensure the continuity and monitoring of fish species in rivers in order to ensure good ecological status. For instance, there are 382 freshwater fish species in Turkey and about 1/3 of these species are endemic. Some of those endemic fish species have a body length of 5 cm. Accordingly, it is not possible for those endemic fish species to ascend conventional technical pool fish passes. In this context, it is necessary to provide passage for small-bodied and weak swimming capacity fish through fish pass structures [49].

Efficient models and mechanisms are required for evaluating efficiency of fish passages. In this thesis, computer vision based methods are proposed for fish detection and movement analysis in images taken from the inside of fish passages. Videos from both field and laboratory are examined in experiments in order to show performance of our method.

1.2 Literature Review

Diverse techniques are used in previous works of image analysis based fish movement analysis. The work by [10] 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. Lie et al. proposed Fast-R-CNN based method for fish detection and recognition in unconstrained underwater videos in [11], where fish recognition is performed using Convolutional Neural Networks (CNN).

In [12], 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 [13]. In that fish counting system, fish is detected using background subtraction method that fuses mixture models and frame differencing.

In [45], shape priors based fish detection method is proposed for the images captured from fish cages. In that work, statistical shape knowledge is added by means of the Gaussian shape probability to a Mumford-Shah functional to yield image energy. They represent the contour by a closed polygonal curve in fish classification phase with the set of the training samples generated from the real fish images.

More similar works in vision-based fishway analysis are done in [14], [15]. In [14], 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. Local and global intensity values and background information are used for training SOM network which consists of three-layer topology with 3 neurons in each layer [14]. Fish detection and particle filter based tracking for counting fish in fish ladder is proposed in [15]. Fish trajectory is also estimated by means of fish tracking. Image is split to grids of W locations and for each location w, observation vector z_w with 4 parameters are extracted using Gaussian and LoG filters on the chrominance channels during the fish detection. Then, background model is learned by computing the Gaussian Mixture Models (GMM) for each location w [15].

In [16], 3D fish tracking system based on DL network that learns the kinematic model is proposed. They propose novel camera installation which consists of one master camera at the top and two slave cameras at sideways, and they fuse data to yield three-dimensional fish trajectories using the multiview images acquired from these cameras. Contrast to traditional dynamic models which are built on prior knowledge about fish kinematics, their proposed system models the fish’s motion process by learning a Long Short-Term Memory (LSTM) network.

Most similar work related to fish tail beat periodicity estimation is done in [17], where fishway flow field is calculated by means of Particle Image Velocimetry (PIV) and autocorrelation is used for manually detecting fish tail beat periodicity in extracted frames. Our contribution is to provide further investigation on measurement of fish tail beat frequency using computer vision based methods including the comparison of Average Magnitude Difference Function (AMDF) and Autocorrelation Function (ACF) methods.

Many different types of fish passage exist [46], [47]. These different fish pass types generally differ in the variation on the approaches of steps, slopes or lifts. For instance, pool-weir, vertical slot, natural and brush fish passage are some of the types that are used in field. Brush fish passage, which is also called as ‘canoe fish pass’ since it also allows canoe pass, is a recent approach in fishway engineering. High turbulent flow in the baffle zone and low velocity field in the brush zone are the major characteristics of the brush type fish pass [49].

In this thesis camera setup is done in the brush fish passage located in İkizdere River, Rize, Turkey for the field experiments. View of the brush fishway structure studied in this work can be seen in Figure 1.3 and 1.4.

Figure 1.3 : Inside view of the brush based fishway model.

Figure 1.4 : View from the field: Brush based fishway model setup on small hydropower plant in İkizdere River, Rize, Turkey is used in experiments.

1.3 Hypothesis

There are diverse measurement tools such (PIV, RFID tagging etc.) that are used for monitoring fish behavior in fishway. Current tools have some disadvantages, for instance tagging fish with chips or RFID tags may alter the way fish moves in certain conditions. The main hypothesis of this thesis is that computer vision based system can be useful for evaluating of the efficiency of fishway design and provided image analysis based measurements support that brush fish passage provides successful criteria for fish migration.

2. FISH DETECTION

2.1 Purpose

Object detection, which is a common interest in computer vision that a lot of research have been done, is a task works on detecting instances of semantic objects of certain classes in digital images or videos. Purpose of this subtask is to locate fish position in videos which is an application of object detection specialized to fish. Fish location is estimated on the image by discriminating moving fish from the background during the fish detection process. Detecting the location of fish in image is the first processing step that is required in order to analyze fish behavior and movements in a video.

Fish detection system in underwater videos of unconstrained and cluttered environment should deal with the high turbulence, overlapping objects and moving particles such as blister, bush in water as seen in Figure 2.1. Underwater images captured inside fish passage in the field also contain highly dynamic moving patterns in background. Considering the fish pass, the migrating fish may be moving very fast and quickly disappear from the range of view of the camera. Since there are illumination changes (the light transmission in water causes degradation of the image etc.), occluded objects and dynamic patterns in the background, fish detection becomes a more challenging problem. 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.

Fish segmentation is performed both on videos captured from fishway camera setup and those taken from controlled environment in a laboratory. Also, dataset for fish detection is created by manually segmenting fish in underwater images (see Section 4 for details).

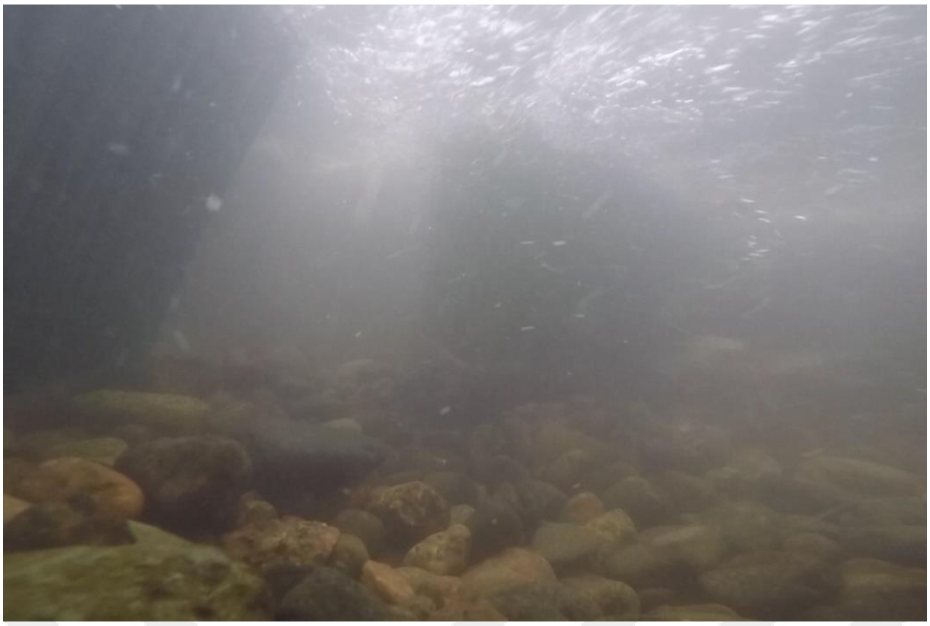


Figure 2.1 : Sample images captured inside Fish passage: Water blisters, flow and illumination changes create complex moving patterns in background.

2.2 Overview of the Proposed Method

Detection of the fish in images is needed for generating heatmap of fish movement patterns. Proposed fish detection system consists of three steps which are detection of candidate regions, feature elimination and candidate classification. Scheme of the proposed fish detection system is presented in Figure 2.2.

Figure 2.2 : Scheme of the proposed fish detection method.

Most of the scenes in fish passage contains high movement of fish and other object due to the flow of the water. Fish have high tail beat movement in fish passage, since they withstand against the current flow. This observation is exploited in order to separate fish regions from background. Several background subtraction techniques are explored for detecting moving objects which is called ‘foreground’ in the literature. The details of the background subtraction methods are given in Section 2.3. Background subtraction is combined with fish detection by exploiting spatial and temporal features of fish regions. Gamma correction is applied in input videos as a preprocessing step. Adaptive background subtraction is performed by means of the variant of the Gaussian Mixture Model (GMM) and used as an extended foreground mask. Then, feature extraction is performed followed by supervised feature learning for fish detection. For this task, deep Convolutional Neural Networks (CNN) is utilized for feature extraction. For fast classification of candidate regions, variant of randomized learning network called Extreme Learning Machines is used [18].

2.3 Background Subtraction

Background subtraction is a common computer vision task in which various techniques exist in the literature. In most applications with static cameras, moving objects constitute regions of interest to be detected. The basic principle of the background subtraction as a technique is to separate moving objects from static objects that are called *background*. Simple background detection methods perform pixel by pixel comparison between the static background frame and the current frame of a video. In conventional approaches of background subtraction, background model is assumed to be stationary. However, dynamic patterns in background exist in most of the real-world applications with outdoor scenes. Therefore, it is important for the success of a background subtraction method to adjust its parameters online in adaptive manner in order to fit the model to dynamic changes in the background. General scheme of the background subtraction process can be seen in Figure 2.3.

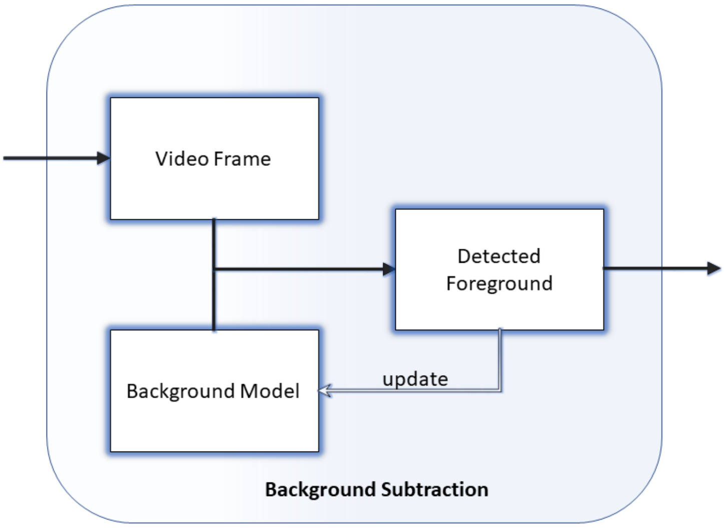


Figure 2.3 : General scheme of the background subtraction process.

