TECHNICAL SOLUTIONS FOR BIOMASS ESTIMATION ACCORDING TO THE CONCEPT OF AQUACULTURE 4.0
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SOLUȚII TEHNICE PENTRU ESTIMAREA BIOMASEI CONFORM CONCEPTULUI DE ACVACULTURĂ 4.0

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ABSTRACT
Aquaculture, as a dynamic field, undergoes continuous evolution requiring continuous improvements in efficiency and new research efforts. Estimating fish biomass is an essential practice in the field of precision aquaculture, obtaining periodic information on fish biomass has been identified as an urgent need, considering the objective of optimizing daily feeding, controlling fish density and finally determining the optimal timing of harvesting. Conventional weighing methods, which often rely on manual procedures, have inherent challenges. Manual weighing processes are labor-intensive, requiring substantial time and human resources. Furthermore, manual handling of fish during weighing procedures induces considerable stress on aquatic organisms, potentially compromising their health and welfare. Consequently, there is a pressing need in the aquaculture industry to explore alternative weighing techniques that alleviate stress levels while increasing operational efficiency. In response to these challenges, contemporary research efforts have increasingly focused on the development of noninvasive and automated weighing methodologies. These innovations aim to simplify the weighing process, minimize human intervention and reduce the level of stress experienced by the fish population. However, estimating fish biomass without human intervention presents significant challenges because fish are sensitive and move freely in an environment where visibility, lighting, and stability are difficult to control. The paper analyzes technological solutions for biomass estimation according to the concept of Aquaculture 4.0.

REZUMAT
Acvacultura, ca domeniu dinamic, suferă o evoluție continuă, necesitând îmbunătățiri continue ale eficienței și eforturi noi de cercetare. Estimarea biomasei piscicole este o practică esențială în domeniul acvaculturii de precizie, obținerea de informații periodice asupra biomasei piscicole a fost identificată ca o necesitate urgentă, având în vedere obiectivul de optimizare a hrănirii zilnice, controlul densității peștilor și, în final, determinarea momentului optim de recoltare. Metodele convenționale de cântărire, care se bazează adesea pe proceduri manuale, prezintă provocări inerente. Procesele manuale de cântărire necesită multă muncă, necesită timp și resurse umane substanțiale. Mai mult, manipularea manuală a peștilor în timpul procedurilor de cântărire induce un stres considerabil asupra organismelor acvatice, putând compromite sănătatea și bunăstarea acestora. În consecință, există o nevoie presantă în industria acvaculturii de a explora tehnici alternative de cântărire care atenuează nivelurile de stres, sporind în același timp eficiența operațională. Ca răspuns la aceste provocări, eforturile de cercetare contemporane s-au concentrat din ce în ce mai mult pe dezvoltarea metodologiilor de cântărire neinvazive și automate. Aceste inovații urmăresc să simplifice procesul de cântărire, să minimizeze intervenția umană și să reducă nivelul de stres experimentat de populația de pești. Cu toate acestea, estimarea biomasei de pești fără intervenția umană prezintă provocări semnificative, deoarece peștii sunt sensibili și se mișcă liber într-un mediu în care vizibilitatea, iluminarea și stabilitatea sunt greu de controlat. Lucrarea discută soluții tehnologice pentru estimarea biomasei conform conceptului de Acvacultură 4.0.

INTRODUCTION
Aquaculture consists of a set of activities, knowledge and techniques for growing plants and some species of aquatic animals, having a particular importance in economic development and food production.

Aquaculture is experiencing rapid growth globally, driven by two significant factors: the persistent increase in demand for seafood and the depletion of fish stocks in the world's oceans. This surge in aquaculture activity underscores the urgent need for sustainable practices to avoid the pitfalls encountered in the history of European agriculture and fisheries sectors. (*FAO, 2018; Paolacci et al., 2022; Varadi et al., 2009).*

To date, traditional methodologies for estimating fish biomass have predominantly relied on manual sampling techniques. However, these approaches are frequently invasive, time-consuming, and require substantial human resources. Consequently, there exists a compelling and pressing necessity to devise noninvasive, swift, and cost-effective alternatives for this estimation process. Emerging technologies such as Machine Vision, acoustics, ambient DNA, among others, offer promising avenues for the creation of non-intrusive, expedited, and economically viable methods to estimate fish biomass in real-world scenarios (*Henriksson et al., 2021; Orduna et al., 2023; Berckmans, 2017; Yule et al., 2013; Cowley and Whitfield, 2002*).

Experimental research has underscored the pivotal role of information technologies, particularly advanced sensors and communication technologies, in expediting the evolution of new tools and methodologies aimed at enhancing the efficiency of fish biomass estimation. Nonetheless, as the demands of intensive aquaculture continue to escalate, there arises a compelling need to enhance not only the accuracy but also the intelligence level of these methodologies. In this context, fostering close collaboration between fisheries experts and engineers emerges as a fundamental approach to refining the accuracy and intelligence level of fish biomass estimation methods, as delineated by the aforementioned technologies (*Alver et al., 2005; Harvey et L., 2001; Li et al., 2019 ; Davison et al., 2015 ; Hicks et al., 2015; Marks and Klomp, 2003*).

Fish biomass, a fundamental metric in aquatic industries and fisheries management, represents the total weight of fish within a given water area. It serves as a crucial indicator for assessing the health and productivity of aquatic ecosystems, informing aquaculture practices, and guiding fisheries management decisions. The estimation of fish biomass relies on quantitative methods that integrate population counts with average weight measurements, offering valuable insights into fish populations' size, structure, and dynamics (*Johnston et al., 2023; Mihneva et al., 2023; Debroy and Seban, 2022; Cowx, 1983; Doi et al., 2015*).

