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Survey of Fish Behavior Analysis by Computer Vision

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Abstract

Assessment of the behavior or physiology of cultured fish has always been difficult due to the sampling time, differences between experimental and aquaculture conditions, and methodological bias inherent. Recent developments in computer vision technology, however, have opened possibilities to better observe fish behavior. Such technology allows for non-destructive, rapid, economic, consistent, and objective inspection tools, while providing evaluation techniques based on image analysis and processing in a wide variety of applications. "Fish", in this study, refers to underwater vertebrate fish belonging to the Pisces class that inhabit almost all available aquatic environments. This study aims to assess current, worldwide fish behavior study methods that use cameras which utilize computer vision. The evolution of computer vision as applied to fish behavior is explored in this paper for all stages of production, from hatcheries to harvest. Computer vision technology is regarded as existing from 1973 to 2018, specifically the Elsevier database. Fish behavior and underwater habitats are explored at large, especially in aquaculture fishing. Based on the methods observed above, relevant viewpoints on the present situation are presented as well as suggestions for future research directions.

Keywords: Computer vision; Fish behaviour; Machine vision.

Introduction

Fisheries worldwide play a vital role in global food supply [1]. In Asia, where about 90% of the world's aquaculture takes place currently, fish are an inalienable part of the economy [2]. In order to effectively manage target fish and thus reap the available benefits of commercial fishing, fishing gear and fishing operations must be optimized for efficiency and accuracy. It remains necessary to better understand the behavior of fish, as well as predation capacity of fish, of course, and behavior of shrimp, crabs, and other aquatic organisms as well; awareness of fishing and environmental factors inherent to physical or chemical stimulation, plus the behavior and the abilities of fish populations yet requires extensive, scientific study to best inform successful fish farming [3,4]. "Fish behavior" refers to fish and other aquatic animals that change their behavioral responses according to their external or internal environments. This study focuses in particular on underwater, vertebrate fish that belong to the Pisces class.

Fish behavior not only involves enriched ethology, fish physiology, fish ecology, and other theoretical disciplines, but also the practical and economic significance of fishery production. In recent years, fish behavior has become an important theoretical basis of fishing and enhancement of fish [5-8]. Conservation and management of fishery resources, specifically concerning environmental pollution and environmental protection, have seen close ties to the study of fish behavior [9-11]. Alongside the development of fishery production, study of fish behavior has guided (and enhanced, and improved) production techniques to apply new technologies. The future of marine aquaculture farmers, as far as effective control of the behavior of fish in a water conservancy, or management of water pollution, are all closely related to fish behavioral study.

The majority of modern fishing gear is evolved through long-term exploration and practical experience, which consciously or unconsciously adapt to the habits of fish behavior. Good fishing gear has been said to be the result of natural selection. To this effect, careful analysis of the specific structure of fishing equipment and the principles of existing fishing gear describe the mechanisms that build an understanding of fish behavior and adapt to it accordingly [12,13].

Several research techniques apply to sampling methods and tools.

- Flag discharge - signs, sign posts, needles, needle nicks, digital chips, and GPS sensors. These items are employed to identify fish and provide their specific location. By contrasting this information against corresponding environmental parameters, the relationship between the fish and the environment, rules regarding migratory patterns, and other relevant information becomes clearer [14,15].
- Basic research. Experimental observations of fish sensory organs, tissue structure, functions, and physiological responses aim to reflect behavior, internal mechanisms, and generation mechanisms in fish. This method does not allow comprehensive observation of fish, which can be destructive to fish and their environment and could also be typically subjective; thus, it is not utilized in this study.
- Underwater observation - diving photography and videography. Direct observation underwater records fish behavior and habits in their natural environment. A mass of observational data thus describes statistically significant trends in behavior. While, direct observation in the field may interrupt fish behavior. Moreover, natural conditions and climate features such as underwater visibility, rapid, and available diving time may restrict observers [16,17].
- Ultrasound image analysis - scan sonar, network port sonar, and digital, three-dimensional sonar. Ultrasonic echo imaging helps

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build an understanding of the relative position of fishing vessels and fish in real-time and is typically utilized to guide fish into cages and adjust nets to improve fishing efficiency [18]. Acoustic telemetry monitors fish swimming behavior, as well. Advances in acoustic technologies, such as multi-beam and side-scan sonars, have facilitated high-resolution maps of seabed habitats across broad regional scales [19]. When seafloor habitat maps are available, fish-habitat relationships can be used to predict species abundance and distribution [20,21]. These are typically sampled using the Acoustic Tracking and Navigation System. Audio commentary plus video information provides species identifications, fish sizes, and counts to help predict deep-water fish assemblages.

- Fish telemetry technology - remote telemetry analysis and satellite tracking devices. The temperature of the water surface, chlorophyll, pollutants, flow ice distribution, sea surface height, and other real-time, continuous, large-scale data can be acquired using satellite remote telemetry technology. Combined with survey data, such as water quality and nutrient content, and other information, quite comprehensive analysis becomes possible, particularly concerning sport fish and fisheries [22].

- Cage observations. Cage observations implement single factor control, behavioral observation, and recording [23-26]. This information helps to build an understanding of formation mechanisms; however, it should be noted that results are affected by subjectivity due to the state of the cage. The natural environment must be mimicked with extreme care and caution in the laboratory environment in order to allow for objective research, which poses a significant challenge.

- Digital model simulation and emulation. Mathematical models and computer visualization techniques can simulate fish and fish movement, demonstrate movement patterns, behavior, and other relevant information. Digital models are characterized by autonomy, which in turn form autonomous agents designed for you in computer animations and interactive media. The first artificial fish were created by Grzeszczuk and Terzopoulos [27] and Tu [28]. These contained a dynamic, biomechanical muscular movement model, plus photo-realistic texture mapping, accurate sensory abilities, motivational behavior modeling, and a decision tree-based action selection mechanism [29-31].

- Computer vision has developed into an excellent method of observing fish behavior automatically. All methods described above can be associated with computer vision technology, as a matter of fact. The distinct advantages of computer vision-based fish behavior analysis include continuous, non-intrusive operation, the large memory capacity, the ability to detect small but significant changes and complex patterns in data which may pass unrecognized by the fishers, objectivity of assessments, and the ability to integrate data from various sources to draw conclusions that may not be apparent from a single data source. This article review fish behavior (specifically vertebrate, underwater fish) using cameras based on computer vision technology.

Literature Review

Animal behavior refers to the means of maintaining homeostasis for the individuals between themselves and the surrounding environment. Animal behavior is thus sometimes called "individual-ecology". All organisms must adapt to changes in their environment in nature – adaptability is the most crucial component of an organism's ability to survive and reproduce. There are three main ways for an animal to adapt to its environment: genetic variation, physiological change, and behavioral response. Behavioral response, the most rapid of the three adaptive approaches, is employed daily by most individual animals.

This study focuses on the behavior of fish, including the observation of the natural environment around them and various classifications. The observation of environment was controlled carefully for quality and objectivity in order to promote orderly and appropriate classification, and provide for easy, rapid follow-up where necessary. Classification of fish requires not only specialization according to species, but also comprehensive analysis of specific behavior, which form the basis for future research.

Monitoring fish schooling behavior, for example, helps scientists study problems that threaten the overall welfare of fish [32,33]. Observations of fish schooling describe the mechanism of fish swimming behavior and offer valuable information regarding aquaculture [34]. Accurate evaluation of various stress factors [35,36] enhances scientific management and reduces the impact of harmful stress responses on fishes' surrounding environments. Correct understanding of fish feeding behavior helps reduce food waste, and altogether facilitate effective and environmentally-friendly feeding practices [37,38]. Analysis of fish taxis behavior assists better design of fishing nets, reduces biting, and otherwise benefits the commercial fishing industry [12,13]. This paper only focuses on the specific types of behavior stated above, though there are many other behaviors that can be analyzed using similar computer vision-based methods.