2.3.1 Frame difference

First approach that is analyzed was frame differencing method. One of the basic approaches for detection of moving objects is frame differencing which calculates the difference between current frame and reference frame and thresholds the result as foreground object. A reference frame representing background is used to compare each frame in this method and global, adaptive or local thresholds may be applied for foreground detection. [13] used more adaptive form of frame differencing method by using dynamic thresholding and background update method as in the Equation 2.1:

$$B_n(x,y) = (1-\alpha).B_{n-1} + \alpha.CF_n(x,y) \tag{2.1}$$

where B_n, CF_n is nth background image and current frame respectively and is used as a background update factor. They combined this method with the Adaptive Gaussian Mixture Model proposed in [26] using "AND" operation for more robust segmentation [13]. However, experiments done in this work 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 (see Section 2.3.2).

2.3.2 GMM based background modelling

Another basic approach is to represent each pixel of the frame with (Gaussian) probability distribution and set threshold according to the variance of distribution [24]. However, variation in the pixel values over the certain time intervals is more complex to represent than the single distribution which is not able to adapt to sudden change in the background. For this reason, mixtures of gaussian components are replaced for better results in the research of past decades [20], [21], [22], [23], [26]. The main principle in background subtraction with Gaussian mixture models (GMM) is to consider the probability of observing the current pixel value by using the weighted sum of multidimensional Gaussian probability density function (pdf) [25]:

$$P(X_t) = \sum_{i=1}^{K} \omega_{i,,t}.\eta(X_t, \mu_{i,t}, \Sigma_{i,t}) \tag{2.2}$$

where K is the number of distributions, $\omega_{i,t}$ is a weight associated to the i-th Gaussian at time t with mean $\mu_{i,t}$ and standard deviation $\Sigma_{i,t}$ and η is a Gaussian pdf given in the following equation:

$$\boldsymbol{\eta}(X_t, \mu, \Sigma) = \frac{1}{(2\pi)^{\frac{n}{2}}|\Sigma|^{\frac{1}{2}}} e^{-\frac{1}{2}(X_t-\mu)\Sigma^{-1}(X_t-\mu)} \tag{2.3}$$

Stauffer and Grimson [25] used constant K components (from 3 to 5) in their algorithm, and they assumed identical variances for each channel of the color space, resulting in a diagonal matrix for covariance matrix:

$$\Sigma_{k,t} = \sigma_k^2 \, \mathrm{I} \tag{2.4}$$

where I is the identity matrix with proper size.

2.3.2.1 Background model estimation

Deciding the background pixel is done in the following manner: Firstly, components are sorted in descending order according to their weights [26], or the ratio $r_j = \frac{\omega_j}{\sigma_j}$ can be used as in [25]. The first B Gaussian distributions which exceed certain threshold T are chosen for a background distribution:

$$B = argmin_b \left(\sum_{i=1}^{b} \omega_{i,t} > T \right) \tag{2.5}$$

Zivkovic [26] uses parameter $cf = 1 - T$ as a threshold that is measure of the maximum portion of the data that can belong to foreground objects without influencing the background model. When a new frame is retrieved at time t+1, the following Mahalanobis distance is calculated for each pixel:

$$sqrt\left(\left(X_{t+1} - \mu_{i,t}\right)^T . \Sigma_{i,t}^{-1} . \left(X_{t+1} - \mu_{i,t}\right)\right) < k\sigma_{i,t} \tag{2.6}$$

where k is a constant threshold and $\sigma_{i,t}$ is covariance. Each pixel is evaluated as part of background or foreground according to this 'closeness' property. After this evaluation, components are updated according to update equations. There exist different update methods for different algorithms such as recursive update equations [27]. The main logic is to increase weights of the matched components and similarly, to reduce weights for unmatched components over the time.

2.3.3 ViBe method

GMM based methods are one of the most popular parametric techniques that use a parametric model for each pixel location. Major drawbacks of GMM base parametric techniques are loss of the sensitivity in detection when background model includes high frequency variations and issues of how fast the background model adapts to change in the background. Another type of approach for background subtraction is sample-based techniques. Visual Background Extractor (ViBe) proposed by Barnich et al. [28] is a sample-based algorithm that introduce a random selection policy and background model initialization from single frame which are the innovative mechanisms for moving object detection.

- **Background modelling:** ViBe algorithm is considerably different in background modelling than non-parametric models [29] and GMM based techniques. For the value at time t of the pixel x, $p_t(x)$, parametric approaches classify $p_t(x)$ as background if it fits with the pdf estimated for the background. On the other hand, in ViBe algorithm, a sphere $S_r(p_t(x))$ with radius r is defined on the center of $p_t(x)$ in order to decide whether it belongs to background or foreground by using the set intersection of $S_r(p_t(x))$ and the set of samples $\{p_1, p_2, \dots, p_n\}$ [28].

$$\# \left\{ S_R\big(p_t(x)\big) \cap \{p_1, p_2, \dots, p_n\} \right\} > \#_{\min} \tag{2.7}$$

  where $\#_{\min}$ denotes the minimal cardinality threshold and # is the cardinality operation. If the inequation in 2.7 holds, $p_t(x)$ is classified as background.

- **Spatial Consistency:** GMM based techniques ignore spatial relationship inside the image. However, temporal distribution of a pixel and its neighborhood is considered together and selection policy of a sample model that is done in a random manner affects the models of neighboring pixels in the ViBe method. More briefly, if the value $p(x)$ of a pixel x is decided to update samples, one of the randomly chosen pixels in the neighborhood of $N_G(x)$ is also updated with $p(x)$, in which $N_G(x)$ denotes the 4x4 or 8x8 neighborhood of a pixel x.

Also, *memoryless property* of the exponential decay with the random sample lifespan policy update allows the update mechanism to adapt to an any time interval [28].

2.4 Candidate Region Detection

Firstly, Gaussian Mixture Model based approach is examined for representing pixel distributions. Since determining the number of components in GMM is critical in highly dynamic scenes, adapting mixture components according to scene is required. Adaptive GMM method proposed in [26] is explored, for dynamic handling of the number of the mixture components. In order not to miss any fish regions, it is aimed to achieve high recall during the background subtraction. The important parameters for achieving high recall in Adaptive GMM based online clustering algorithm are the threshold $\mathrm{c_{thr}}$ and the parameter c_f. For the new sample $\overrightarrow{x}^{(t)}$, it is decided to be a background object according to variance threshold $\mathrm{c_{thr}}$:

$$p(\overrightarrow{x}^{(t)}|BG) > c_{thr} \tag{2.8}$$

$$B = argmin_b \ \left(\sum_{m=1}^{b} \hat{\pi}_m > (1 - c_f) \right) \tag{2.9}$$

Recent approaches are further investigated since the accuracy of contour area of fish during segmentation is important when calculating tail beat frequency. GMM based and other background subtraction approaches are compared with the aid of the recent survey performed in [23]. Visual Background Extractor performed better in our test videos and it was robust enough in the high water turbulence conditions. Therefore, candidate region detection is performed by means of ViBe algorithm with 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 candidate region detection on the ordinary underwater video [48] can be seen from the Figure 2.4. Frame difference technique has the largest deficiency by means of the missing parts inside the masks of foreground components, while the Adaptive GMM and ViBe techniques have more stable results.

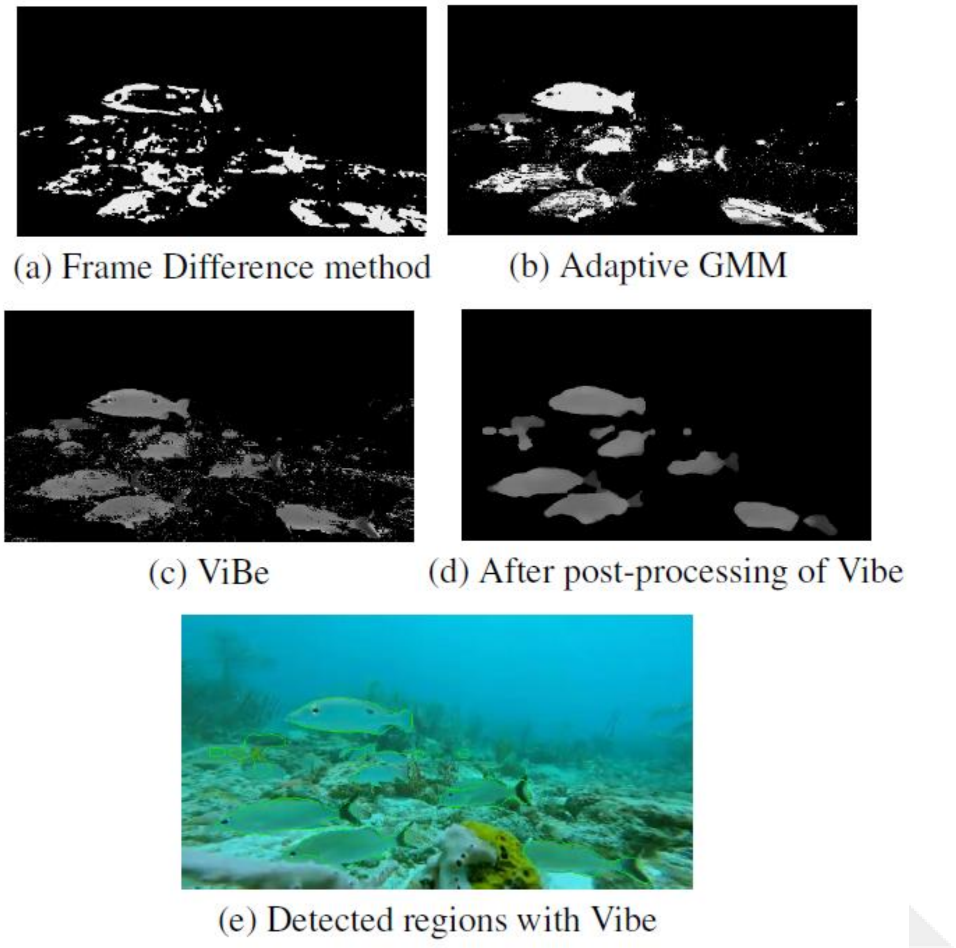


Figure 2.4 : Comparisons of detected fish regions with different techniques. (Source image is from the 1171. frame of the internet video in [48]).