Fish biomass estimation is a critical component of current aquaculture methods, covering the rigorous measurement of counting, weight, and length from the time of fry introduction until the final sale of fish. Fish biomass is a reliable metric that provides valuable information about both fish and the environment. However, calculating biomass in highly populated and protected aquatic habitats is an unavoidable and daunting challenge in modern aquaculture undertakings (*Abinaya et al., 2022; Bjerkeng et al., 1991; Proud et al., 2019; Lee et al, 2012; Shepard et al., 2015; Emmrich et al., 2012; Ríha et al., 2023; Zhang and Megrey, 2010).*

Fish biomass measurement serves as a cornerstone for evaluating recruitment rates and discerning the impacts of both fisheries management practices and environmental variables on marine systems. The dynamic nature of biomass is evident through its temporal variability, which can undergo substantial fluctuations over relatively short periods. Notably, analyses conducted by Assessment Working Groups (AWGs) under the purview of the International Council for the Exploration of the Sea (ICES) reveal significant shifts in the biomass of key species. Over the past two decades, the biomass of herring has exhibited a variation factor of 1.4, while for sprat and cod, this factor stands at 4.4, underscoring the dynamic nature of fish stocks. Nevertheless, when considering the broader context of long-term ecosystem dynamics, a mere 20-year interval appears minuscule. Climatic trends, pivotal in shaping marine environments, operate across temporal scales spanning centuries. Thus, to unravel the underlying causes of fluctuations in fish stocks, biomass estimates encompassing more extensive temporal frameworks are imperative. In this regard, extending the analysis horizon beyond short-term fluctuations becomes essential for elucidating the intricate interplay between environmental factors and the sustainability of marine ecosystems (*Thurow, 1997; Wilson et al., 2018; Chen and Andrew, 1998; Ault et al., 2018; St. John et al., 1990; Block et al., 2019; Yin et al., 2022; Lopez et al., 2016; Yulianto et al., 2015; Bianchi et al., 2021; Hossain et al., 2018; Lian et al., 2018*).

Understanding the distribution patterns of species stands as a fundamental aspect in unraveling their ecological dynamics and assessing the risks of extinction, thereby informing conservation efforts aimed at safeguarding populations. However, obtaining precise estimates of species distribution poses a significant challenge, particularly in environments characterized by intricate microhabitat topography and dense vegetation, as commonly encountered in aquatic systems. In recent years, the emergence of environmental DNA (eDNA) analysis has revolutionized the documentation of aquatic vertebrate species distributions. By detecting minute, species-specific DNA fragments suspended in the water column, eDNA offers a promising avenue to enhance the accuracy and cost-effectiveness of distribution surveys while facilitating the detection of rare or invasive species. Noteworthy examples include the utilization of eDNA techniques to confirm the presence of bullfrog tadpoles, silver and bighead carp, as well as various frog and salamander species across diverse aquatic habitats. The application of eDNA methodologies not only broadens our understanding of species distributions but also presents a powerful tool for informing conservation strategies and ecosystem management practices in aquatic environments (*Takahara et al., 2012; Wanghe et al., 2024; Kindong et al., 2020; Murakami et al., 2020; Radinger et al, 2023; Doi et al., 2017; Kim et al., 2018*).

Fish biomass estimation without human involvement presents considerable issues since they are sensitive and move freely in an environment with challenging control over sight, lighting, and stability. The paper analyzes technological solutions for biomass estimation according to the concept of Aquaculture 4.0.

MATERIALS AND METHODS

In prevailing biomass estimation methodologies, routine sampling is conducted to determine the average weight of fish inhabiting ponds, while the quantity of extant fish is typically ascertained through a comparative analysis between the initial population count and the number of deceased fish. Hence, the estimation of fish biomass involves the multiplication of the average weight by this quantity. Nevertheless, manual sampling methodologies pose risks of physical harm or significant stress to fish, thereby impacting their well-being and developmental trajectory. Moreover, manual sampling processes typically entail substantial time investments and are associated with a labor error margin ranging between 15-25%, thereby presenting challenges in accurately gauging fish weight via noninvasive means. Additionally, while the enumeration of individuals under ordinary circumstances is feasible, quantification becomes problematic in scenarios of extensive mortality, theft, or predation incidents. The translation of recorded daily feed intake into fish biomass through the feed conversion ratio (FCR) may lack sufficient precision. Consequently, there is an imperative to adopt noninvasive, expeditious, and cost-effective approaches for fish biomass estimation to address the intensive demands prevalent in aquaculture operations (*Li et al, 2019; Mahon, 1990*).

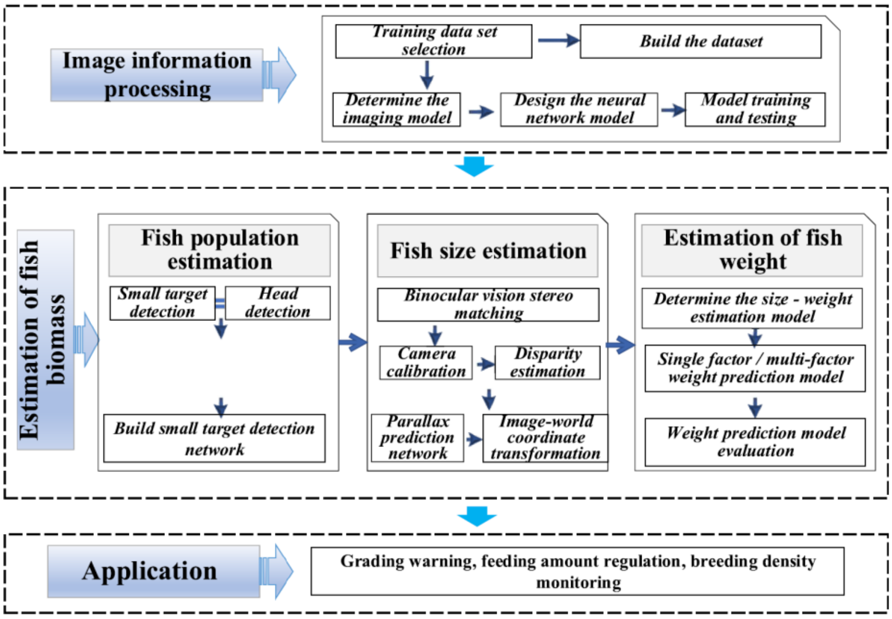


Fig. 1 - Stages of vision-based biomass estimation (*Li et al, 2019*)