Captured video based on computer vision

The first automatic, surface-deployed underwater cameras triggered by a bottom-contact switch were made in the 1940s. Autonomous underwater vehicles (AUVs) were developed mainly in the 1970s [39-41]. Monitoring fish and underwater habitats, as mentioned above, requires non-destructive observation methods. These are generally carried out through underwater visual technology, especially underwater video techniques. Many researchers have investigated the use of underwater video to analyze fish behavior and habitats. Murphy and Jenkins, for example, reviewed observational methods used in marine spatial monitoring of fishes and associated habitats [16]. Mallet and Pelletier reviewed underwater video techniques used for observing coastal marine biodiversity over an almost sixty-year-period, with a specific focus on fish schooling behavior. They used Google Scholar to search relevant keywords and divided the results into remote underwater video (RUV), baited remote underwater video (BRUV), towed video (TOWV), and diver-operated video (DOV) categories [17].

Fish surveys are classically conducted with underwater visual census (UVC), but this method causes bias due to human presence. With the advent of digital technologies, video recording has become a more appropriate tool for fish surveys [42-46]. Compared to UVC, video recordings allow collection of more data in space and time, and they are not subjected to any intervention beneath the water as records are compiled later on in the lab. Xiao G et al., used the semantic behavior of fish extracted from video data obtained by computer vision, realizing the purpose of biological water quality detection [47]. Chabanet et al., for example, successfully utilized a Video Solo system (RUV system) to gather observations without a necessary human presence. They believed repeated sampling during the middle of the day was a fairly secure strategy, and used their fully autonomous, long-term research system to study the variability of fish populations in the Indian Ocean over a two-year-period. They observed 6224 individuals of 75 species belonging to 16 families and found that fish assemblages were variable at different times [48].

In another relevant example, White et al., used a BRUV system to quantify the spatial distribution of elasmobranchs at the ecosystem scale [49], knowing that many reef shark species have high site fidelity and habitat dependence. Their BRUVS provided a noninvasive, non-destructive, and minimally disruptive approach to identifying reef sharks' limited site fidelity and broad-scale individual movements. While further study is needed, as it remains difficult to identify whether these reef shark species show spatial or seasonal patterns in their behavior. Pelletier et al., monitored coral reef fish using high-definition (HD) video technology and underwater visual censuses (UVC) technology in the south-west lagoon of New Caledonia, South Pacific [45]. They compared the two methods to find that HD video is a more cost-effective monitoring technique and indicated that HD video allows for effective fish identification by computer vision due to its larger screen size over UVC technology, as well as longer image analysis and more systematic operation. Prato, et al., applied UVC to monitor the fish combination of multiple sections in Marine reserve and can realize realistic assessment of the whole Marine fish composite structure [50].

The first underwater, remotely operated vehicles (ROVs) equipped with video for scientific operations were developed by American and Japanese research teams. These devices typically include a control center with computer devices connected by cables to the camera which permit direct surface control by its operator. Early ROVs were developed to count scavengers at very low depths [51-53] and more recently, to survey benthic and fish communities while minimizing biases introduced by diver presence [54-59]. ROVs can be used to examine finer-scale fish-habitat associations. *In situ* visual surveys have been applied to a wide variety of deep marine systems to identify strong associations between demersal fish species and substrata, depth, and relief [60-65]. S. Matzner et al., proposed a semi-automated method for ocean and river energy device ecological monitoring, the key contributions of this work are the demonstration of a background subtraction algorithm, compared with the fish underwater video automatic detection algorithm, it can greatly reduce the artificial time and cost [66].

Classification of fish species based on computer vision

The research team led by Zion successfully utilized a method of moment-invariants (MI) algorithm coupled with geometrical considerations to determine species' sizes and explore schooling behavior [67]. The first step in their observation was accurate recognition of species. Species identification and classification is not only a prerequisite for normal observation of fish, but also for accurate identification of fish aggregation behavior. Tayama et al., utilized a method which employed various dimensions to produce shape descriptors to sort species accordingly and achieved a sorting reliability of 95% for four species of fish [68]. Wagner et al., similarly, used simple shape features of sea fish to show that it may be possible to sort species according to shape, and achieved a sorting accuracy of 90% for nine species of fish [69]. Strachan used a simple shape grid with width lines drawn parallel to fish to estimate their length based on binary images, and achieved high accuracy compared to manual measurements [70]. Strachan also utilized color and shape parameters to sort fish by species and reached 99% sorting reliability for 23 species of fish [71]. Later, the same researcher made use of a prototype machine designed to sort fish by species and size at sea [72]. Strachan and Kell identified haddock fish stocks from two different fishing regions using 10 shape features and 114 color features. By analyzing these set features, they achieved 100% classification of the calibration set and 90.9% and 95.6% correct identification of fish from these two stocks, respectively [73].

Length measurements of fish are routinely taken onboard research vessels, at accuracy up to ±1 cm. Measurements are typically gathered using either electronic measuring boards or manual measuring boards, where one-person measures fish while another note the measurements, which are later entered into a computer. Both methods require each individual fish to be manually handled. Computer vision systems that can automatically measure the length of fish in a laboratory, however, have been described [70,74] and proven reliable, at error rate of less than 1 cm.

Informed by the wealth of previous research, White et al., designed a computer vision system that accurately identifies and measures different species of fish [75]. The system uses a camera mounted over the conveyor which transports the fish. Moment-invariant method image processing algorithms. The system showed 99.8% sorting accuracy for seven species of fish and measured length with a standard deviation of 1.2 mm. In the end, the system showed promising applicability for fishing ships. Hao M et al., designed a set of machine vision system, it can accurately measure the length of the fish, the system is mainly through two ways, one is that it should be get two-dimensional fish images captured by the camera, then through the Hough transform to calculate the length of the fish, the other is by getting more pictures of the fish to realize 3d reconstruction, through the appropriate detection to measure the length of the fish, The system works well [76] (Figure 1).

Fish species classification survey also needs to be standardized, Caldwell ZR, et al., used the visual census technology, through the assessment for coral reef fish populations, to implement the standardization of fish population survey method [77]. S Hasija, et al., overcome the difficulties of underwater image classification and computer calibration, this paper proposed a matching method based on improved image sets, the method used a graphical embedded discriminant analysis method, it can realize precise classification of the fish species [78].

Fish Behavior

This section reviews notable applications of computer vision to fish behavior detection. Computer vision analysis is discussed as applied to schooling behavior, swimming behavior, stress responses, feeding behavior, taxis behavior, reproductive behavior, and migratory behavior.

Different behaviors have different performance characteristics.

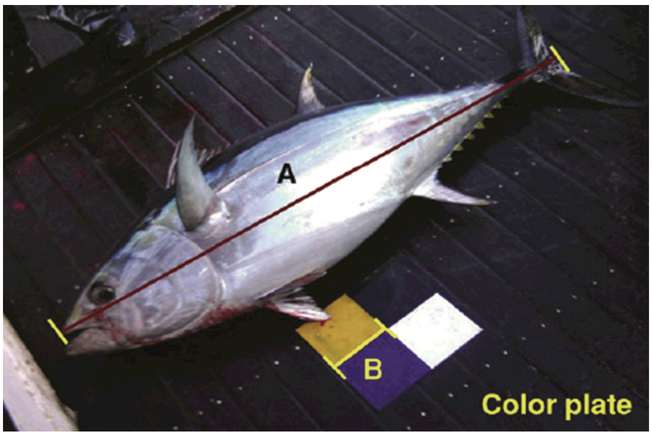

Figure 1: Using relation between A and B to calculate fish length [76].

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We divided fish behavior into 5 categories. Most of behavior characteristics are based on the fish classification. We put the classification into the fish behavior. From Figures 2 and 3 we could see that accounts for 28.04% of behavior are schooling behavior. Observation of fish aggregation relationships between different species could be used for more schooling behavior. The second behavior of the paper is feeding behavior, which plays an important role in fishing, and directs affect the health of fish. Researchers also use the swimming behavior to analysis and explore the ultimate limit behavior of fish. Stress behavior direct effect on the swimming behavior. Stress behavior can monitor the water quality and other factors. Taxis behavior is the fate to catch fish.