2.5 Feature Learning

Recently, there are much research having the focus of feature learning methods, especially applied to computer vision problems. As a result, a wide variety of techniques which are capable of learning features from labeled or unlabeled data are proposed [30], [31], [32]. CNNs, a successful deep learning method widely used in vision applications, learn features which generalize very well across different tasks [33].

Transfer learning is a powerful technique that helps transforming domain of the visual classification task. CNNs trained for ImageNet [34] classification with over a million labeled examples are highly representative and has successful generalization in feature extraction and transfer learning. After a research on deep CNN architectures for our fish detection task, well-known AlexNet architecture is chosen for its simplicity [35].

Although, more powerful deep CNN architectures can be easily replaced with our fish detection scheme. Weight outputs from the layer named ‘fc7’ are extracted to be used as features of size 4096.

2.6 Fish Classification

Resulting features from the feature extraction step is grouped to 2 classes; fish and background. In order to extend our dataset, fish regions are cropped manually and background regions by utilizing fish passage videos from Kassel Lab [37] and from the fish passage setup in İyidere small hydropower plant at Rize, Turkey [9]. Also, our dataset is further extended by including ‘Labelled Fishes in The Wild’ LFW dataset [36]. Some of the example positive (fish) and negative (background) images from the final fish classification dataset are given in Fig. 2.5 and Fig. 2.6, respectively.

Figure 2.5 : Positive examples from the fish classification dataset.

For detection task, both performance and efficient running time is important, since the foreground mask obtained in Sec. 2.1 generates multiple candidate regions for high recall. Support Vector Machines (SVM) and Extreme Learning Machines (ELM) are evaluated for fish classification. They both provides comparable performance, but ELM outperforms SVM in terms of speed and is order of magnitude faster than SVM during the training, thanks to its randomized nature. Our training framework consists of single hidden layer with the single-step kernel version given in the following steps [18]:

For input samples X = $[x_1\ x_2\ \ \ \cdots\ \ \ x_n] \in R^n$ and single hidden layer nodes are given as H = $[h_1\ h_2\ \ \ \ldots\ \ \ h_n] \in R^m$ with size N, standard ELM network model is represented as:

$$\sum_{i=1}^{N} \mathrm{W}_o g(W_i * X_j + b_i) = Y_j, \tag{2.10}$$

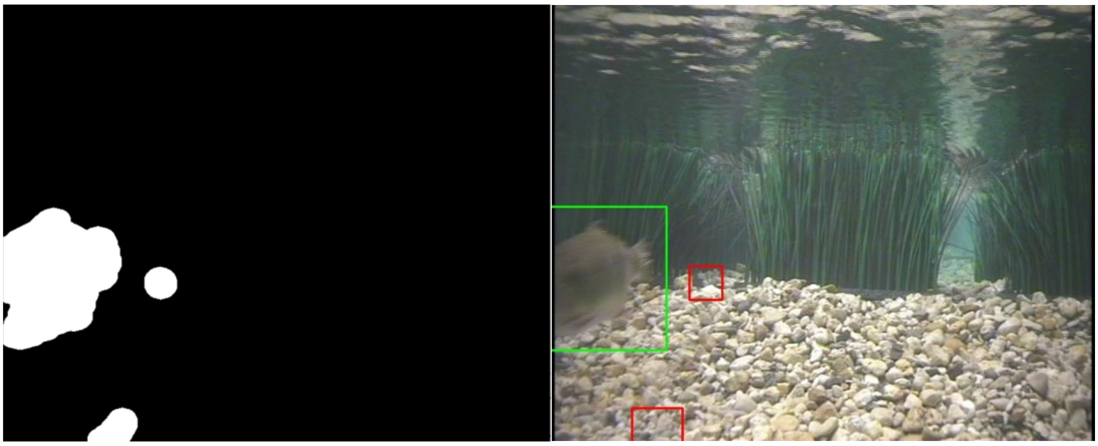
where W_o, $W_i, g(x)$ and b_i represents hidden layer output weights, input weights, activation function and threshold of the ith hidden node, respectively and output response is denoted as Y_j.

1. Fill the hidden layer input weights ($\boldsymbol{W_i}$) with random values
2. Estimate the hidden layer output weights ($\boldsymbol{W_o}$) by solving linear system (2.10) with least-squares fit using output response matrix $\boldsymbol{Y}$**:**

$$\boldsymbol{W_o} = g(\boldsymbol{W_i} * \boldsymbol{X}) + \boldsymbol{Y} \tag{2.11}$$

Figure 2.6 : Negative examples from the fish classification dataset. They are extracted as a random patches from the backgorund images.

Parameter size of the model is proportional to the increasing number of hidden nodes in ELM network. Tests are performed on different parameters of hidden nodes and activation functions in our experiments (see Section 4). Our detection scheme detects fish by classifying candidate regions found in the moving object detection mask and it can be seen in the sample result from our end to end fish detection framework shown in Figure 2.7.



(a) (b)

Figure 2.7 : Candidate dynamic regions are classified for fish detection: (a) Foreground mask image found after the background subtraction step, (b) result of our fish detection framework where green rectangle represents regions classified as fish and red rectangle represents candidate regions that are classified as background.

The proposed framework exploits the highly dynamic nature of fish in underwater. Instead of sliding each sub-window for fish detection as in the conventional sliding window approach, only regions of a moving objects (foreground) are considered in the fish classification step. This dramatically reduces the number of patches to process, and speeds up the overall running time of the proposed framework.

3. FISH TAIL BEAT FREQUENCY ESTIMATION

3.1 Periodicity Estimation

Periodicity detection is an important task in signal processing that is widely used in diverse applications, since it characterizes many natural motions including animal locomotion. Fish tail beat frequency is an important parameter that is correlated with fish swimming speed and energy consumption and is helpful in examining in which area fish rests or withstands against flow. In the particular case of this thesis, 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 algorithm. Although more recent approaches for periodicity estimations with advanced topological computations exist as in [38], self-similarity based techniques are used as in [39], [40], since they are robust against moderate amount of variance in different views. In the following subsections two efficient methods are described for tail beat periodicity detection; Average Magnitude Difference Function (AMDF) and Autocorrelation Function (ACF) respectively. In practice, adequate size of history buffer has to be chosen in both methods because of the sampling theorem. To correctly resolve the all frequencies in the input, the sampling frequency must be greater than twice the highest frequency in the input signal.

3.2 Autocorrelation Function

Autocorrelation is the function that identifies correlation of signal with its lagged form. Autocorrelation function is useful for identifying an appropriate time series model of signal. For a two-dimensional discrete signal $x(m,n)$, Autocorrelation function is calculated using equation 3.1 where M and N correspond to size of dimensions of the signal, respectively, and $\bar{x}(m,n)$ is its complex conjugate.

$$ACF(i,j) = \frac{1}{M}\frac{1}{N}\sum_{m=0}^{M-1}\sum_{n=0}^{N-1} x_{m,n}\bar{x}_{m+i,n+j} \tag{3.1}$$

The value of $ACF(i,j)$ raises when $x(m,n)$ gets similar $x(m+i,n+j)$, and it will have peaks at periods of $x(m,n)$ ACF calculation has quadratic time complexity in time domain when the Equation 3.1 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:

$$\mathcal{F}_R(f) = \mathcal{FFT}\big(x(n)\big),$$

$$S_R = \mathcal{F}_R(f)\mathcal{F}_R^*(f) \tag{3.2}$$

$$ACF() = \mathcal{IFFT}(S_R)$$

$\mathcal{F}^*$ denotes complex conjugate of $\mathcal{F}$ and $\mathcal{IFFT}()$ denotes Inverse Fast Fourier transform. Equation 3.2 is used in this technique for reducing complexity of ACF to $O(nlog(n))$ time.

Temporal distribution of ACF values computed from fish tail regions in the video named ‘troutfs.avi’ can be seen in Figure 3.1. Here, each peak-to-peak distance of the signal denotes the periodicity of the input signal. ACF is calculated with the buffer size of 140 in the Fig. 3.1 and peak-to-peak frame intervals are consistent at the value of about 33.