Fish mass estimation holds paramount significance for farmers as it furnishes crucial fish biomass information essential for optimizing daily feeding practices, controlling stocking densities, and determining the optimal harvest time. However, the mass of fish tail fins contributes negligibly to the total body mass. Moreover, the tail fins of free-swimming fish commonly exhibit deformities or bending, thereby introducing measurement errors and consequently impairing the accuracy of mass predictions by computer vision systems. To address this challenge, a novel non-supervised method for fish tail fin removal has been proposed to enhance the development of mass prediction models based on ventral geometrical features sans the tail fin. Initially, the automated removal of fish tail fins was achieved through the utilization of the Cartesian coordinate system coupled with image processing techniques. Subsequently, distinct features were extracted from fish images both with and without the tail fin. Finally, the correlational relationship between fish mass and the extracted features was evaluated using Partial Least Square (PLS) analysis. In this study, tail fins were systematically eliminated, and the mass estimation model based on area and area square exhibited superior performance on the test dataset, yielding a high coefficient of determination (R^2) of 0.991, a root mean square error (RMSE) of 7.10 g, a mean absolute error (MAE) of 5.36 g, and a maximum relative error (MaxRE) of 8.46% *(Hao et al., 2022*).

Length serves as a fundamental metric in the realm of aquaculture engineering, providing crucial insights into fish growth and facilitating effective monitoring protocols. In the intricate process of fish breeding, the segregation of fish based on size is imperative to optimize growth conditions and ensure favorable developmental trajectories. Furthermore, as fish reach maturity, size-based grading becomes essential to align with market demands and enhance economic value. The size of fish within breeding ponds not only serves as a barometer for growth monitoring but also aids in predicting factors such as sex and age, pivotal for management practices. Fish quality, intrinsically linked to size, underscores the significance of accurate length measurements in assessing overall product value. Traditional manual measurement techniques, however, pose inherent challenges, including the risk of fish injury or mortality and susceptibility to subjective biases. Addressing these limitations, machine vision systems emerge as a transformative solution, offering rapid, precise, non-invasive, and cost-effective approaches to fish length determination. In aquatic environments, where fish are in constant motion, acquiring accurate size measurements without physical contact presents unique challenges. Machine vision systems surmount these obstacles, providing a viable means to capture fish length data in real-time, thus revolutionizing size assessment methodologies in aquaculture settings. By harnessing advanced technology, the integration of machine vision systems heralds a new era of efficiency and accuracy in fish length measurement, facilitating informed decision-making and optimizing aquaculture practices (*Bravata et al., 2020; Dutta et al., 2016; Sture et al., 2016; Zhou et al, 2023*).

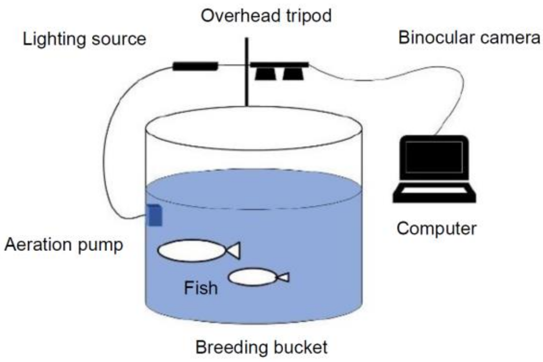


Fig. 2 - Experimental stand scheme (*Zhou et al, 2023*)

Utilizing binocular cameras equipped to capture both RGB and depth images, the acquisition of RGB-D data from fish specimens was facilitated, laying the groundwork for comprehensive analysis. Subsequently, the RGB images undergo selective segmentation employing the contrast-adaptive Grab Cut algorithm, thereby delineating distinct features and enhancing accuracy in subsequent processing stages. To discern the structural state of the fish, a skeleton extraction algorithm was deployed, designed to accommodate specimens with intricate, curved anatomies. Addressing inherent challenges associated with underwater imaging, the study meticulously analyzed and corrected errors stemming from water refraction, ensuring fidelity in measurement outcomes. Leveraging the RGB image data, optimal measurement points were identified and converted into precise 3D spatial coordinates, thereby facilitating accurate determination of fish length. The experimental results showed that the mean relative percentage error for fish length measurement was 0.9% (*Zhou et al, 2023*).

Employing advanced computer vision image processing techniques, an optimal model was developed to accurately evaluate the body weight of Asian sea bass, both with and without fins. Over the course of one month, image data of 25 randomly selected fish were systematically collected on a weekly basis. Subsequently, the collected data underwent a meticulous partitioning process, wherein a 40-60% split-test was employed. Specifically, 40% of the data, comprising 10 fish (100 images), served as training data, while the remaining 60% (15 fish; 150 images) constituted the out-samples or validation dataset. To initiate the experimental phase, a total of one hundred Asian sea bass, averaging 30 g in weight, were procured from a private fish farm and housed in two 1,000-L fiberglass tanks, accommodating 50 fish per tank. The fish were subjected to a carefully regulated feeding regimen, receiving floating pellet feed with a minimum protein content of 35% twice daily (at 0800 h and 1700 h) until satiation. A flow-through water system was employed to maintain optimal environmental conditions within the tanks, ensuring the well-being of the fish. Each tank was equipped with three air stones to facilitate adequate oxygenation, while water quality parameters including dissolved oxygen (DO), water temperature, pH, total ammonia-nitrogen (TAN), and nitrite-nitrogen (NO_2-N) were monitored and maintained within recommended ranges. Specifically, dissolved oxygen levels, water temperature, pH, total ammonia-nitrogen, and nitrite-nitrogen were maintained above 4 mg/L, within the range of 26 - 32 degrees Celsius, within 7.5 - 8.5, less than 1 mg/L, and less than 1 mg/L, respectively. To ensure the acclimation of the fish to their new environment, feeding and monitoring protocols were rigorously implemented until the average fish weight reached the desired range of 80 to 100 g, signifying readiness for subsequent experimental procedures (*Jongjaraunsuk and Taparhudee, 2021*).

