Computers and Electronics in Agriculture 88 (2012) 125–132

Contents lists available at SciVerse ScienceDirect

Computers and Electronics in Agriculture

journal homepage: www.elsevier.com/locate/compag

Review

The use of computer vision technologies in aquaculture – A review

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ARTICLE INFO

Article history:
Received 10 March 2012
Received in revised form 15 July 2012
Accepted 16 July 2012

Keywords:
Computer vision
Aquaculture
Biomass
Gender
Species
Welfare

ABSTRACT

Computer vision technology is a sophisticated inspection technology that is in common use in various industries. However, it is not as widely used in aquaculture. Application of computer vision technologies in aquaculture, the scope of the present review, is very challenging. The inspected subjects are sensitive, easily stressed and free to move in an environment in which lighting, visibility and stability are generally not controllable, and the sensors must operate underwater or in a wet environment. The review describes the state of the art and the evolution of computer vision in aquaculture, at all stages of production, from hatcheries to harvest. The review is organized according to inspection tasks that are common to almost all production systems: counting, size measurement and mass estimation, gender detection and quality inspection, species and stock identification, and monitoring of welfare and behavior. The objective of the review is to highlight areas of research and development in the field of computer vision which have made some progress, but have not matured into a useful tool. There are many potential applications for this technology in aquaculture which could be useful for improving product quality or production efficiency. There have been quite a few initiatives in this direction, and a tight collaboration between engineers, fish physiologists and ethologists could contribute to the search for, and development of solutions for the benefit of aquaculture.

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1. Introduction

Following its continuous development for the last three decades, computer vision technology is now a common sophisticated inspection technology. Advances in hardware have resulted in cameras and peripheral equipment with higher sensitivity and faster capabilities that are less expensive, and simpler to use and incorporate into control systems. Advances in image processing and classification methods have enabled the rapid extraction of fine details from images and more accurate data interpretation for control decisions. As a result, computer vision technologies are being used by almost all industries for a variety of inspection tasks. However, these technologies are still not widely used in aquaculture.

A recent publication by Mathiassen et al. (2011) reviewed the potential of various imaging technologies, including computer vision, for the inspection of fish and fish products. They looked at four major areas of application: research, process understanding and optimization, automated sorting and grading, and automated processing, all of which are related to postharvest operations. These operations can present complex inspection challenges, such as high

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http://dx.doi.org/10.1016/j.compag.2012.07.010

speed or detection of hidden internal quality attributes. On the other hand, in most cases, the environment and conditions under which the technology operates are controllable (e.g. lighting, product position with respect to the sensor, mechanical stability). Application of computer vision technologies in aquaculture, the scope of the present review, is more complicated in this respect. The inspected subjects are sensitive, prone to stress and free to move in an environment in which lighting, visibility and stability are not controllable in most cases. The equipment must operate underwater or in a wet environment and is expected to be inexpensive.

The present review describes the state of the art and the evolution of computer vision technology in aquaculture. It complements the abovementioned review by focusing on aquaculture operations and inspection needs in all stages of production, from hatcheries to harvest. It is organized by inspection tasks which are common to almost all production systems: counting, size measurement and mass estimation, gender detection and quality inspection, species and stock identification, and the monitoring of welfare and behavior. This order more or less follows the order of complexity of the inspection missions. The order of presentation of the relevant publications within each section is generally chronological, but mono- and stereovision technologies are grouped separately. A few publications of work conducted in the context of fisheries, ecology or the postharvest industry are also described, in cases in which the inspection task is similar in these fields or where an image-processing algorithm or method could also be useful in aquaculture. To complete the picture, commercially available imaging technologies are also described, as well as a few non-imaging technologies presenting alternative methods. Studies which have made use of computer vision in the laboratory, such as for studying the effects of diets or chemicals on fish behavior or quality, are not described in this review since their objective was not to develop the technology as a solution to an inspection problem.

The objective of this review is to highlight areas of research and development in the field of computer vision which have made some progress, but have not yet matured into useful tools for aquaculture. There are many potential applications for the technology in aquaculture which could improve product quality or production efficiency. My hope is that this review will spark the renewal of a research or development process which will take the technology another step forward.