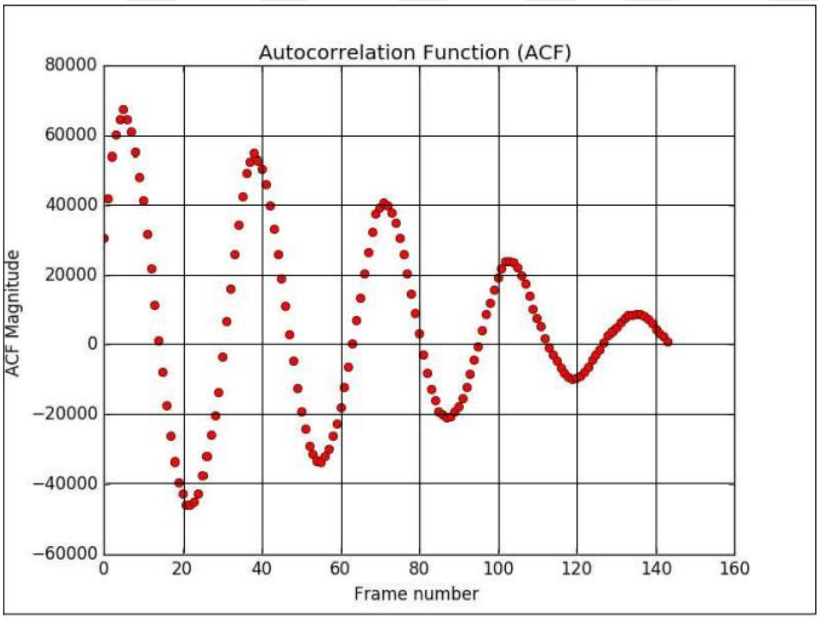


Figure 3.1 : Plot of ACF in fish tail regions from the video named ‘troutfs.avi’.

ACF data with the temporal buffer size of 50 that is computed from the video named ‘uvs080910-012.avi’ can be seen in Figure 3.2. Here, the peak-to-peak frame interval is at around 30.

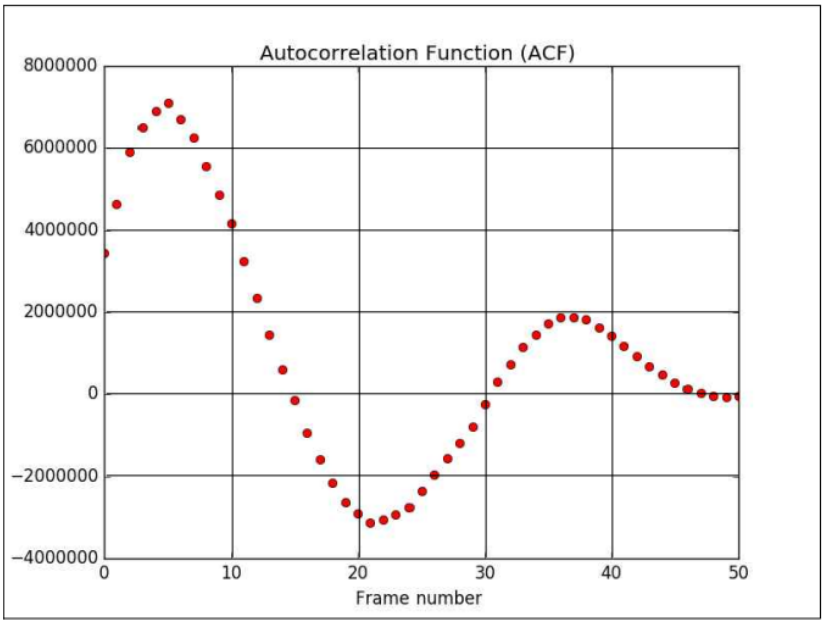


Figure 3.2 : Plot of the ACF computed from the video named ‘uvs080910-012.avi’.

3.3 Average Magnitude Difference Function

Two-dimensional image sequences containing fish tail beat movement can be modeled as periodic or quasiperiodic signal. Average Magnitude Difference Function (AMDF) which represents temporal difference between signal itself and its delayed version is analyzed for periodicity estimation. AMDF mostly used in the periodicity detection of 1D signals as well as in video analysis such as in the work of Gunay et al. [39] for detecting frequency of fire to remove artificial flashing lights. Calculation of AMDF for 1D discrete signal s(n) is presented in Equation 3.3:

$$F(l) = \sum_{n=1}^{N-l+1} |s(n+l-1) - s(n)|, \qquad l = 1,2,\dots,N \tag{3.3}$$

where N is the number of samples in s(n). Since our input is 2D cropped regions from video frames, single vector is formed from each region $\vec{s}(n)$ by concatenating all rows of input region. Then, AMDF calculation is done as follows:

$$F(l) = \sum_{n=1}^{N-l+1} |\vec{s}(n+l-1) - \vec{s}(n)|_1, \qquad l = 1,2,\dots,N \tag{3.4}$$

In Equation (6), L_1 norm is simply used to yield singular value for each magnitude in time sequences.

Maximum value among the second derivative of the AMDF magnitudes denotes the periodicity of the input signal as it can be seen in the calculation steps in the pseudocode of the AMDF which is given in Figure 3.3. AMDF data show periodic character for periodic inputs. Cut points of the AMDF provides information about the periodic intervals of the input signal. Second derivative of the AMDF is calculated since it has the highest values around the cut points.

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

Figure 3.3 : AMDF pseudocode

Temporal distribution of AMDF values computed from fish tail regions in cropped parts of test videos can be seen in Figure 3.4 and Figure 3.5. Importance of the accurate fish detection can be seen by comparing the Fig. 3.4 and Fig. 3.5, in which bad Intersection Over Union (IOU) ratio causes the distortion of the signal in Fig. 3.5.

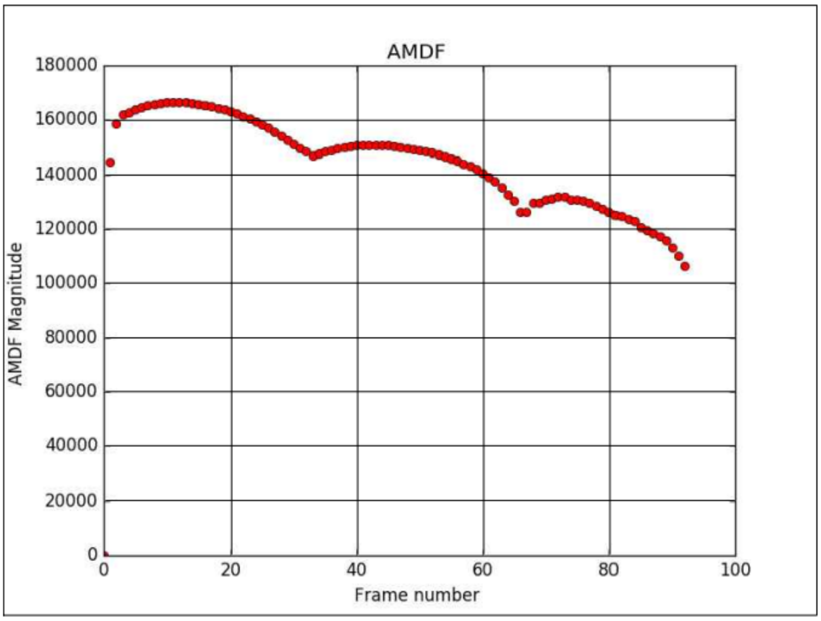


Figure 3.4 : Plot of average magnitudes of AMDF in fish tail regions.

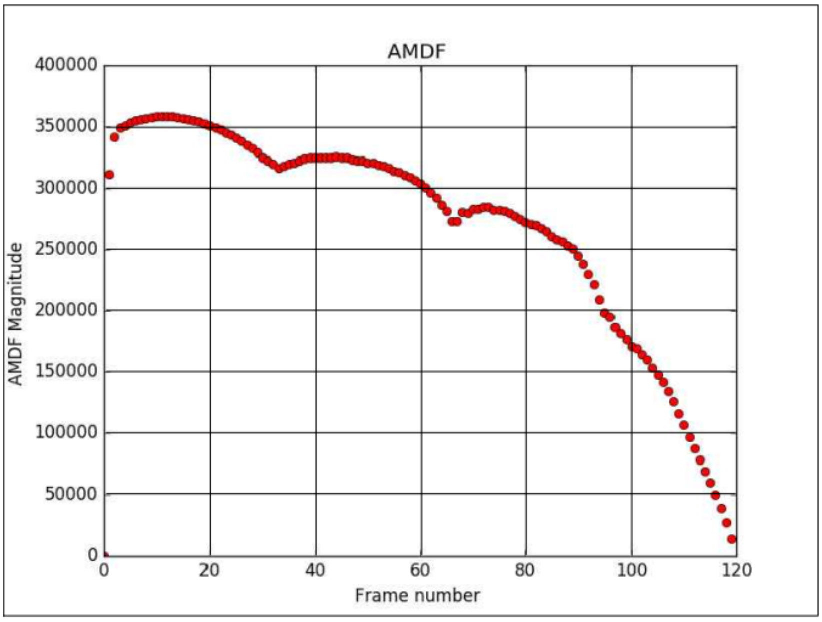


Figure 3.5 : Plot of average magnitudes of AMDF in fish tail regions. Periodic pattern is distorted at the end due to the partially falsely cropped region during the fish detection phase (See Figure 3.3 for comparison).

4. DATA COLLECTION AND EXPERIMENTS

4.1 Fish Detection

Experiments are performed in fish passage videos obtained from Kassel Lab, and from the field in İyidere small hydropower plant in Rize, Turkey [9]. To evaluate the performance of our system 250x250 cropped background regions are generated from the background fish passage objects and underwater images as a negative test set. Moreover, positive samples (fish regions) are extracted from the underwater fishway videos and labeled fish trajectories.

Train and test set sizes of the fish detection dataset are given in Table 4.1. The performance of ELM in different hidden node sizes and activation functions is evaluated. In the fish classification stage of the proposed fish detection framework, different ELM parameters are considered while conducting experiments. Increasing the number of hidden nodes seemed to saturate in certain range and after that it is getting worse in accuracy. The result of the proposed system is presented in Table 4.2.

Table 4.1 : Size of the train and test sets used in experiments.

Train		**Test**	
positive	**negative**	**positive**	**negative**
5437	**4850**	**607**	**539**

Table 4.2 : Result of the classification accuracy for different ELM parameters in purposed fish detection framework.