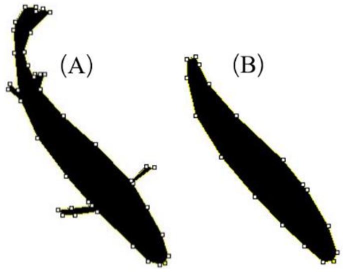


Fig. 3 - Experimental fish image (*Jongjaraunsuk and Taparhudee, 2021*)
A - with fins; B - without fins

The comparative analysis of results derived from the whole-body images and those excluding fins was conducted utilizing various statistical metrics. Specifically, the average coefficient of determination obtained from the validation dataset, comprised of 15 fish (150 images) per test ($N_{150}R^2$), and the coefficient of determination derived from the comprehensive validation dataset, consisting of 60 fish (600 images) from all tests ($N_{600}R^2$), were scrutinized using mathematical models such as RMSE (Root Mean Square Error), MAE (Mean Absolute Error), MARE (Mean Absolute Relative Error), MXAE (Maximum Absolute Error), and MXRE (Maximum Relative Error). To evaluate the significance of the mean difference between the datasets, an independent sample T-test was performed at a 95% confidence level. Statistical analysis was executed using the IBM SPSS Statistics Base 24.0 software suite for Windows, facilitating robust and comprehensive examination of the data (*Jongjaraunsuk and Taparhudee, 2021*).

Previous research has underscored the efficacy of linear mathematical models in predicting fish weight with greater accuracy and fewer errors compared to power or polynomial models. This finding has been demonstrated across various species including grey mullet (Mugill cephalus), St. Peter's fish (Sarotherodon galilaeus), common carp (Cyprinus carpio), and jade perch (Scortum barcoo). However, for large fish with an average size exceeding 1,000 g under aquaculture conditions, exploring alternative mathematical models may be warranted. For instance, in the case of sea bass ranging from 250 to 2.800 g, the utilization of a power model has been proposed in previous studies (*Konovalov et al., 2018; Viazzi et al., 2015; Zion 2012*).

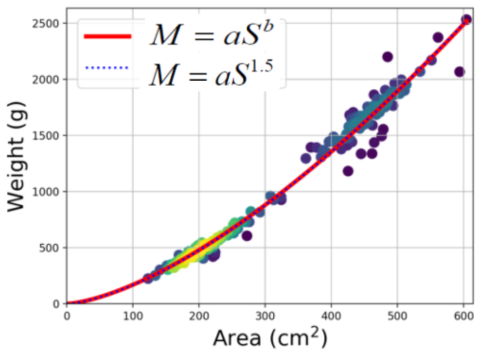


Fig. 4 - Correlation of measured fish weight (g) and manually segmented fish body image area (cm^2)
(*Konovalov et al., 2018*)

Nevertheless, when comparing image formats encompassing fish with and without fins, linear modeling has been deemed sufficient in capturing the variability in fish weight accurately.

Acoustic systems, such as echo sonars or multibeam sonars, offer distinct advantages over optical methods in underwater environments. Unlike optical systems, which rely on reflected light and are subject to limitations in light level and visibility, acoustic systems produce images based on reflected sound. The emergence of high-frequency multibeam sonars, often referred to as "acoustic cameras," represents a relatively recent technological innovation initially employed for structural surveillance and inspection in marine environments. In a study conducted off the coast of French Guiana, a BlueView P900-130 acoustic camera was deployed in rocky marine habitats to assess the total abundance, size structure, and spatial distribution of a demersal fish population. The study evaluated the relevance of utilizing an acoustic camera for achieving these objectives by comparing acoustic data with those obtained from traditional fishing surveys (*Artero et al., 2021; Braga et al., 2022; Graham et al., 2004; Kim et al., 2005*).

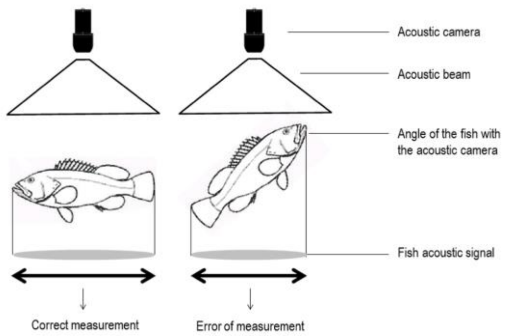
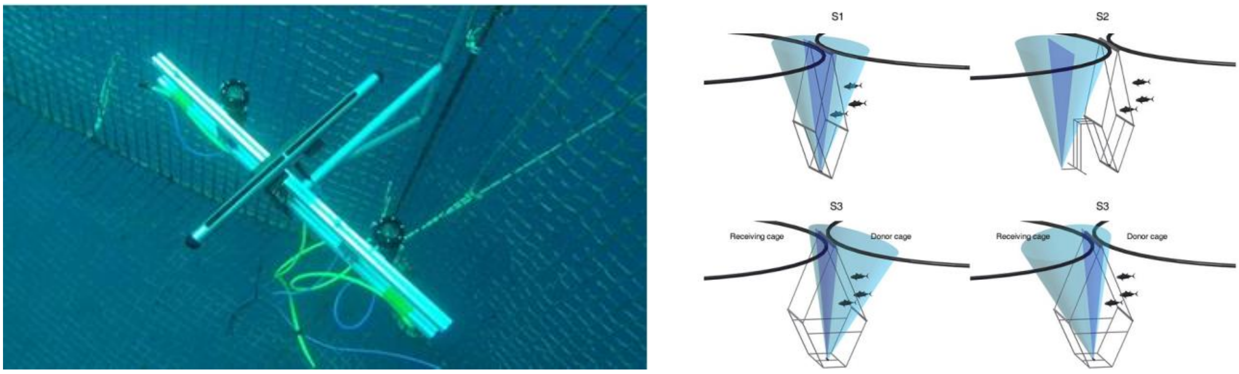