Schooling behaviour

Fish schooling behavior is characterized by cooperative behavior among fish, specifically cooperation in temporary and loose clusters. Schools are comprised of permanent community structures, in which clear division of labor and organization is present. Monitoring fish schooling behavior is a growing concern within the study of fish stress and overall welfare (Figure 4).

Basic measures of displacement and velocity are not sufficient to characterize schooling behavior, so a mathematical model that allows quantitative comparison between cases is needed. Matuda and Sannomiya were the first to develop a mathematical model (S&M model) that describes fish schooling behavior in a water tank [79-81].

The S&M model is as follows:

$$
\begin{aligned}
&m\ddot{x} = F_i\left(t, x_i, x_j, \dot{x}_i, \dot{x}_j\right), F_i = F_{di} + F_{ai} + F_{bi} + F_{wi}^{+} + F_{wi}^{-} + \\
&F_{gi}^{+} + F_{gi}^{-} + F_{ri} = vf_{di} + vf_{ai} + k_b f_{bi} + k_w^{+} f_{wi}^{+} k_w^{-} f_{wi}^{-} + \\
&k_g^{+} f_{gi}^{+} + k_g^{-} f_{gi}^{-} + F_{ri} + \ldots, i, j = 1, 2, \ldots, \mathrm{N}; \mathrm{i} \neq \mathrm{j}
\end{aligned}
\tag{1}
$$

where m is the mass of an individual and $\ddot{x}_i$ is the acceleration of an individual. Each function of Eq. (1) includes unknown force-magnitude parameters and distance parameters. The functions F_{di}, F_{ai}, F_{bi}, F_{wi}^{+}, F_{wi}^{-} and F_{ri} are identical to those in the original S&M model. In this study, we consider the influence of structures in the water tank, just as the force of a wall was considered in the original model. Manna D et al., proposed a model of fishing, in the process, fish and predators showed their learning behaviors, they could achieve a balance through their learning behavior between predation and prey [82]. We also consider F_{gi}^{+} and F_{gi}^{-} as newly defined by Suzuki et al. [32]. As indicated in their study, future, simultaneous tracking of fish schools and individuals advances the understanding of survival advantages conferred to individuals. Adjustments in school compactness and elongation provide valuable information as schools migrate and search for patchy-distributed prey (Figure 5).

Fish size–frequency distributions provide vital information on population-level processes. Dunbrack used in-line stereo, remotely operated videography technology based on computer vision to provide the length measurements of free-swimming fish and length–frequency data for a group of Bluntnose Sixgill Sharks (Hexanchus griseus) [83]. Seiler et al., used an Autonomous Underwater Vehicle (AUV) plus image-yielding methods to estimate fish school size, abundance, and habitat [33]. In their study, 53% of the world's Ocean Perch were observed and measured with known accuracy using a stereo camera system yielding length-frequency distributions. They confirmed a positive relationship between rockfish abundance and increasing depth in most habitat types. In 2015, Rieucau G et al., used the high-resolution imaging sonar technology of computer vision to conduct quantitative analysis of the learning behavior of fish groups by monitoring the fish in the tidal pool in real time [84].

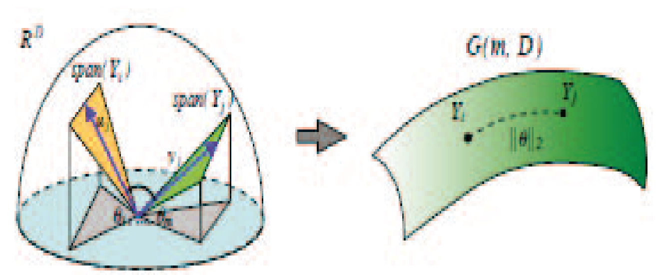

Figure 2: Mapping of subspaces from Euclidean space, RD to the Grassmanian Manifold G (m, D) [78].

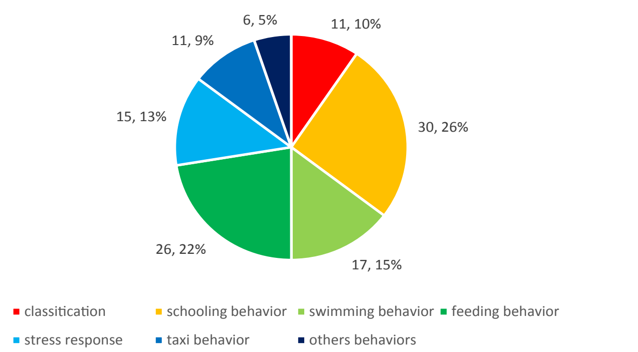

Figure 3: The proportion of the different fish behaviour in reference papers.

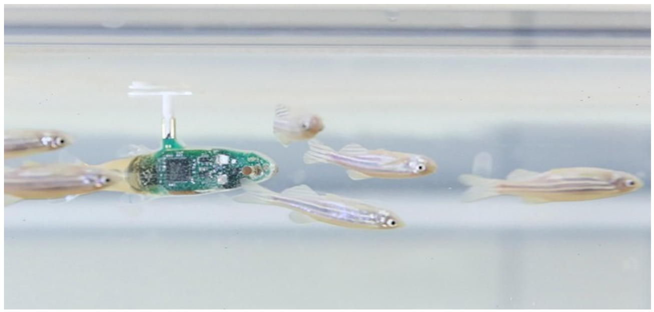

Figure 4: Fish schooling behaviour.

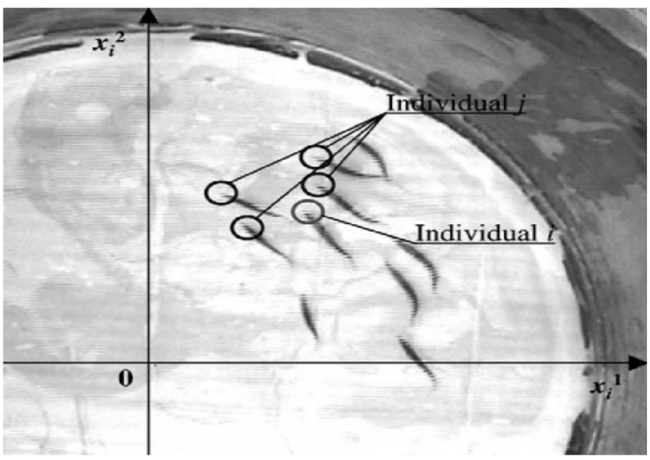

Figure 5: X-Y position describes fish schooling behaviour [32].

The external structure of fish schools varies considerably according to fish shape, size, and other considerations. Different fish species show different schooling structures. Even the same species of fish may vary their school structure according to time, place, fish physiological states, and environmental conditions.

Partridge was the first researcher to use 3D coordinates to detect fish behavior [85]. He mounted a mirror at a 45º angle above an observation tank to determine fish location in 3D coordinates based on computer vision. His experiment indicated fishes' instantaneous velocities increased with school size, and that as inter-fish distances decreased, leader/follower relationships became common in two-fish schools. Pairs of fish tended to swim one behind the other, on the same level. Fully formed fish schools must satisfy certain criteria to be defined as below. Gerlotto observed clupeid schooling behavior by vertical scanning multi-beam sonar, which builds 3D morphology of internal structures [86], to evaluate fish schools' shapes and dimensions in such a way that a school can be defined based on its morphology. They measured geometrical properties (overall dimensions, volume, surface, and others,) and relative distribution of densities inside the school (heterogeneity, and existence of nuclei). They confirmed that these dimensions were evaluated reliably and described behavioral mechanisms that constitute fish schools. Carey et al., studied a combination of traditional video census techniques with high-resolution imaging and seafloor vision technology but were limited to fixed sensors and/or limited field-of-view instruments [87]. In effort to remedy this, they designed a Laser Line Scan System (LLSS) capable of imaging continuous swaths of the seafloor. Data was acquired frame-by-frame to analyze fish distribution and abundance of benthic biological resources. Cuvelier et al., investigated the abiotic and biotic spatial factor distributions of fauna in the Lucky Strike vent field (Mid-Atlantic Ridge, MAR) using computer vision [88], providing the first insights into small-scale heterogeneity and zonation patterns on a MAR vent edifice using a novel faunal mapping technique and high-resolution image. Their study revealed a patchy zonation of biological assemblages around fluid exited on the Eiffel Tower hydrothermal construct. In another relevant study, a solid-state memory (SSM) video camera system was designed for extended deployment as a remote underwater video device with applications for measuring fish abundance and diversity [89]. In this system, characteristic values based on computer vision classified fish species, then ascertained fish symbiotic behavior for different fish in the aquatic environment. Yoshida et al., used underwater videography technology based on computer vision to evaluate fish behavior and aggregation in Tioman Island [90]. Notably, they found that mean residence times were shorter for schooling fishes. They also examined problems inherent to video capture observation of reef fishes using a systematic combination of approaches to provide a comprehensive evaluation of the underwater videography method.