2. Counting

Objects are counted in a wide range of industries, by various methods, optical ones being the most common. One of the basic and most important requirements for all aquaculture operations is a means for counting stocks. Counting eggs, larvae, fry and fish at various growth stages (from the nursery to marketing) can be of crucial importance, helping growers to accurately stock their containers, ponds or cages, manage precise feeding strategies and design a marketing schedule. Commercially available fish-counting devices are designed for various ranges of fish sizes. Vaki's ''Bioscanner'' (Vaki Aquaculture Systems Ltd., Iceland) is based on optical detection of fish (3 g–12 kg) as they slide along a chute; the AquaScan ''Fishcounters'' (AquaScan AS, Norway) is used for counting fish (0.2 g–18 kg) while being transferred through a pipe or over a flat, wide channel, and SRI's ''Fish Counter'' (Smith-Root Inc., WA, USA) is based on electrical conductivity and used for assessment of upstream and downstream fish movement in rivers. Vaki also has ''Nano'' and ''Macro'' counters for fish fry of 0.05–20 g or larger than 0.2 g, respectively, based on computer vision systems, with a reported accuracy of 98%. Impex's TPS counters (Impex Agency Hoerning ApS, Denmark) are designed for a few ranges of fish sizes (between 0.2 and 50 g), also with a reported accuracy of 98%.

The AGM Rognsorterer (Maskon AS, Norway) sorts salmon and trout eggs according to size and quality by imaging the eggs from two sides and processing the images. Spinnaker Electronics Corp. (FL, USA) has a device (''Larcos'') which uses image processing to count shrimp being transferred through a 4'' tube. They claim the device can count fry and larvae but details on the counting accuracy or method are not provided.

Older electronic methods and devices for fish egg (Witthames and Walker, 1987) and fish (Joyce and Rawson, 1988) counting had a few limitations, one of which—relying on object singulation and size uniformity—limited their value for commercial operations. Newbury et al. (1995) took top-view images of artificial fish (grey mullet, *Mugil chelo*, all of one size) arranged in quantities from 10 to 100 (at intervals of 10) and various overlapping arrangements. They estimated the fish count by processing the images using three methods: (1) simple pixel count; (2) summation of the image histogram in the frequency domain, and (3) classifying the frequency histograms (pooling every 5, 10 or 25 bins together) by a neural network. All three methods proved to be of limited accuracy (85%, 88% and 94%, respectively), considering the limitations of their methodology (artificial fish, no movement, no background noise and results presented for training sets only). Yada and Chen (1997) used a weighing device to count seedling fry. However, accurate weighing of batches of fry amounting to only a few milligrams requires analytical scales, a protected environment and is too slow to work with in practice. Friedland et al. (2005) used a commercial software package to count plated fish eggs. They carefully prepared a sample and scanned it to get an image. Because of the sample preparation, no overlaps occurred in the images. Touching eggs in the image were separated by a simple dilation-erosion algorithm. Eggs were differentiated from ovarian tissue pieces in the image by characterizing seven geometrical features and their typical value ranges. False-negative classification errors were estimated at 1%. Alver et al. (2007) developed an autonomous rotifer sampling and counting system, which extracts samples of rotifers from first-feeding tanks and takes multiple images of known volumes of sample while back-lit. Tests indicated that the accuracy of the rotifer-density measurements was close to the statistically possible accuracy determined by sample size. They claimed that by adjusting the sample volume and number of images acquired from a sample, the accuracy could be adjusted according to requirements.

In a typical ornamental fish farm there are many spawning containers arranged with minimal space between them. In tropical fish farms, daily counting of thousands of fry is performed manually. To minimize the labor associated with this daily counting operation and to reduce counting errors, a computer vision system based on processing images of batches of fry harvested from the broodstock containers was developed (Zion et al., 2006). The image-processing algorithms used shape models of the various species and detected the number of overlapping fish comprising complex image segments. The device and method were tested extensively and proved to be 98% accurate for counting day-old fry of various species as well as fish of larger sizes, such as guppy after 2 weeks in husbandry tanks.