Fig. 5 - Scheme for fish measurement error using an acoustic camera (*Artero et al., 2021*)

Acoustic and computer vision techniques converge to pioneer an automated process for estimating the biomass of tuna during transfers. This innovative approach integrates a side scan sonar operating at 200 kHz and a stereo camera strategically positioned to capture the ventral perspective of the fish. These instruments serve as the primary acquisition equipment, meticulously designed to gather comprehensive data during transfer operations. A floating structure has been ingeniously devised to house the sensors between cages during transfers, effectively creating a transfer canal. This configuration facilitates seamless data acquisition as the fish migrate from the donor to the receiving cage, ensuring uninterrupted monitoring of biomass dynamics.



a *b*

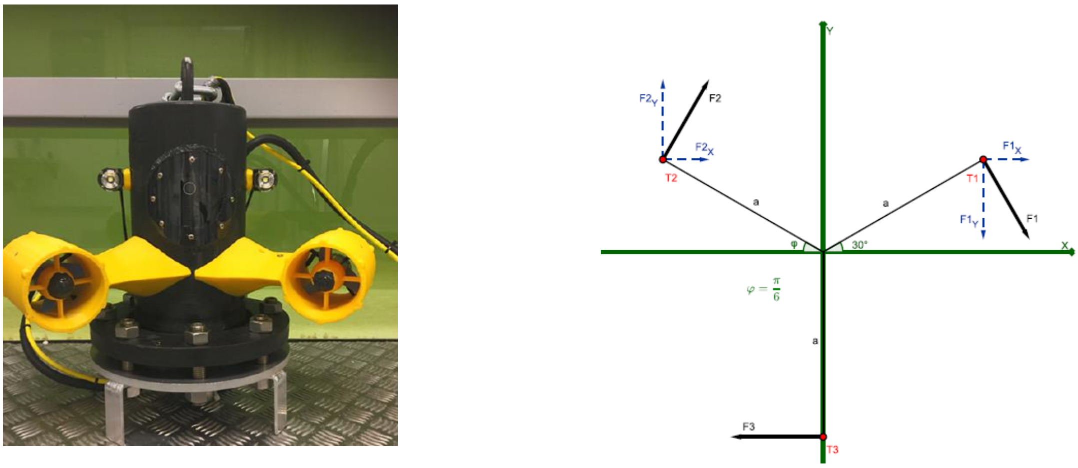
Fig. 6 - Side scan sonar for biomass estimation of tuna during transfers, (*Puig-Pons et al., 2019*)

a – 200 kHz side scan sonar and stereo camera; b – Design of the proposed and tested floating structures.

The process of biomass assessment unfolds through a systematic methodology that involves both counting the transferred tuna and analyzing a representative sample of the stock (*Puig-Pons et al., 2019*).

In aquaculture, vision technology based on underwater robots is used for biomass estimation, solving the problem of low efficiency of traditional manual contact measurement, avoiding health issues in fish, and greatly improving work efficiency. However, the underwater environment has low visibility and many disturbances, and fish images collected based on light vision require further processing. The clarity and enhancement of underwater images based on artificial intelligence algorithms remain the focus of research. Additionally, problems such as fish body overlap, low resolution, and blurred outlines of small target fish still pose difficulties in current research.

The design and implementation of a novel Remotely Operated Vehicle (ROV) tailored for aquaculture inspection within marine environments represent a pivotal advancement aimed at furnishing essential insights into fishery nets. This ROV constitutes an integral component of the pioneering "Sea Farm" initiative. In instances where the ROV encounters operational issues, it is intended to be transported by a floating platform. Equipped with a winch, the platform facilitates the descent of the ROV into the seawater and its subsequent retrieval post-operation. The structural design incorporates three wings, each housing a dedicated thruster for propulsion. Through the coordinated efforts of these thrusters, the ROV boasts omnidirectional maneuverability, enabling efficient navigation within its marine environment (*Osen et al., 2017*).



a *b*

Fig. 7 - Remotely Operated Vehicle for aquaculture, (*Osen et al., 2017*)

a – ROV prototype; b – Thruster forces.

Understanding the abundance and size distribution of fish within semi-intensive rearing systems in traditional ponds is crucial for effective sales lot planning and management. Typically, this information is acquired through sampling, which necessitates direct catch methods that are both stressful for the fish and time-consuming to manage. To achieve this objective, a portable-fixed multibeam imaging sonar employing commercial technology was employed, focused on estimating the abundance of gilthead seabream (Sparus aurata) within a fish farm's ponds through sonar image analysis (*Gutiérrez-Estrada et al., 2022*).