#Number of Hidden Nodes	**Accuracy (%)**	
	tanh	**sigmoid**
16	**75.0**	74.0
20	74.9	**78.1**
40	70.8	77.9
60	76.9	77.5
80	72.9	69.4
100	72.3	72.9
200	69.2	69.5

4.2 Fish Tail Beat Estimation

Experiments for evaluating tail beat periodicity estimation performance of the proposed AMDF method is performed. Tail regions are cropped from detected fish images in sequential frames of videos. Then, tail beat frequency is estimated as described in Section 3. Results obtained from evaluated fish passage videos are presented in Table 4.3. Real frequency values of the test videos are calculated by inspection. Results show that AMDF is promising method in estimation of fish tail beat frequency. While evaluating the performance of periodicity estimation, videos from the Lauder Laboratory is also used [41].

Several preliminary tests are performed on fish segmentation techniques discussed in Section 2, since false alarms in tail segments directly affect the success of the tail frequency detection. Therefore, manually collected fish segmentation masks are used 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, ground truths are collected from videos by inspection. Fish tail oscillation between the opposite end points from time t_0 to t_1 is shown in Figure 4.1.

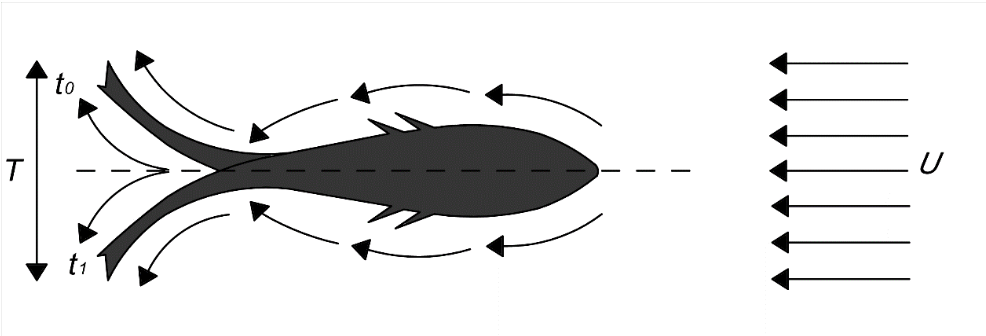


Figure 4.1 : View of fish tail periodicity calculation.

Tail beat periodicity is evaluated 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:

$$T = |t_1 - t_0| \tag{4.1}$$

$$f_{TB} = 1/2T \tag{4.2}$$

Firstly, tail beat periodicities are computed with proposed methods, and using sampling rate of video frequency is derived using equation 4.3, 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.

$$f_{TB} = fps/Fr_{interval} \tag{4.3}$$

Test results of detected frequencies in AMDF and ACF methods are given in Table 4.3. Among the test videos, 'rize1.mp4' video contains the lowest tail beat amplitude and highest tail beat frequency movements. Estimation in the lower tail amplitude movement is a harder case due to the weaker temporal difference in video sequences. It can be seen from the results of the 'rize1.mp4' video which has the lower accuracy for the both two methods compared to other samples. Temporal distribution of ACF and AMDF magnitudes computed from fish tail regions in video named 'troutfs.avi' can be seen in Fig. 3.1 and Fig. 3.2 respectively. 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 by means of the mean squared error is given in Table 4.4.

Table 4.3 : Result of the classification accuracy for different ELM parameters in purposed fish detection framework. Experimental results of the proposed fish tail beat frequency estimations techniques.

Videos	Troutfs.avi	rize1.mp4	uvs-012.avi
Frame Rate (fps)	30	60	25
#N 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 4.4 : Mean squared error of the AMDF and ACF techniques.

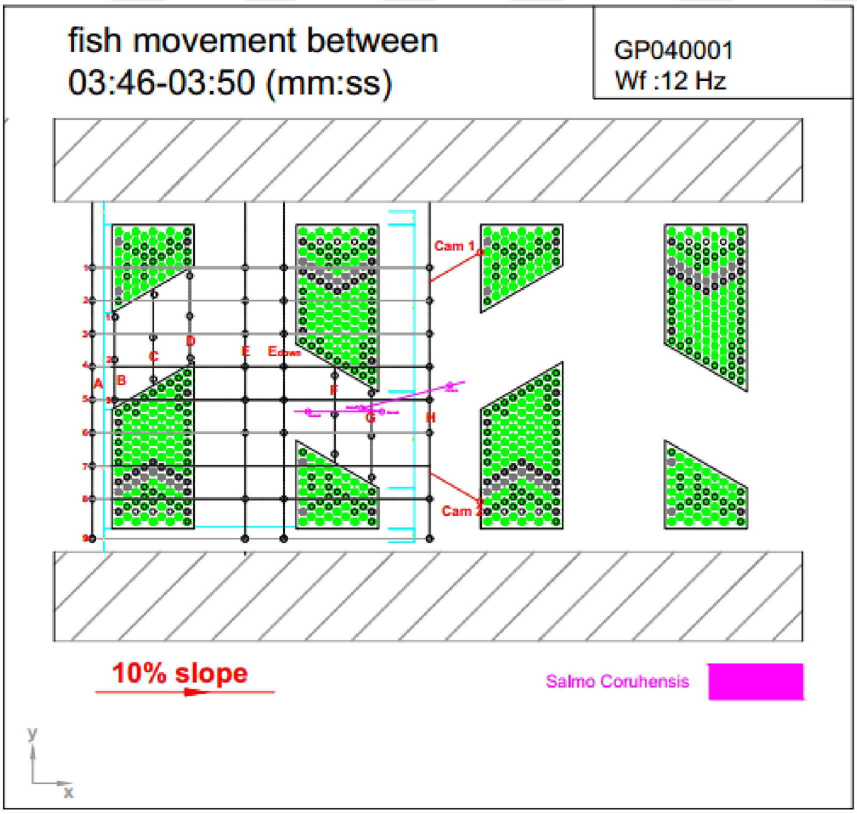
Method	**Total #N of Frames**	**MSE**
AMDF	1269	0.142
ACF	1269	0.086

4.3 Data Collection

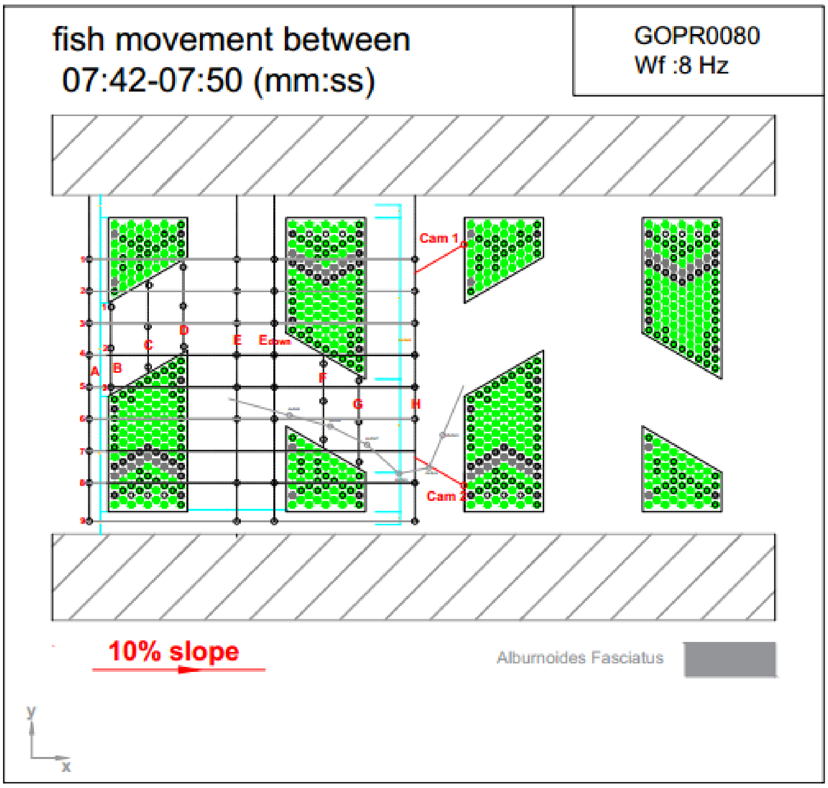
Fish trajectory data provide important information to understand behavior of a fish inside the fish pass. Fish trajectories are labelled manually from 12 different videos for data collection proposes in this thesis.

Three of the sample drawings from the labeled fish trajectories embedded in the plan of the fishway in İkizdere River are shown in Fig. 4.2. Top view of the brush fishway is given in Fig. 4.3-a, whereas fish resting areas and camera directions inside the fishway are shown in Fig 4.3-b. Brushes are drawn as green areas with dot circles whereas the walls are displayed as sloped lines inside a rectangle in the fishway plan in Figure 4.2 and Fig 4.3. All drawings in Fig. 4.2 and Fig. 4.3 are created as a schematic diagram by means of the well-known AutoCAD software.