Fish cohabitation behavior also reflects fish distribution. Jamieson et al., distinguished C. yaquinae from C. armatus in instances of cohabitation using image-specific morphometric characteristics [91]. Their analysis was intended to provide a reliable method of identification from deep-sea imaging systems in the absence of standard fishing techniques. Gonçalves et al., suggested the existence of individual peacock blenny and salaria pavo using video images of a conspecific nesting male, comparing their images with those of a freshwater species already known to react to video imaging [92]. The lack of certain depth cues in video images such as those derived from motion parallax, binocular stereopsis, and changes in focus may lead to an incorrect interpretation of the stimulus, however. Butail et al., built a framework for analysis and classification of schooling behavior using methods based on generative modeling and nonlinear manifold learning in computer vision [93]. In the same year, Hardinge et al., successfully counted individual fish in a single video frame, where, combined with calibration calculations, stereo-video imagery provided 3D locations of points and objects. Hardinge also calculated the lengths of fish simultaneously with their distance obtained from stereo-BRUVs. Their data suggested that stereo-BRUVs baited with 200 g of crushed pilchards effectively sampled temperate reef fish assemblage [94].

Fish distribution is one important component of fish schooling behavior, as is chasing behavior. Kato et al., developed a computer image processing system for quantifying zebrafish behavior and were the first to successfully obtain tracking information for multiple fish (up to three,) in a single tank. Using this system, they automatically quantified the behavioral patterns of single zebrafish or pairs of zebrafish. They concluded that fish chasing behavior (schooling) of zebrafish is largely dependent upon vision [95]. Boom et al., developed a novel, data-driven methodology to observe long-term and continuous trends in local fish assemblages, in an attempt to support marine ecologist research on video monitoring [96]. Their analysis method can be used to identify ecological phenomena such as changes in fish abundance and species composition over time and area. This research tool enabled marine ecologists for the first time to analyze long-term and continuous underwater video records. Stien et al., described an economical and efficient video analysis procedure for registering vertical fish distribution in aquaculture tanks [97]. Because their method allows for accurate description of vertical distribution over time, is cost effective and easy to implement, and will likely become the standard for describing fish behavior in aquaculture tanks.

The classification of various fish school is a dynamic process involving many complex trade-offs. Different species may trade off specific advantages provided by different school shapes and structures to relative extents [98,99]. A semi-automated image analysis that measured the size, shape, and structure of schools of Atlantic bluefin tuna in Open Ocean was applied by Newlands and Porcelli in 2008 [100]. They found that individual fish within schools gain the advantages necessary to migrate over large distances, while maintaining high sustained swimming speeds.

Video-image analysis is an efficient tool for microcosmic experiments, as it can be used to depict the modulation of individual behavior based on sociality. Menesatti et al., proposed a video-image analysis system for microcosms that portrays the modulation of individual behavior based on social interactions. Their study indicated that inter-individual differences in activity seem to be the result of social interactions [101]. However, animals in isolation also show inter-individual phenotype differences in activity [102]. Menesatti's study was an important first important step toward recognizing activity modulation based on social interactions [103].

Petrell et al., developed a video-based system that used computer vision to measure average fish schooling size in a nonintrusive manner [103]. The primary purpose of Petrell's research was the design of a potentially commercial, reliable, fast, accurate, durable, and low-cost video fish sizing system for use in seawater and fresh water environments. Cadrin developed an image analysis system that diversified morphometric methods and expanded the potential application of morphometry as a tool for fish schooling identification [104]. The study device increased the effectiveness of morphometry for identifying widely varied fish schools. Fernö et al., examined patterns of feeding behavior and reserve accumulation in maturing and immature fish of the same age, while accounting for the fact that schooling groups have been observed to disperse gradually after sunset (1988). Juell observed swimming behavior patterns during daylight and found that salmon typically form circular schools in which most individuals swim in the same direction (polarized), avoiding the cage center and walls [23].

Fish schooling behavior research not only requires images to analyze, but also a fairly large reserve of data. Rosenkranz et al., presented a detailed technical description of a novel, high-speed, megapixel benthic imaging system developed first by the Alaska Department of Fish and Game, with design assistance from Woods Hole Oceanographic Institution's HabCam project. The image datasets they collected described a vivid, new underwater world that was highly valuable to biologists who work with computer software, digital image files, and image processing systems [105,106].

In all, for the fish schooling behavior, you can know the fish schooling model namely the S&M model, you can also use 3d coordinates to detect fish schooling behavior, through the use of advanced technology such as AUV, vertical scan multi-beam sonar and laser line scan system to estimate the size of the fish and quantity, above all is the development of the fish schooling behavior for so many years.

Swimming behaviour

The overall availability of aquaculture information is enhanced significantly by knowledge regarding specific mechanisms of fish swimming behavior. In this discussion, "fish swimming behavior" includes swimming posture, speed, direction, distribution, the relationship between the environment and swimming behavior, and the relationship between climate and the swimming behavior. When observing fish swimming behavior using computer vision, both normal and abnormal states are analyzed.

The computer vision was first applied in monitoring fish swimming behavior with the purpose of observing the relationship between swimming and the climate specifically. Beyan C et al., obtained the continuous video frames through the computer vision to detect and track the changing speed of fish in different temperature, it is concluded that the relationship between climate and swimming [107]. Two previous studies [108-110] used cameras to detect Atlantic salmon swimming patterns to find that fish swimming speed not only varied with season and time of day but also is influenced by light intensity and feeding activity, too. Oppedal et al., used this method to investigate Atlantic salmon swimming in a long-term study, and inferred that Atlantic salmon show different swimming behavior while in different seasons and different light [111]. Sutterlin et al., found swimming direction (either clockwise or counter-clockwise) can differ from cage to cage [26].

Fish swimming ability is an important consideration in commercial fishing enterprises, specifically for selecting suitable trawling speed, mode of trawl operation, cage length, and the minimum speed of fishing boats. Jiang et al., proposed an automatic tracking method based on a particle filter to measure the swimming posture of koi [24]. Xydes et al., proposed an algorithm which focused on improving the localization accuracy and temporal resolution of acoustically tagged fish by filtering the position measurements received from an acoustic receiver array. They found their algorithm, which utilized a meshed Bayes filter and particle filter, showed decreased errors in location predictions [112]. Creton described a high-resolution imaging system with computer vision that automatically analyzed the location and orientation of zebrafish larvae in multiwell plates. Optomotor response analysis suggested that the zebrafish imaging system effectively quantified known behaviors [34]. Sadoul developed a computerized method which extracted a dispersion index for rainbow trout shoal, plus an index of swimming activity, using the macro and differences in background algorithms to calculate the two indexes of group behavior [8]. The process was validated by artificially increasing step-by-step cohesion (or swimming speed) of the group and comparing reference values of dispersion and swimming speed with estimated values (Figure 6). Cha et al., proposed a simple vision method for quantifying fish swimming behavior that sampled frames from a video recording of swimming fish and combined them into a time-lapse composite image [113]. Barry used a program called Ctrax based on computer vision to detect fish behaviors [35]. Ctrax accurately tracked 10 individual fish for 1 min and derived X–Y coordinate data in a ready analyzable format, calculated the swimming absolute velocity and the swimming velocity, the rate of change in orientation and the distance to the wall as well.