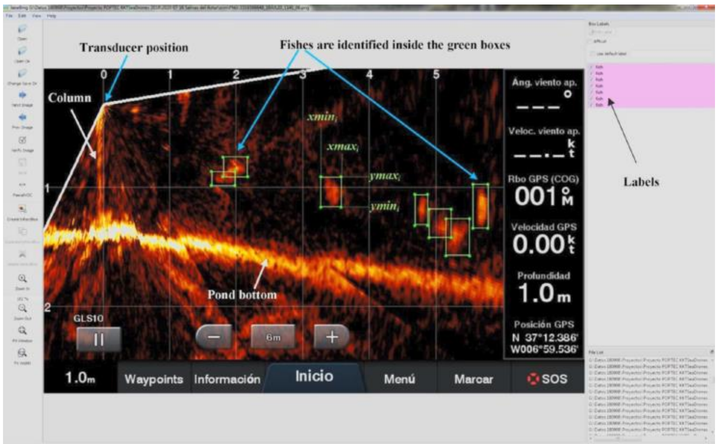


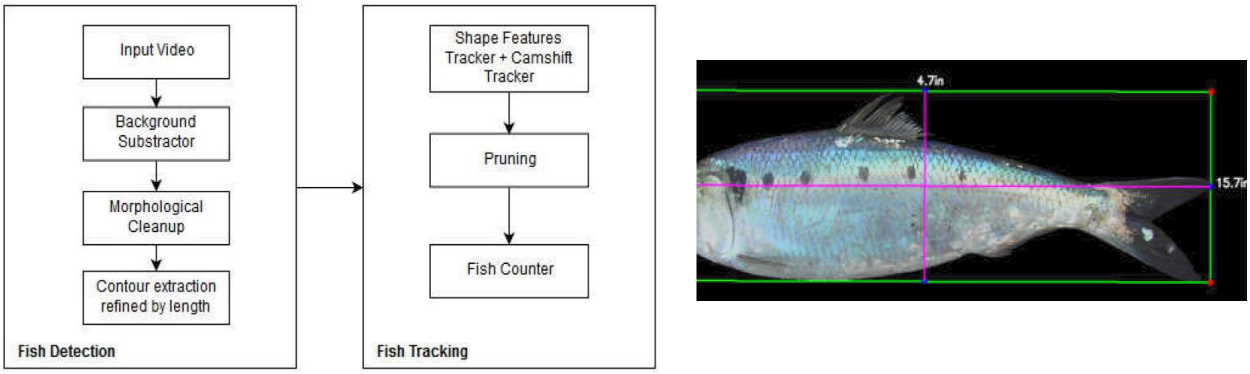
Fig. 8 - Sonar image treatment with the software LabelImg, (*Gutiérrez-Estrada et al., 2022*)

Imaging sonars (ISs) represent high-frequency acoustic devices that are experiencing growing utilization in the examination of fish populations across marine and freshwater environments. While acoustic devices offer valuable insights, they possess limitations in accurately quantifying species richness. Previous endeavors aimed at identifying fish species utilizing IS technology have predominantly concentrated on assemblages characterized by either low species richness or high morphological diversity (*Sible y et al., 2023*).

A fully automated IoT-based submersible Remotely Operated Vehicle (ROV) was designed to notify users of any detected fish diseases, enhancing overall management and health monitoring capabilities. The ROV operation is facilitated through IoT integration and controller functionality, enabling surveillance both underwater and outside water, equipped with a plethora of features. Fish size measurement utilizing underwater cameras involves several steps. Initially, the camera captures the motion of the fish, enabling the determination of its distance from the camera. Subsequently, the system computes the "pixels per metric" ratio, which serves as a reference for size estimation:

$$Pixels\ Per\ Metric = \frac{Fish\_width}{Known\_Object\_width} \tag{1}$$

To accurately determine the size of the fish from the image, calibration is essential using a known reference object. This reference object allows for the establishment of a relationship between the number of pixels in the image and the corresponding physical distance in metric units (*Rohit et al., 2019*).



a *b*

Fig. 9 - Underwater camera principle of a fully automated IoT-based ROV system, (*Rohit et al., 2019*)

a – Fish tracking and counting architecture; b – Fish Size Measurement.

Common methods of ocean remote sensing and seafloor surveying primarily involve the utilization of airborne and spaceborne hyperspectral imagers. However, the presence of the water column impedes the penetration of sunlight to deeper regions, thus constraining the range of observation. As an emerging technology, underwater hyperspectral imaging (UHI) serves as an extension of hyperspectral imaging technology adapted for air conditions, and is currently experiencing rapid advancement for applications in both shallow and deep-sea environments.

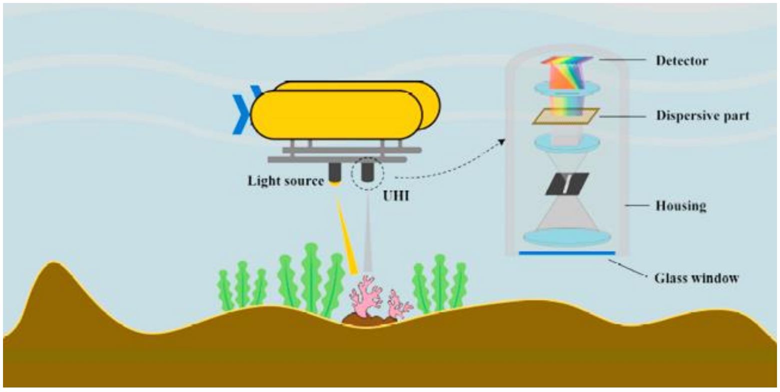


Fig. 10 - A schematic representation of underwater hyperspectral imaging (UHI) for mapping, (*Liu et al., 2020*)

UHI holds significant promise for utilization in marine fisheries and aquaculture, particularly in shallow and coastal regions. Its capabilities make it well-suited for monitoring changes in food availability, waste accumulation, and seabed composition within these environments (*Liu et al., 2020*).

RGB cameras mounted on an underwater vehicle possess the capability to capture imagery with exceptionally high spatial resolution, a fundamental requirement for ensuring precise estimation of biomass (*Overrein, 2023*).

Echo sounders enable the real-time monitoring of the complete fish population over extended periods. Nonetheless, prevailing methodologies for the automatic interpretation of echograms predominantly concentrate on species classification, thereby inadequately encapsulating the spatiotemporal characteristics inherent in the data (*Måløy, 2020*).