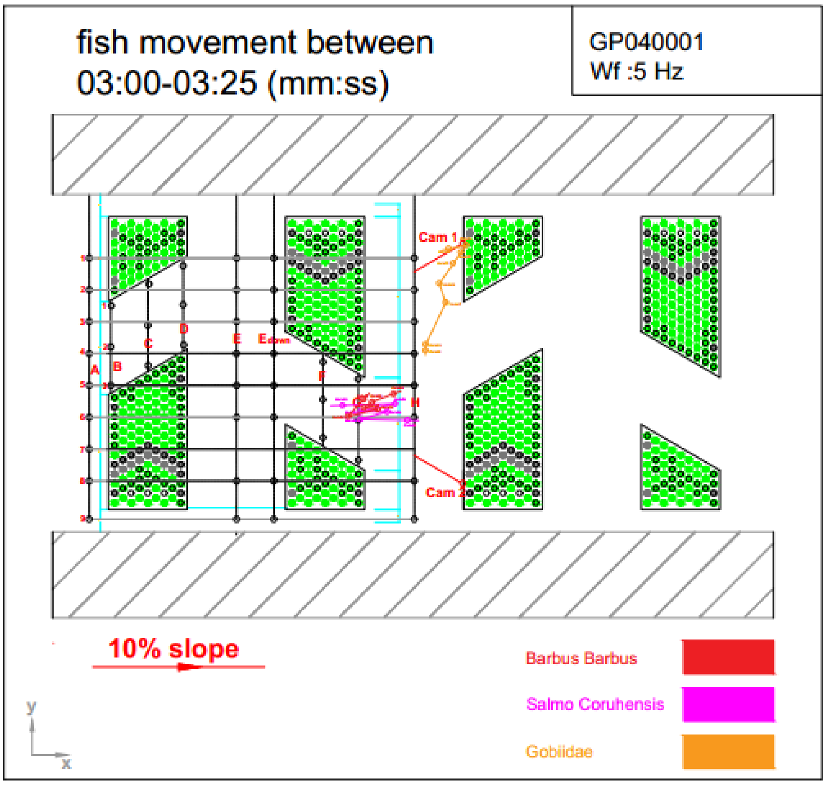
It is observed that fish use the back of the brush blocks, which is reduced velocity and turbulent kinetic energy region, as refuges without losing their motivations. Most of the fish pass through the porous blocks by following main flow region which is besides the small brush block (Fig. 4.2-a and 4.2-b). The fish trajectories are consistent with the Gao et al. (2016) observations that the during their migrations fishes tend to avoid regions in which the turbulent kinetic energy exceeds about 0.3 m2/s2, but rather prefer regions with turbulent kinetic energy (TKE) in the range from about 0.1 to 0.3 m2/s2 and use areas with the lowest energy levels, i.e. TKE < 0.1 m2/s2 as resting regions [9], [50].



(a)



(b)

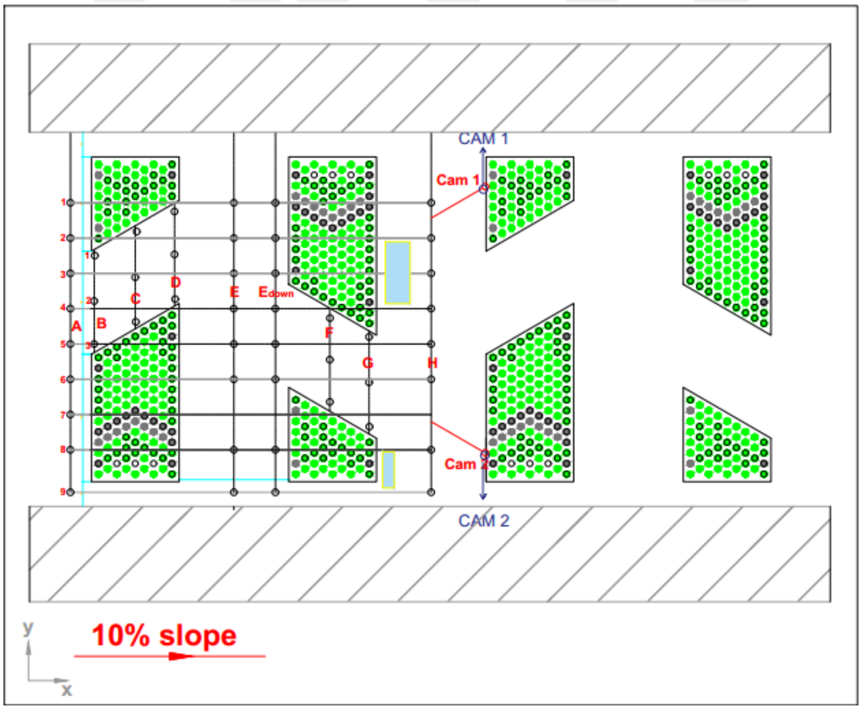


(c)

Figure 4.2 : Fish trajectory drawings for the species *Salmo coruhensis* (a) in the video named 'GP04001.mp4', *Alburnoides fasciatus* (b) in the video named 'GOPR0080.mp4', and *Barbus Barbus*, *Salmo coruhensis*, *Gobildae*, (c) respectively.

Particularly, Fig. 4.3-a consists of the actual top view image of the fishway, and Fig. 4.3-b contains the top view shematic diagram of the same fishway. Flow patterns (S flow) in the diagonal brush fish pass can also be seen from the Fig. 4.3-a.

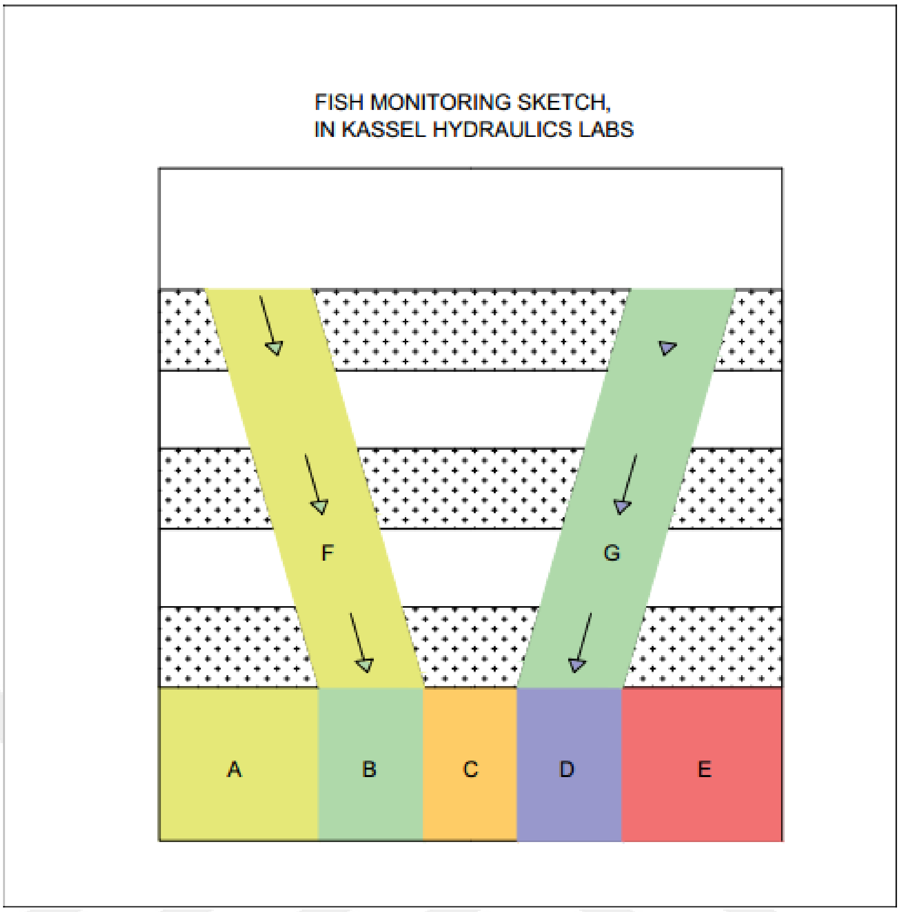
(a)



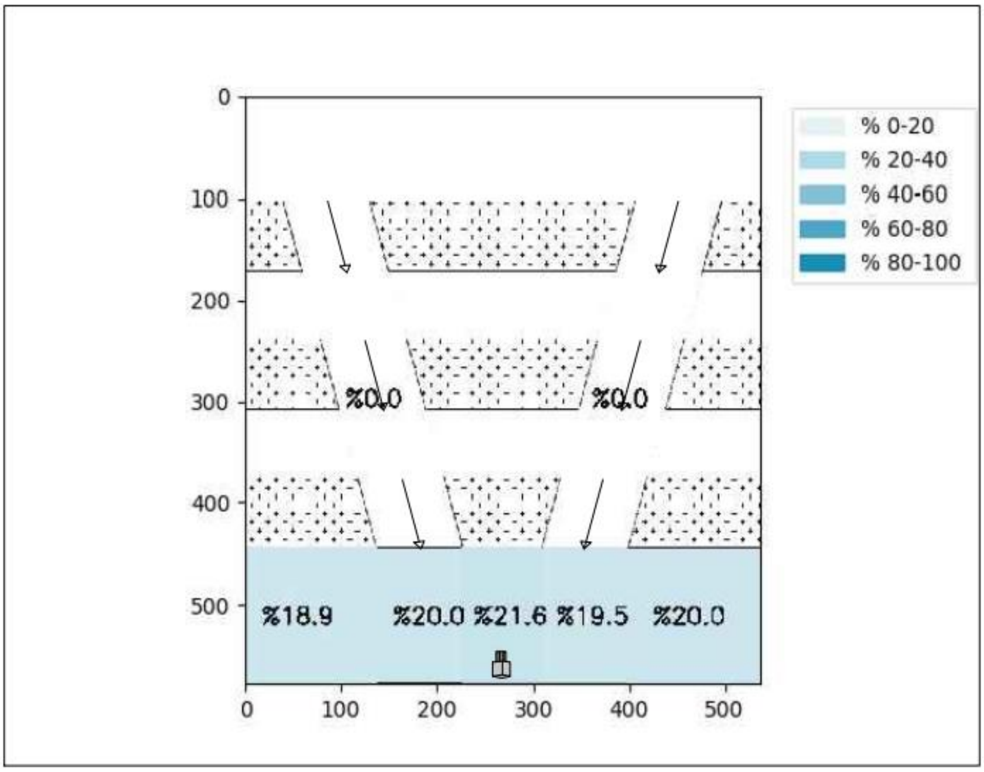
(b)

Figure 4.3 : View of the fishway from the top (a) and AutoCAD drawing of the fishway plan (b) in which camera directions (red lines) and fish resting area (blue rectangles) are displayed.