Although visual information can help to monitor fish behavior *in situ*, quantitative analysis solely from images is difficult. Torisawa et al., proposed a technique for quantitative monitoring of fish bearing and tilt angles from still pictures [114]. Their method is generally applicable for monitoring fish bearing and tilt angles during field surveys.

Fish swimming behavior is more precisely described in the three-dimensional plane than the 2D plane. Ruff et al., proposed non-invasive, 3D measurement technology based on optical stereoscopy and computer image analysis for continuous monitoring of size, position, shape, and spatial orientation of single fish in multi-fish cages [115]. Their method did not describe fish swimming behavior but did lay a foundation for future research. Kato et al., developed a 3D computer-image processing system to quantitatively score goldfish behavior. Three directions (straight, right turn, and left turn,) were quantified as percentages (59+12%, 20+4%, and 20+4%, respectively,) of an hour-long period of goldfish movement. Their image processing system formed simple and quantifiable behavioral analysis of moving goldfish [116]. Ben-Simon et al., designed a video-based eye tracking method for accurately and remotely measuring the eye and body movements of freely moving fish. Using a unique triangulation method that corrected for air–glass–water refraction, they were able to measure detailed 3D positions of fishes' eyes and bodies with high temporal and spatial resolution [117].

Swimming parameters and relationships between swimming direction and tidal currents are vital to overall understanding of fish behavior. Pinkiewicz et al., developed a video system that detected fish shapes on video, and from these shapes quantified changes in swimming speed and direction continuously throughout the day [25]. Their study showed that there was variability in both swimming speed and direction, and that there may be a link between swimming direction of fish and tidal currents acting on their particular cage. Calfee R D et al., used computer video and digital image analysis to analyze the influence of copper content in water on fish swimming behavior [118].

Goldfish often serve as experimental animals for vision research, particularly their psychophysical behavior, and are thus often the subjects of fish behavior research studies. Kato, for example, developed a computer image processing system which acquired the positional coordinates of goldfish moving freely in an aquarium and determined turning directions. The computer image processing system was a useful tool with which the study could quickly and easily quantify the fish behavior [119].

Overall, fish swimming behavior affected by season, time, light intensity and the feeding activity, through the automatic tracking method based on particle filter and eye tracking method based on video to keep track of fish swimming behavior, at the same time, the computer image processing system to quantify the behavior of fish also made great contribution.

Stress response

Fish stress response is a nonspecific physiological response to supernormal stimuli (stressors) produced by a variety of environmental factors. Without stress response, fish could not adapt beyond the normal range of physiological regulation of environmental changes. Too strong or too lengthy a stress response is harmful, however, resulting in slowed growth, decreased reproductive capacity, low immune function, and heightened morbidity and mortality. Thorough analysis and evaluation of the impact of various stress factors on the production of fish is crucial as far as scientific management of fish populations. Stress falls into one of two categories according to its intensity and duration: acute stress (due to water temperature, dissolved oxygen, or salinity fusion) or chronic stress (due to sub-lethal ammonia or nitrite aquaculture water, for example) [35,36].

Acute stress: Creton described a high-resolution imaging system based on computer vision that was unique in its ability to automatically analyze the location and orientation of zebrafish larvae in multi-well plates [18]. The system automatically quantitatively analyzed optomotor response and used large-scale screens to identify genes, pharmaceuticals, and environmental toxicants that influence fish behavior. Other studies have also shown that behavior can automatically analyzed using large data sets. Yahagi et al., proposed an automatic biological monitoring system that introduced and analyzed acute toxicities to fish, developed using image processing techniques. Their system functioned based on behavioral pattern analyses, in which fish in a test chamber were monitored online continuously [9]. Levin designed a program based on computer vision to explore prey interactions, in which a robotic instrument simulated an organism engaged in kinetic dialog with the experimental animal. The stimulation process caused a response in the fish, which, in turn, triggered movement of the stimulus [120].

Stress response behavior in fish does not exist in isolation-it is closely related to swimming behavior. In one relevant study, Kane et al., analyzed digitized video data using the Video Script processing system. Behaviors such as speed, changing directions, time spent moving, and angular velocity on an isolated individual were monitored with video tracking technology to determine environmental stressors [11]. In 2010, Ma et al., monitored water quality in real-time by investigating fish stress responses; after determining current position coordinates of fish with a tracking algorithm and neural network, mapped these to a grid. Their method effectively differentiated motion trajectories of fish, which are motivated by stress response. Accurate information regarding stress response behavior can be employed as a precautionary system for aquatic farms, drinking water treatment plants, and other related industries [15].

3D technology, throughout its development, has continually grown in popularity among researchers, favored for its cost-effectiveness, efficiency, and accuracy. In 2015, Alzu 'Bi H et al., through real-time monitoring of the three-dimensional trajectory of zebrafish before and after the introduction of the pain, to observe the stress reaction of fish, quantified by machine learning algorithms, realize through the fish's behavior changes to achieve the classification of the fish [121]. Zhu and Weng used a systematic, 3D video monitoring system in 2007 to investigate the effects of acute ethanol exposure on goldfish schooling behavior. Data provided by 3D monitoring systems has significantly improved aquatic animal model studies [10] (Figure 7).

Chronic stress: Hypoxic environments are a common problem for growing fish. Aided by computer vision, Israeli monitored behavioral variations of a school of fish (Carrasius auratus) while the fish were subjected to hypoxic stress conditions [122]. Stressed fish differed from controls with the following behavioral responses: 1) their center of gravity moved upwards and horizontally away from the transparent wall, 2) swimming speed was apparently reduced, 3) there were strong fluctuations in all three directions associated with spreading and contracting of the school, and 4) the periodic amplitude of the motion in the vertical direction increased. Xu et al., presented a new image-processing algorithm for quantifying the average swimming speed of a fish school in an aquarium by computer vision [123], comparing changes in behavioral parameters and ventilation frequency in hypoxia-tolerant tilapia while ambient oxygen levels were reduced, maintained at several different low levels of DO, and returned to normoxia. Behavioral and ventilator parameters were shown in their study to predict different degrees of severe hypoxia, though there were relatively large fluctuations.

Fish that swim in school's benefit from increased awareness of the external environment, including improved predator recognition and assessment. Fish school size varies according to species and environmental conditions. In 2013, Jeon et al., proposed a Hidden Markov Model (HMM) based on computer vision to characterize fish schooling behavior in different sized schools and used measured stress responses to quantize fish schooling behavior to determine water quality [124] (Figure 8).

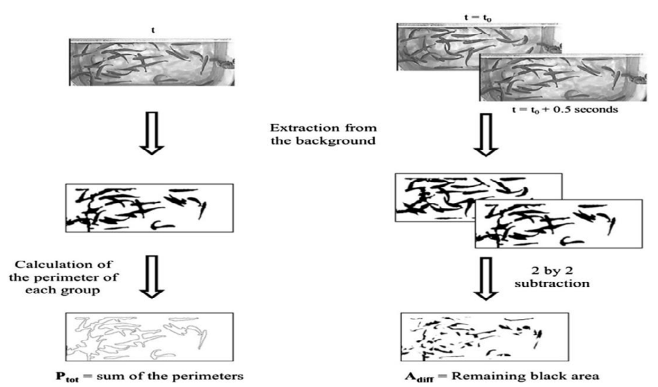

Figure 6: Calculation of group behaviour index from images extracted from a video taken from the top of a tank [8].

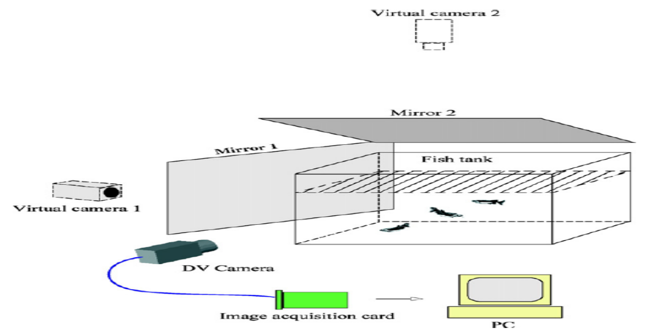

Figure 7: Detecting fish behaviour in 3D with one camera [10].