Autonomous underwater vehicles (AUVs) represent unmanned submersibles programmable to navigate in three dimensions beneath the water's surface. The technological evolution necessary for their dependable deployment, mission control, performance optimization, and retrieval has undergone significant advancement over the past decade. Presently, numerous AUVs operate effectively within offshore industries and across applied and academic oceanographic disciplines. AUVs boast compact dimensions, emit minimal noise, and offer cost-effective operation, unaffected by weather conditions.

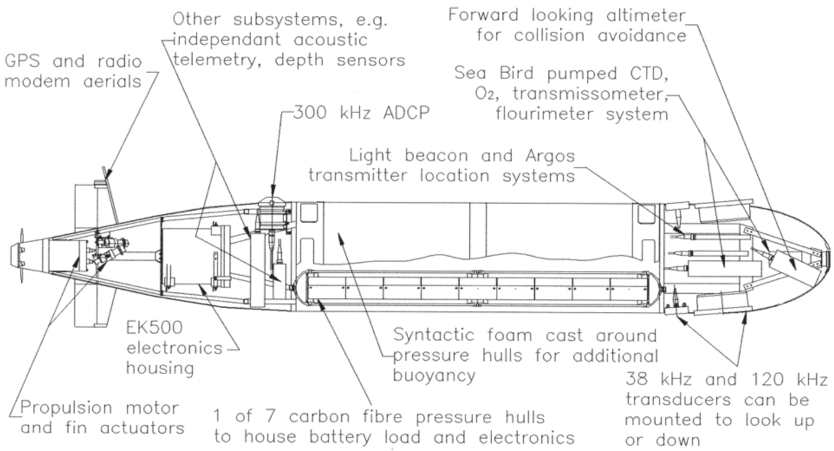


Fig. 11 - View of Autosub-2 with the payload configured for acoustic surveys of aquatic fauna - SIMRAD EK500, scientific, multi-frequency vertical echosounder (*Fernandes et al., 2003*)

Case studies demonstrate how these attributes benefit fisheries-acoustics science, drawing from past research conducted in regions like the North Sea and Southern Ocean while projecting potential future applications (*Fernandes et al., 2003*).

The SeaBED AUV is ingeniously engineered for a multifaceted exploration, encompassing photographic transects, side scan sonar, and bathymetric surveys. Its structure comprises two torpedo-like components connected by vertical struts, creating a cohesive unit for underwater operations. Despite its compact design, the AUV boasts notable dimensions: measuring 1.5 meters in length, 2.0 meters in height, and weighing approximately 250 kilograms, although the weight may fluctuate slightly depending on the payload it carries (*Tolimieri et al., 2008*).

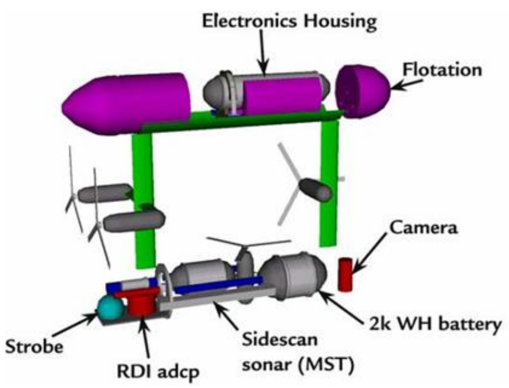


Fig. 12 - SeaBED autonomous underwater vehicle scheme, (*Tolimieri et al., 2008*)

Within the realm of marine research, the SeaBED AUV emerges as a pivotal tool, particularly in estimating the biomass of fish populations.

The aim of this paper is to provide a comprehensive overview of the evolution of various techniques utilized for mass measurement, enumeration, or direct estimation of fish biomass. This review serves as a valuable resource for researchers seeking to comprehend the current landscape of approaches to biomass estimation, providing actionable insights for enhancing the precision and efficiency of intensive fish farming practices.

RESULTS

Table 1 shows the biomass estimation technologies according to the type of underwater robots.

Table 1

The biomass estimation technologies according to the type of underwater robots

Type of Underwater Robot	Biomass Estimation Technology	Reference
ROV (Remotely Operated Vehicle)	Acoustic Imaging (sonar)	*Osen et al., 2017* *Gutiérrez-Estrada et al., 2022* *Sibley et al., 2023* *Christ and Wernli, 2014* *Rundtop and Frank, 2016* *Måløy, 2020*
	Optical Imaging (video cameras)	*Macreadie et al., 2018* *Rohit et al., 2019* *Zhang et al., 2024*
	Multispectral Imaging	*Liu et al., 2020* *Overrein, 2023*
AUV (Autonomous Underwater Vehicle)	Side scan Sonar	*Fernandes et al., 2003*
	Section Scanning Sonar	*Tolimieri et al., 2008*

Below are presented some mathematical models that contribute to the repertoire of mathematical approaches used in biomass estimation, reflecting the various methodologies used in ecological research and natural resource management.

1. *Logistic Growth Model (Verhulst, 1838):*

$$N(t) = \frac{K}{1+\frac{K-N_0}{N_0}e^{-rt}} \tag{2}$$

This model describes the growth of a population in a limited environment, where $N(t)$ represents biomass at time t, N_0 is the initial biomass, K is the carrying capacity, r is the growth rate, and e is the base of the natural logarithm.

2. *Schaefer Fish Stock Assessment Model (Schaefer, 1954):*

$$F(B) = rB(1-\frac{B}{K}) \tag{3}$$

This model uses a differential equation to estimate fish biomass (B) based on fishing rate (F), natural growth rate (r), and carrying capacity (K).

3. *Fox Model (Fox, 1970, Musick and Bonfil, 2005):*

$$B_{t+1} = B_t + rB_t\left(1-\frac{lnB_t}{lnK}\right) - C_t \tag{4}$$

The Fox surplus production model is used to estimate the surplus production of a fish stock, which represents the additional biomass that can be sustainably harvested beyond what is required to maintain the stock at its current level, where B represents biomass, K represents carrying capacity, r represents intrinsic rate of population increase and C is catch.