During the data collection stage, fish presence heatmap is generated simultaneously while the labelling of the fish regions of the underwater images of the videos acquired from inside of the prototype fish passages in the Kassel laboratory [37] (See Figure 4.4).


FISH MONITORING SKETCH,
IN KASSEL HYDRAULICS LABS
F
G
A
B
C
D
E

(a)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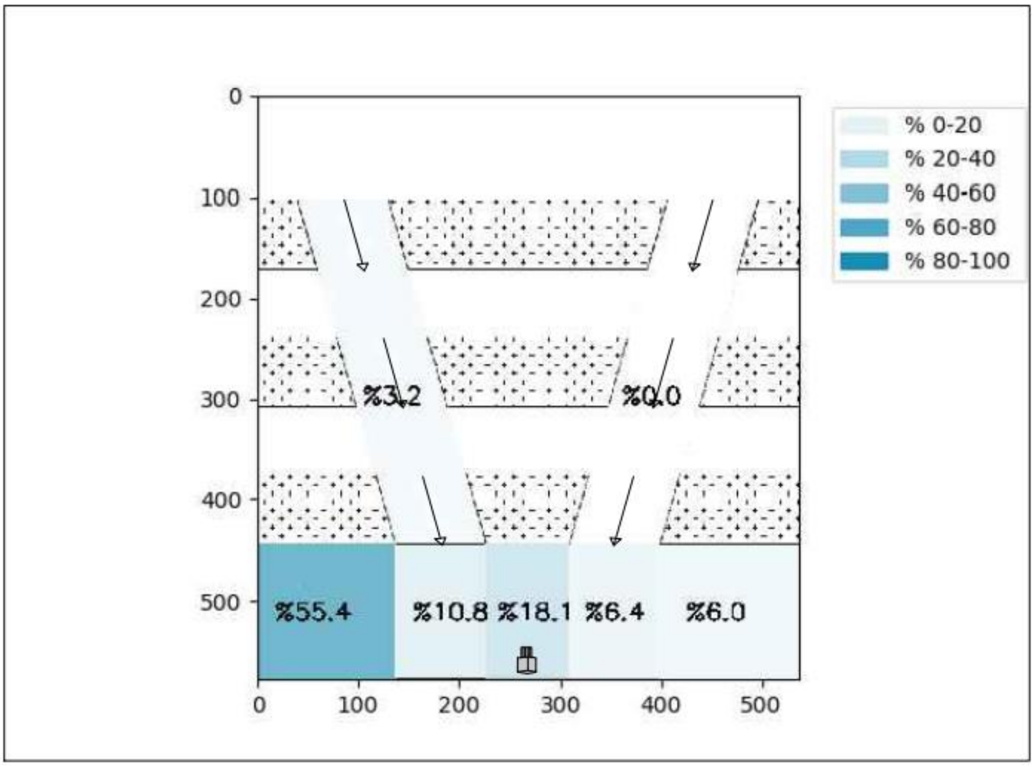
%0.0
%0.0
%18.9
%20.0
%21.6
%19.5
%20.0
% 0-20
% 20-40
% 40-60
% 60-80
% 80-100

(b)



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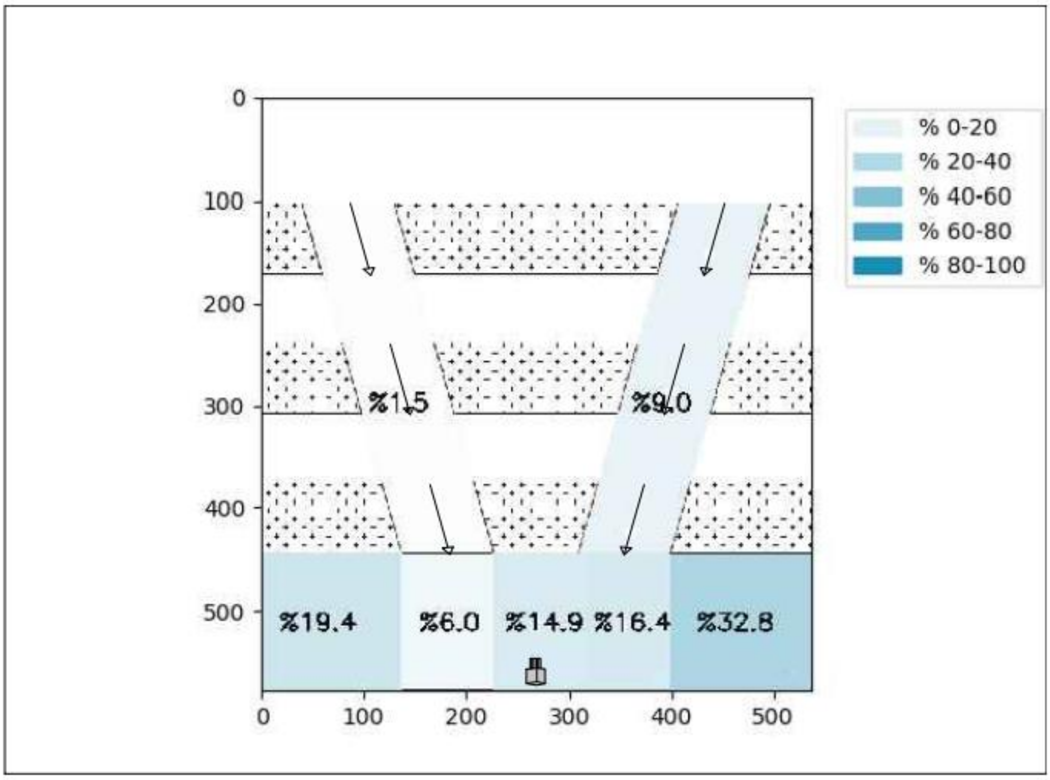
% 0-20
% 20-40
% 40-60
% 60-80
% 80-100
%3.2
%0.0
%55.4
%10.8
%18.1
%6.4
%6.0

(c)



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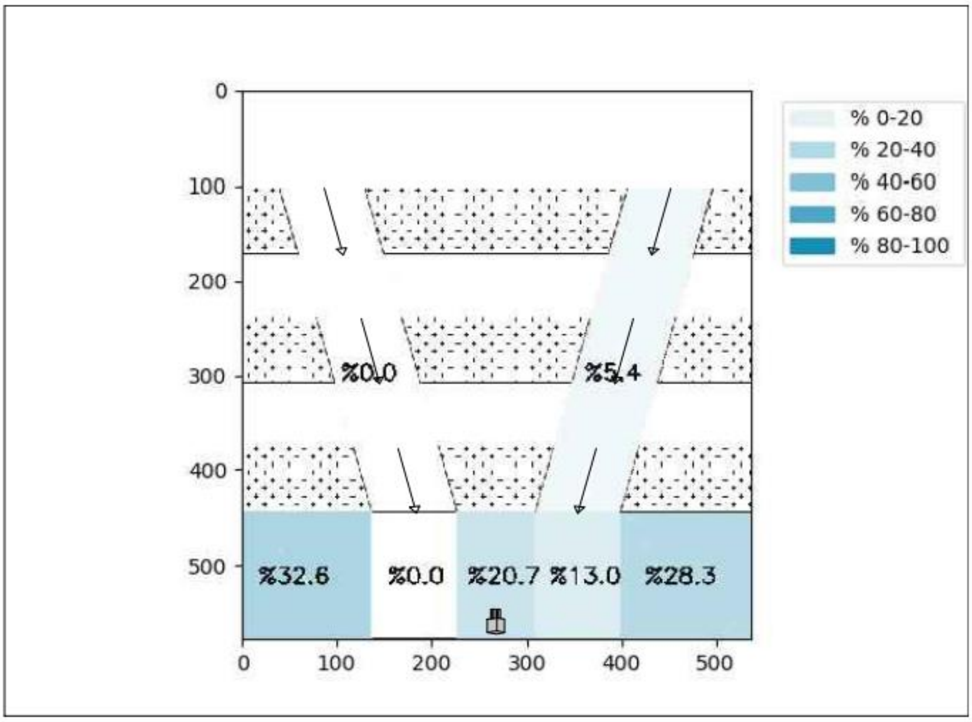
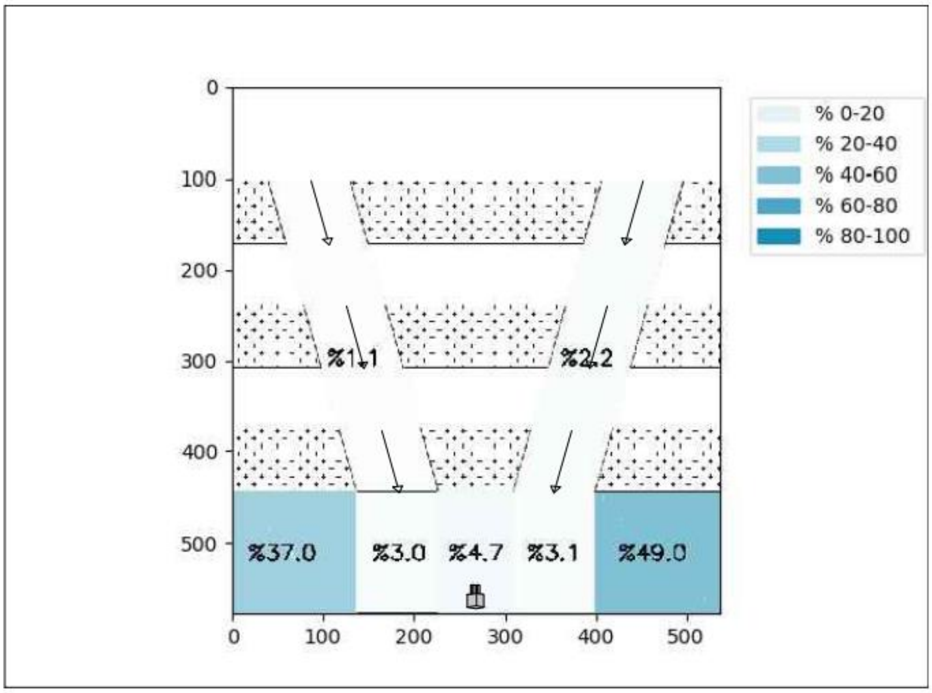
% 0-20
% 20-40
% 40-60
% 60-80
% 80-100
%1.5
%9.0
%19.4
%6.0
%14.9
%16.4
%32.8

(d)



(e)



(f)

Figure 4.4 : Fish heatmap data, generated in the data collection process, indicates the fish presence intensities according to regions: (a) heatmap regions, (b) heatmap graph of the video named 'uvs080910-047.avi', (c) heatmap graph of the video named 'uvs080910-048.avi', (d) heatmap graph of the 'uvs080910-050.avi', (e) heatmap graph of the video named 'uvs080910-052.avi', (f) heatmap graph of the video named 'uvs080910-055.avi'.