Sub-lethal ammonia environments are also a common problem for fish. The behavioral responses of schools of young Koi fish (Cyprinus carpio) to sub-lethal ammonia concentrations were monitored in one relevant study using CCD cameras and computer image processing. Several geometrical parameters of the schools, such as the position of the center of gravity and the distribution of fish, were calculated continuously and plotted versus time [125]. In general, remote methods of continuously monitoring alterations in fish behavior under stress show the potential to accurately detect early signs of stress in fish populations.

Long-term drug exposure also results in chronic stress. Pittman and Ichikawa developed a video-based movement tracking and analysis system that used iPhones to quantify behavioral changes following psychoactive drug exposure in zebrafish [126]. These apps were able to track multiple animals' social interactions as well as tracking their individual paths, using a sophisticated range of data selection options and wide array of variables to quantify animals' behavior and allow the user to produce accurate descriptions of complex behaviors in diverse situations by visualizing the animals' tracks.

Stress is not solely driven by environmental factors. Water quality testing also forms chronic stress. By integrating biological monitoring methods with computer vision technology, an acute toxicity test was performed to study the effects of different concentrations of Cu^{2+} on zebrafish [127]. Behavioral parameters of fish schooling behavior were extracted with computer vision technology, then multi-classification based on SVM evaluated the parameters, indirectly measuring water quality. The study found that higher Cu^{2+} concentration caused stronger reactions in the fish school. Zheng et al., designed a system that measured the impact of pollution on Japanese medaka's respiratory rhythms with computer vision technology in real time. Results showed that heavier fish were more tolerant to copper ions [127]. Gorissen M and Flik G were mainly talked about a series of responses to the body's functioning on the stress environment of fish, to show the people how to cope with the existing high-pressure life [128].

The stress response of fish may come from the environment such as low oxygen, is also likely to come from the water quality test, and the method of monitoring the stress response of fish has image processing technology, video tracking technology, 3d video monitoring system, such as the above detailed describes the development of the process.

Feeding behaviour

Feeding behavior is a very important area of study for aquatics animal researchers. Fish predation can be divided into three stages: stimulating and energizing, searching and positioning, and predation and feeding. In production conditions, feed management strategies can be used to regulate and control growth performance in farmed fish. This study divides fish feeding measurement into two parts: individual fish feeding, which describes generalized fish feeding behavior; and detecting uneaten food to deduce fish feeding activity.

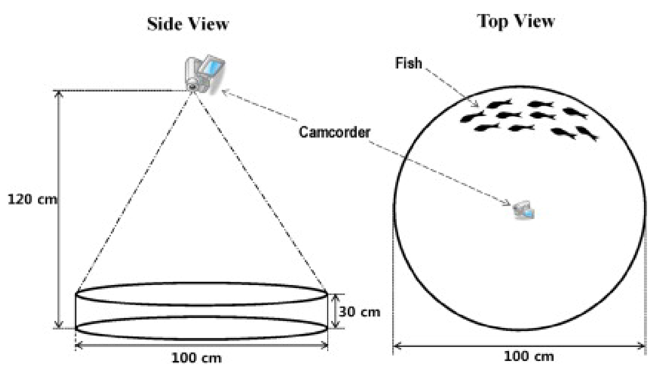

Figure 8: Schematic diagram of the experimental equipment [124].

Detecting fish feeding behaviour: Food availability, feeding motivation, and light intensity have been shown to induce extensive seasonal and diel variation in vertical distribution (Bjordal et al., 1993; Huse and Holm, 1993; Juell et al., 1994; Ferno et al., 1995). Hilder P E et al., studied the foraging behavior of southern Bluefin tuna, they concluded that light intensity is one of the important factors affecting the behavior of feeding. Moreover, the environment of low light intensity is more suitable environment for fish feed [129].

In early years, scientists focused on fish feeding behavior using underwater video techniques. Martinez et al., used underwater video recording equipment to observe Atlantic halibut's feeding behavior, for example, and found that halibuts reacted swiftly to the presence of food, swimming toward the surface at speeds up to 1-5m/s. The halibuts were curious, easily stimulated, readily responsive to the offer of food, and moved upward immediately once they detected movement at the cage surface [130]. Clark et al., observed Atlantic cod feeding behavior in sea pens to determine food acceptance and activity levels, distributing three different diets in different environments to determine how behavior was influenced by seasonal changes in water temperature. Their research indicated that fish activity levels decreased as temperature decreased; however, food handling frequency and rejection rate increased for fish fed formulated diets while remaining constant for fish fed capelin diets [37]. Kadri et al., monitored 19 individual Atlantic salmon in sea cages by underwater computer vision to identify whether the amount of food obtained by individual one-sea-winter salmon was related to social status. Their data showed that in order to prevent individual fish from monopolizing the food supply, it was necessary to distribute food unpredictably in time and space [109,110].

Research has also shown that light is an important ecological factor, particularly in migrations of marine invertebrates and fish. Champalbert and Le Direach-Boursier used a phototaxis device based on computer vision to demonstrate that the behavior of young turbot is highly dependent on feeding conditions, regardless of stage. In turbot that were relatively active, regardless of the light conditions, food given in sufficient quantities usually induced temporarily increased activity and subsequently reduced activity for a few hours per day [131]. Sunuma et al., used a CCD camera and sensor to record barfin flounder feeding behavior in self-feeding systems by computer vision, and their results suggested that self-feeding shows feasible application [132].

A large number of scientists, in fact, have used underwater observation techniques to study the relationship between feeding behavior and environment. Azzaydi et al., performed comparative experiments based on computer vision to study relationships between fish feeding rhythms and environmental parameters and proposed that daily feeding rhythms varied according to both water temperature and photoperiod. Feeding strategies affected both biomass increase and feed efficiency ratio, while the feeding system had no effect on body composition nor on weight homogeneity of the different groups [133].

Andrew et al., used underwater cameras based on computer vision to collect data on feeding behavior and swimming speeds of three fish species. They found that cross-species swimming speeds were similar before feeding but differed considerably during feeding. They also hypothesized that to improve growth and production efficiency in aquaculture requires decreased competition between fish during feeding [134]. Martins et al., researched fish behavior (including resting and swimming activity, waiting-in-feeding area, and feeding rate,) using video cameras based on computer vision. Fish size distribution did not affect fish growth performance, but feeding behavior was proven an important factor, where heavier fish were more active and faster swimmers than low-weight fish [7]. Noble et al., similarly recorded fish feeding behavior using an underwater camera based on computer vision. They found that on-demand feeding improved total growth and growth heterogeneity, and reduced competition and aggression (2007). The same research team found that time-restricted feeding had no significant impact on fish growth or other production parameters after implementing a 1-meal self-feeding regime that was shown to increase fish aggression during both feeding and non-feeding periods [135]. Schwalbe et al., investigated fish feeding behavior using comparative experiments with an HD digital video system based on computer vision. They demonstrated the role of the lateral line system in prey detection within dark environments [136]. Attia et al., explored self-feeding activities via laboratory demand-feeding experiments and determined that self-feeding activity was dependent not only on feeding motivation and social organization, but also on individual learning capacity and risk-taking behavior [136,137]. J Horie et al., developed a pinger for classification of feeding behavior of fish based on axis-free acceleration data and computer vision. By inserting the acceleration data recorder in the fish's peritoneal cavity, it obtained the acceleration data to classify the feeding behavior of the fish [138] (Figure 9).

Light environments have important implications for visually-mediated behaviors. White et al., used an image analysis method based on computer vision to measure the contrast of Daphnia against their background. This research revealed that natural variation in the ambient irradiance spectra especially at long wavelengths will influence the efficiency of the fish foraging in different light conditions [139].