4. *Pella and Tomlinson Model (Pella and Tomlinson, 1969):*

$$\frac{dB}{dt} = rB(1-\frac{B}{K}) - F(B) \tag{5}$$

The Pella-Tomlinson model is based on the assumption of a logistic growth function for fish populations. The model estimates the total biomass B of the fish stock at a given time, taking into account the current biomass, the intrinsic rate of growth r, and the carrying capacity K of the environment.

$\frac{dB}{dt}$ represents the rate of change of biomass over time.

$F(B)$ represents the fishing mortality rate, which is a function of the current biomass B.

5. *Multispecies Trophic Network Model (May, 2019):*

$$\frac{dN_i}{dt} = r_i N_i (1 - \sum_{j=1}^{n} c_{ij} \frac{N_j}{K_j} \tag{6}$$

This model describes the population dynamics of species i in a trophic network, considering interactions with other species j, growth rates (r_i), carrying capacities (K_j), and consumption coefficients (c_{ij}).

6. Stochastic Differential Equations (SDE) Biomass Model (Gard, 1989):

$$dX_t = \left(\mu - \frac{\sigma^2}{2}\right) dt + \sigma dW_t \tag{7}$$

This model uses stochastic differential equations to describe biomass variations over time, where X_t represents biomass at time t, μ is the average growth rate, σ is the standard deviation of the stochastic process, and dW_t is a Brownian variation.

7. von Bertalanffy Growth Model for weight (Von Bertalanffy, 1957):

$$W(t) = W_\infty (1 - e^{-k(t-t_0)})^3 \tag{8}$$

This model describes the sigmoidal growth pattern observed in many fish species, where growth is rapid early in life, slows down as the fish approaches its maximum size, and eventually levels off, where $W(t)$ represents the weight of the fish at age t; W_∞ is the theoretical maximum asymptotic weight that the fish can reach; k is the von Bertalanffy growth coefficient, which represents the rate at which the fish approaches its maximum weight; t_0 is the theoretical age at which the weight of the fish would be zero and e is the base of the natural logarithm. The von Bertalanffy Growth Model is widely used in fisheries science and management to estimate growth parameters for fish populations, assess population dynamics, and inform fisheries management strategies.

8. Biomass Dynamic Models (Colvin et al., 2012):

Biomass Dynamic Models (BDMs) utilize a variety of equations and mathematical formulations to describe the dynamics of fish populations within ecosystems. While the specific equations used can vary depending on the model and its purpose, here are some general components and equations commonly found in Biomass Dynamic Models*:*

a. Population Growth Equation:

The population growth equation describes how the biomass of a fish population changes over time. It often includes terms for population growth, mortality, recruitment, and other factors affecting population dynamics. A basic form of the population growth equation may be represented as:

$$\frac{dN}{dt} = f(N,t) - M(N,t) \tag{9}$$

where: N represents the population biomass, t represents time, $f(N,t)$ represents the rate of population growth, $M(N,t)$ represents the rate of mortality.

b. Recruitment Equation:

The recruitment equation describes the addition of new individuals to the population. It often includes terms for spawning stock biomass, environmental conditions, and other factors influencing recruitment. A basic form of the recruitment equation may be represented as:

$$R(t) = f(S(t), E(t)) \tag{10}$$

where: $R(t)$ represents recruitment at time t, $S(t)$ represents spawning stock biomass at time t, $E(t)$ represents environmental conditions at time t.

c. Growth Equation:

The growth equation describes how individual fish grow over time. It often includes terms for growth rate, food availability, and other environmental factors. A basic form of the growth equation may be represented as:

$$\frac{dW}{dt} = G(W,t) \tag{11}$$

where: W represents individual fish weight, $G(W,t)$ represents the rate growth.

d. Fishing Mortality Equation:

The fishing mortality equation describes the impact of fishing on the fish population. It often includes terms for fishing effort, fishing mortality rates, and selectivity of fishing gear. A basic form of the fishing mortality equation may be represented as:

$$F(t) = E(t) \cdot S(t) \cdot \frac{F_{max}}{E_{max}} \tag{12}$$

where: $F(t)$ represents fishing mortality at time t, $E(t)$ represents fishing effort at time t, $S(t)$ represents selectivity of fishing gear at time t, F_{max} represents maximum fishing mortality rate, E_{max} represents maximum fishing effort.

These models represent a diverse set of mathematical approaches used for biomass estimation, incorporating advanced technologies and modern data analysis methods to provide accurate and relevant estimates in various ecological and scientific contexts.

CONCLUSIONS

By analyzing the technological solutions for biomass estimation according to the concept of Aquaculture 4.0, it can be concluded that:

- the estimation of fish biomass through the integration of optical and acoustic cameras represents a significant advancement in real-time, non-contact, non-destructive, safe, and reliable fish population assessment methodologies;
- the utilization of underwater vision for biomass estimation, coupled with the integration of data into big data platforms for decision-making processes, presents a promising avenue for enhancing the accuracy of bait casting in intelligent aquaculture practices;
- it is crucial to acknowledge the challenges posed by underwater environmental conditions, including illumination variations and multiple disturbances, which significantly increase the complexity of underwater image processing;
- future research efforts should focus on the refinement of image processing algorithms to mitigate the impact of underwater environmental disturbances on biomass estimation accuracy;
- the integration of advanced technologies, such as artificial intelligence and machine learning, holds potential for enhancing the robustness and efficiency of underwater image processing techniques;
- the integration of Machine Vision, acoustics, ambient DNA, and other innovative technologies holds immense potential for transforming the way fish biomass is estimated. By adopting non-invasive, rapid and cost-effective methodologies, timely and reliable information essential for sustainable fisheries management and conservation efforts can be obtained;
- mass prediction methods that exclude fish tail fins could more accurately estimate fish mass compared to models that incorporate tail fins. This methodology holds promise for extending mass estimation to free-swimming fish underwater in aquaculture settings.

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