Intensity map of the fish presence is measured in terms of the normalized *fish times second* unit. So, one fish belonging in some region for a one second is considered to have an intensity of one fish-second. Only seven regions shown in Fig. 4.4-a, which are A, B, C, D, E, F, and G, namely, are considered in the data collection process. For each region R_i, calculation is done as:

$$R_i = \sum_{t=0}^{T} N_{fish} \tag{4.4}$$

Where N_{fish} is the number of fish inside the region R_i at frame t and T is the total number of frames in a video. Then, each region R_i is normalized as:

$$R_i = \frac{R_i}{\sum_{j=0}^{7} R_j} \tag{4.5}$$

60 fps GoPro camera is deployed in underwater during the field experiments. Some of the acquired images are selected to use for data collection and to generate fish detection dataset. Some of the original images and their manually labelled masks from the dataset can be seen in Fig. 4.5.

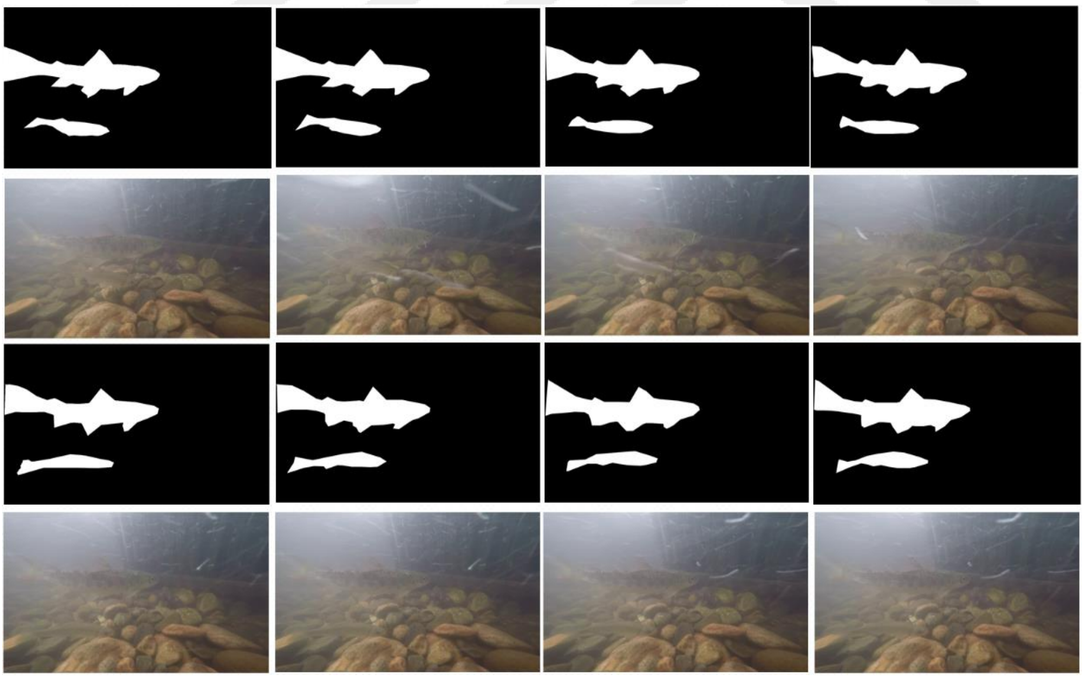


Figure 4.5 : Some of the labelled fish mask images from the video named 'GOPR0005.MP4', acquired from the camera inside the fish pass (İkizdere River).

Also, fish tail regions are cropped manually in order to create fish tail dataset. Sample fish tail images and their masks are shown in Fig. 4.6. Fish tail mask images are beneficial while conducting experiments on fish tail beat estimation, since they provide pure evaluation of the proposed fish tail beat estimation techniques on ground truth not bothered with the case of the imperfect fish segmentation.

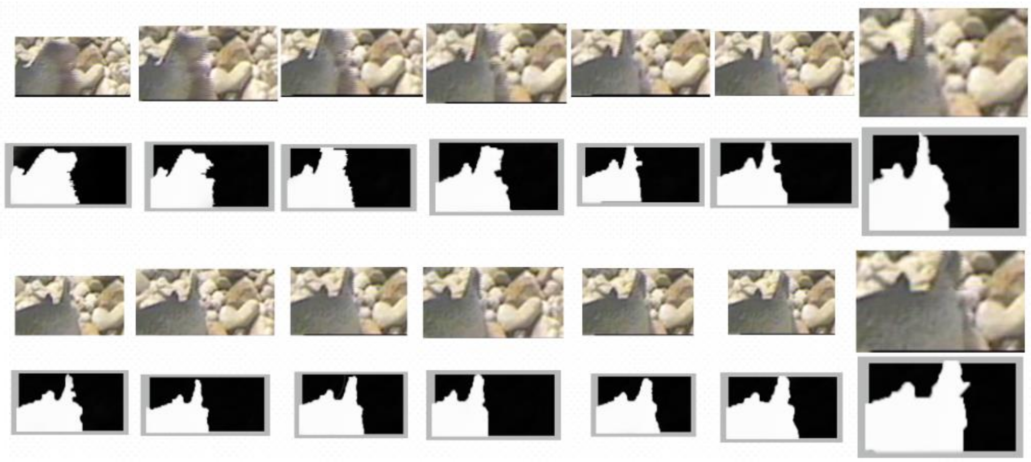


Figure 4.6 : Some of the labelled fish tail mask images from the video named ‘uvs080910-012.avi, acquired from the brush fishway model in Kassel Lab.

5. CONCLUSIONS AND RECOMMENDATIONS

In this thesis, computer vision and signal processing based new analysis tools and techniques are proposed and investigated for fishway evaluation. Efficient fishway design has become increasingly important with the growing human activity at global scale in riverine environments. Lack of adequate data and tools for identifying biological, hydraulic, and other physical parameters is the main challenge in fish passage design.

Fish energy expenditure and fish behavior is crucial in order to evaluate fish pass structures. For this purpose, a computer vision based approach for fish movement analysis is proposed in this thesis. Also, image analysis based methods are proposed for fish tail beat frequency estimation.

Fish trajectories and fish presence maps are obtained during the dataset creation and data collection process which involves the studies both in a controlled environment and the field. The field measurements reveal that a wide spectrum of different flow characteristics is provided in diagonal brush fish pass. There are several migration corridors with different hydraulic conditions and they continue through the complete fish pass. The cleverness of the fish is used to seek the convenient corridors and to avoid zones not suitable for their migration preferences. So, once a fish has selected a migration corridor, it can be sure that the hydraulic situation does not change along this corridor.

The proposed fish detection framework is tested on a test set that includes challenging underwater images having haze, low contrast, color distortion and moving background objects. In candidate region detection stage of the fish detection framework, moving objects are detected by means of the BS techniques. ViBe method has advantage in fast background initialization, adaptation to illumination changes and noise resistance when considering the Adaptive GMM and frame differencing techniques. Adaptive GMM method is better at detecting objects having similar color range to the background, but more noisy result is obtained in Adaptive GMM comparing to ViBe method. Frame differencing technique has shortcomings in highly dynamic scenes.

Low miss rate in detections was the major factor for using ViBe algorithm in the candidate region detection stage. In the fish classification stage of the proposed fish detection framework, different ELM parameters are considered in training. When considering severe environmental changes such as variations in water turbidity and moving background objects due to high flow speed inside fish passage, results obtained from the proposed framework seems promising.

The other contribution on this thesis is the proposed fish tail beat frequency estimation techniques. To the best of my knowledge, this study is the first work in the literature that proposes signal processing based techniques that extract the fish tail beat frequency from video frames automatically. Fish tail beat frequency is a significant parameter that is used in the calculation of Strouhal number of fish. Since fish tail beat frequency is an indicator of fish energy expenditure and other important biological and physical parameters of fish, the measuring fish tail beat frequency is crucial in the evaluation of the fish passage efficiency. Experiments suggest that proposed image processing based fish tail beat frequency estimation approach may be utilized for fish passage analysis. One important advantage of the proposed image analysis based techniques is that they don't require physical interaction with fish, and have not any effect on the movement of fish. Results shows that this work can be further extended to replace other tail beat estimation techniques used in fishway measurements.

The proposed framework is tested both in a lab environment and in the field. Results show that the proposed system can be useful for fish passage analysis. Results also indicate that such a solution would be useful for quantifying fish movement related with the flow field. This will pave the way for a deeper understanding of how fish process and use the flow information.

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PUBLICATIONS/PRESENTATIONS ON THE THESIS

- **Yıldırım, Y.**, Toreyin, B.U., and Kucukali, S., Verep B., Turan D., Alp A., Image Analysis Based Fish Tail Beat Frequency Estimation for Fishway Efficiency. *European Signal Processing Conference, 2018 26th European*. Accepted, Rome, Italy.
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