Notably, fish arrival times are often close to their predicted values in relevant studies. Hadal fishes, common research animals, are close to the average size and activity level of benthic teleost fishes. Jamieson et al., used baited camera landers to capture the first images of living fishes by computer vision in the hadal zone (6000–11000 m) in the Pacific Ocean in 2009 [140]. The common abyssal macrourid (Cory phaenoides yaquinae) was observed at a new depth record of approximately 7000 m in the Japan Trench in the same study. These observations provided documented information regarding swimming and feeding behavior of benthic teleost fishes and derived the first estimates of hadal fish abundance.

In another early study, a computer-aided video system was used to

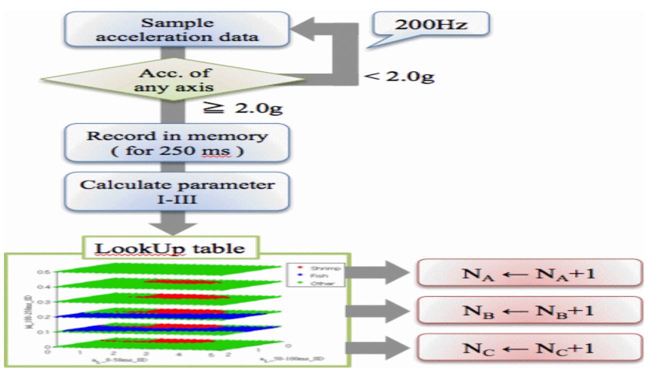

Figure 9: The calculation flow of the pinger.

measure fish larvae positions in 3D [141]. Experiments were conducted to reveal changes in cod and turbot larvae behavior from hatching to metamorphosis in response to feeding and starvation. The point at which feeding activity increased and swimming speed during active periods decreased was determined an effective indicator of the time of first feeding in marine fish larvae.

Successful fish farm management requires accurate information on fish biomass in order to control feeding regimes, stocking densities, and ultimately the optimum time to harvest fish stock. Beddow et al., predicted optimized fish feeding parameters with a high degree of accuracy using a stereo-camera system, at the distinct advantage of greatly reduced stress levels in the fish compared to other biomass estimation techniques [142]. Zhou, et al., Mainly by near infrared imaging technology in computer vision to obtain the images of the foraging activities, fish and fish is calculated according to Delaunay triangle subdivision of the foraging behavior of value, and then used to quantify the value and analyzing the change of the foraging behavior of fish [143].

At the same time, the method of monitoring the feeding behavior of fish is also progressing. Horie et al., developed a pinger for classification of feeding behavior of fish based on axis-free acceleration data and computer vision. By inserting the acceleration data recorder in the fish's peritoneal cavity, it obtained the acceleration data to classify the feeding behavior of the fish, promote the development of the fish feeding behavior detection [138].

Detecting uneaten food: Research has shown that measuring uneaten food is an effective method of deducing fish feeding behavior. Foster et al., used color camera and image analysis algorithms based on computer vision to detect uneaten food pellets and determine fish feeding behavior [144]. Fish may be caused by a desire to feed if pellets are detectable there, while variable daily feed discharge rates (kg/min^{-1}) under similar ration level were correlated with underwater light levels. The study used underwater cameras to obtain images of fish and pellets based on computer vision and suggested that fish may also have been highly habituated to feed in small groups, thus making alternative behaviors unlikely or difficult to discern [145] (Figure 10).

Madrid et al., as an example of controlling feeding behavior with pellets, tested the performance of a device based on computer vision for continuously collecting and detecting uneaten food pellets. The device used in the study reflected and controlled feeding behavior

Figure 10: Detecting uneaten food from under the observation area in order to control feeding switch [145].

using a sensor to estimate food consumption and adjust the feeding schedule accordingly. Fish feeding rhythms tended toward activity in the morning and afternoon, but less at night [39]. Personage and Petrell successfully designed an automatic detection system based on computer vision to measure wasted pellets, where pellets were in sufficient numbers to overcome system inaccuracies and cameras were correctly positioned and maintained. When wasted food was detected, the computer sent a control signal to the feeder [146] (Figure 11).

Liu et al., developed a computer vision-based feeding activity index (CVFAI) to study recirculating aquaculture systems (RASs), applied to measure the feeding activity of fish in arbitrary given duration. The CVFAI provided information to automatically determine the endpoints of fish feeding procedures in the RAS [147] (Figure 12).

Vassallo et al., used computer vision to determine dimensions, water adsorption properties, floating times, and settling velocities of a typical, increasing sequence of pellets under laboratory conditions controlled to reproduce Mediterranean Sea water [148].

Infrared photoelectric sensors, a specific type of computer vision technology, have also been used to form images which aid aquaculture research. Chang et al., developed a control computer vision system that utilized an infrared photoelectric sensor to detect gathering vs. non-gathering behavior of eels, where the decision to stop feeding was able to be determined before the water became overly polluted [149].

Feeding behavior mainly includes testing fish feeding behavior, mainly use the underwater video technology underwater cameras, and detection of fish eat the rest of the food, mainly used in color video camera techniques include computer vision and image analysis algorithm and infrared sensors.

Taxis behaviour

A taxis is the movement of an organism in response to a stimulus such as light or the presence of food. Taxis are innate behavioral responses. A taxis differs from a tropism (such as turning response, often growth toward or away from a stimulus,) in that the organism has motility and demonstrates guided movement toward or away from the source of the stimulus. Taxis is sometimes distinguished from a kinesis, a non-directional change in activity in response to a stimulus [150].

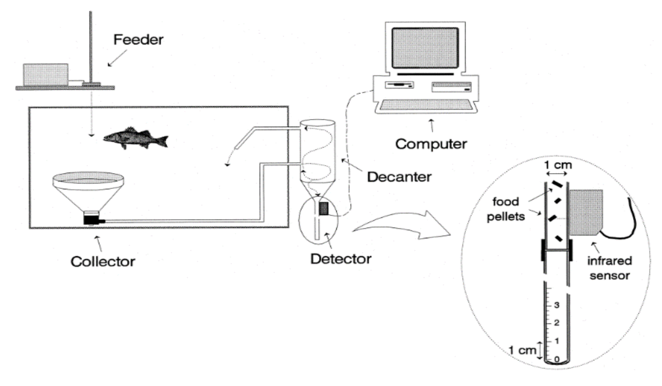

Figure 11: First machine to automatically detect uneaten food [146].

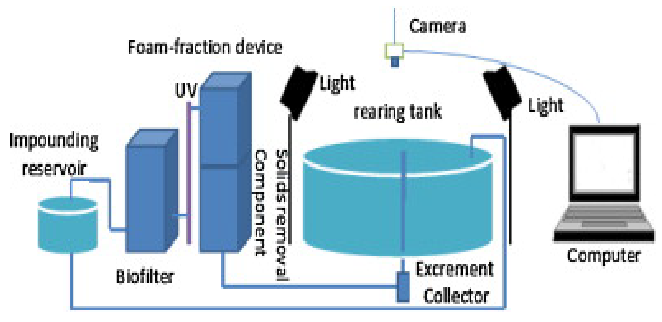

Figure 12: The experimental RAS structure and image capture system.

Two innate responses in guppies (Poecilica reticulata), positive phototactic and rheotactic responses, can be used to manipulate fish movements in order to control their behavior. Karplus et al., introduced a method that used positive orientation of phototactic and rheotactic responses in Poecilica reticulata to guide them through narrow channels established with a computer vision system. Females spent about 4 s in the entry section prior to deciding which channels to enter, whereas males spent about 30 s. They developed an image-processing algorithm for sex determination and quality sorting of live, red-blond strain guppies (2003). This system was later improved by Karplus et al., where they attempted to separate guppies that moved in groups individually by introducing an obstacle into a narrow channel or narrowing the transparent pipe [151].

An image-processing algorithm applied to images of common carp (Cyprinus carpio), St. Peter's fish (Oreochromissp.) and grey mullet (Mugil cephalus), successfully discriminated among species in several studies, where fish were proven able to be manipulated to swim through a narrow, transparent channel in a such a way that they could be sorted using computer vision [13]. Fish behavior is a crucial consideration in commercial trawling where catch reduction is important [152], and, notably, selectivity may lead to biased assessments of fish abundance in fisheries. A range of biogeographical and depth patterns have been identified in effort to remedy this [153-155].

Fish taxis behavior can be evaluated according to fish trawling behavior. Gabr et al., used Juvenile masu salmon (Oncorhynchus masou) with average body length of 13 cm as the experimental fish under computer vision. To evaluate square meshes and sorting grids as successful, size-selective catch reduction devices in finfish trawls, Gabr and his research team conducted a simulated trawling experiment to assess the effects of illumination, towing speed, and mesh or grid orientation on the escape behavior of undersized fish [156]. Papadakis et al., developed an inexpensive way to analyze many behavioral variations under a large variety of stress factors remotely, while eliminating any behavioral interference. Their system successfully recorded and analyzed fish behavior with an image difference algorithm (IMAQ absolute difference, LabView,) and a standard object detection algorithm, while identifying all fish interactions with the net [157]. In order to evaluate the potential for selective retention in a midwater survey trawl, in conjunction with acoustic surveys of walleye pollock, Williams et al., examined fish behavior using an integrated approach of optical, acoustic, and recapture net methods. They also developed a stereo-camera system that provided length, position, and orientation information, plus a dual-frequency identification sonar that tracked fish targets in the trawl [158]. B. j. Williamson et al., improved a modified nearest neighbor algorithm to filter the fish group and used the multi-beam detector to achieve robust tracking of the position of the fish [159]. Bryan et al., examined flatfish orientation with Kuiper's one sample tests of uniformity and compared mean orientations of stationary and reacting flatfish with Wilcoxon rank. Their quantitative analyses indicated that flatfish herding occurred along trawl sweeps, and that the effective area swept was greater than the wing spread [159] (Figure 13).

Other Behaviours

Other scientifically significant fish behaviors in addition to those mentioned above include homing behavior, spawning behavior, cooperation behavior, and singing, which are reviewed briefly below.

Certain marine fish possess homing abilities along with strong fidelity to their habitats and spawning sites. Mitamura et al., explored the homing behavior of diadromous fish with four hydrophones, (relatively little research attention has been given to non-diadromous fish.) Their results indicated that black rockfish predominantly use their olfactory sense for homing [160].

Spawning is also an important fish behavior. Dou et al., investigated spawning behavior of artificially matured Japanese eels (Anguilla japonica) in captivity using a DVD video imaging system. On many occasions, eels of both sexes (paired either male–female or female–female) were found to "cruise together" in water columns for a short time period or frequently come together prior to releasing eggs and ejecting sperm, suggesting the possibility of group mating in artificially matured Japanese eels [161]. González-Rufino et al., estimated fish fecundity with a stereometric method, analyzing histological images of fish reproductive cells based on computer vision. Their method was proved highly reliable for automatic fish fecundity estimation from histological images of fish ovaries [162].

Cooperation behavior is, remarkably, not a solely human phenomenon. Cleaner fish (Labroides dimidiatuscan) are a great example. Pinto et al., explained cooperation behavior as helpers attempting to increase their image score, which in turn increases the probability that bystanders will help them in the future [163]. Image scoring by an audience indeed leads to increased levels of cooperation in nonhuman animals, as well. Bshary and Grutter studied altruistic behavior in Labroides dimidiatus, and found experimental evidence for cleaning mutualism, where fish engaged in image-scoring behavior. Further, trained cleaner fish fed more cooperatively in an "image-scoring" situation over a "non-image-scoring" situation [164].

Dolphin singing behavior is another extraordinary facet of fish behavior. In one relevant study, Esfahanian et al., explored the effects of two feature sets on two classifiers and assessed their performance and computational complexity, classifying dolphin whistle types without tracing contours from spectrograms of dolphin whistles based on computer vision [165].

Discussion and Conclusion

This review has focused on the evolution of computer vision technologies over the past forty years as applied to fish behavior, from simple hardware observation equipment to image processing and analysis and object tracking systems. Rapid progress in the computer vision field has turned study of fish behavior into a powerful industry. Problems identified by growers require technological solutions, and developments in hardware and software have enhanced the capabilities of cameras and peripheral equipment, reduced their cost, and enabled faster image processing and accurate data interpretation. Advancements in technology continually provide better data, for example, where 3D technology has proven to reflect fish behavior more accurately than 2D. Inspecting agricultural products also requires gentle handling to avoid damage, which computer vision helps to facilitate. Unlike most other techniques, computer vision provides visual information on conditions within cage systems and builds permanent records of the stock. Figure 14 shows the geographic distribution of the number of papers, each circle is the number of papers, nevertheless, there are not many teams using these computer vision techniques. Numerous studies have been published in Japan (19 papers from 1985 to 2016), the United Kingdom (20 papers from 1995 to 2017) and USA (19 papers from 1999 to 2017), and in comparison, relatively few papers from other countries. These articles are published in Europe, East Asia, America and Australia. It has a great relationship with their geographic location, because most of them are next to the sea, rich fishery resources and a long coastline.

Figure 15 shows year distribution and the behavior distribution of the papers, each bar is the number of papers. Nevertheless, there is no continuous distribution in these papers. Schooling behavior is nearly always continuous. Current research does not appear alternatively. There have been a lot of vacant time in fish, it shows that this technology is already mature. Swimming behavior, feeding behavior and stress behavior are the initial stage from the early nineteen nineties. Stress behavior and other behavior appear later. The behavior research has a relationship computers' development. With the increase of computer processing speed, the expansion of the storage space, the high-quality of HD equipment, scientists in the acquisition of fish behavior and analysis of fish behavior more quickly, more convenient, which has prompted the study more deeply.

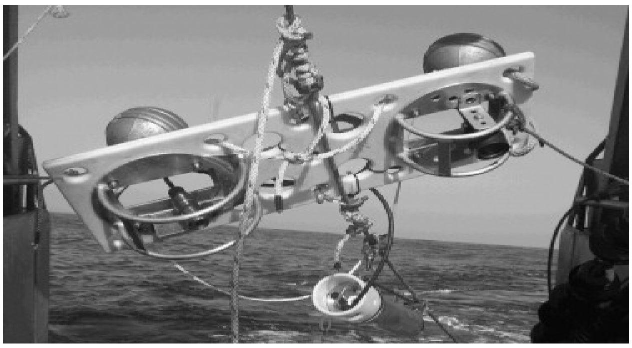

Figure 13: Video camera system [159].

Figure 14: Geographic distribution of the papers.

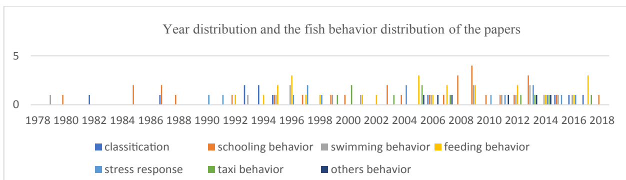

Figure 15: Shows year distribution and the behavior distribution of the papers.

Other notable conclusions of this paper can be summarized as follows:

- Generally maximizing the quality of video information and absolving remaining issues associated with analysis of video information seems possible through integration with actuators and existing remote sensing technology, such as ultrasonic telemetry.
- The technological progress seen in the last decade is expected to continue; simultaneously, system autonomy, storage capacity, and sensor resolution will all likely increase. Human-operated systems will continue to be prevalent, particularly for researching fish behavior. Multiple sensors and high definition cameras will increase in popularity and availability.
- Intelligent, underwater monitoring systems can be developed online to monitor and track fish.
- Increasingly robust algorithms can manage severe environments.
- Stereo-video techniques show considerable promise and should be utilized more often by researchers.

The development of computer vision technology played a great role in promoting the development of the fish species classification, fish schooling behavior, swimming behavior, stress response, feeding behavior, taxi behavior. So, in the future, we will still need to apply the latest science and technology and computer vision to the behavior of fish detection, to promote the development of fish behavior analysis and research.

Acknowledgments

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