In some computer vision systems which are designed for various inspection tasks (as described in following sections), the inspected targets are segmented from the background and from each other. In some of these systems, counting of the analyzed objects is provided as a byproduct.

3. Size measurement and mass estimation

Fish length is commonly used to describe its ''size''. However, mass is used in trade or to estimate load in production systems.

Methods developed to measure fish length or image area and relate it to mass are reviewed in this section.

Relationships between fish shape features and mass have been investigated for many years as measures of structural indices, for growth-rate assessment or for ecological purposes (Huxley, 1924; Le Cren, 1951; Nieto-Navarro et al., 2010; Spencer, 1898). The most common mathematical model characterizing the relationship between fish length (L) and mass (W) is the power model $W = aL^b$, where a and b are empirically characterized species- and strain-dependent parameters (Fulton, 1904). Beddow and Ross (1996) measured the conventional dimensions of the lateral profiles of Atlantic salmon (*Salmo salar*) manually and concluded that single-factor regression equations are inadequate for predicting their mass. Multifactor regression equations predicted the mass of individual fish more accurately (98%), suggesting that morphologically different strains would require different calibration equations.

With the advances in optical imaging and image-processing technologies, attempts have been made to develop sophisticated sensors and methods to characterize various fish dimensions, and then infer the mass. Poxton and Goldsworthy (1987) compared predictions of mass and growth using both length and area. Calibration equations were found to be dependent upon size class and level of ration consumed by the fish. Strachan (1993) used a computer vision system to estimate fishes' length from their binary images, acquired while being carried by conveyor through a lit chamber. He used mid-points to draw a center line for length estimation and achieved an accuracy of ±3% compared to manual measurements. Zion et al. (1999) found that the masses of grey mullet (*Mugil cephalus*), St. Peter's fish (*Sarotherodon galilaeus*) and common carp (*Cyprinus carpio*) could be closely estimated from their image area (correlation coefficients higher than 0.95). Odone et al. (2001) took simultaneous top- and side-view images of singulated and oriented fish, extracted 13 dimensional features and used a support vector machine to predict their mass with an absolute accuracy of 97%. Recently, side-view image areas of dead or anesthetized Alaskan pollock (*Theragra chalcogramma*), rainbow trout (*Oncorhynchus mykiss*) and four salmon species—pink (*Oncorhynchus gorbuscha*), red (*Oncorhynchus nerka*), silver (*Oncorhynchus kisutch*), and chum (*Oncorhynchus keta*), were shown to correlate very well with their mass using power models (Balaban et al., 2010a, 2010b; Gumus and Balaban, 2010). In the case of salmon, a model predicted their mass from their area irrespective of species. Hufschmied et al. (2011) used a linear-regression model to estimate sturgeon (*Acipenser baerii*) mass from their top-view image area with an average relative error of 5.7%. They developed an in situ sorting device comprised of a channel through which fish swim voluntarily, with background lighting and a camera mounted on top. Images were acquired and processed to identify fish that were fully within the field of view. The channel was then shifted to one of two directions to let the fish out according to its estimated mass.

A periodical routine carried out in many ornamental fish farms involves estimation of the average fish mass at various growth stages. This is done to monitor growth rates and to plan accurate feeding. A sample of 50 to 100 fish is drawn from a population of thousands of fish. The fish are collectively weighed and counted so that the average mass can be calculated. Since this is a labor-intensive practice, it is completely avoided in some farms. Zion et al. (2012) developed image-processing algorithms to estimate the average mass of groups of small ornamental fish (e.g. guppy, platy, molly etc.). Power-models relating top-view image area of single fish to their mass were calculated for various species and strains, with a coefficient of determination (R^2) higher than 0.956.

In cases in which fish cannot, or should not be forced into an oriented position or kept at a known distance from the imaging system, stereovision must be used, as it enables sensing the depth dimension but adds some complexity. Ruff et al. (1995) demonstrated the use of stereoscopy techniques for measuring individual fish dimensions and positions in cages containing many fish. They tested their system and methods in a 2-m diameter land-based tank containing sea water with two fish. Their cameras were mounted vertically with respect to each other, on a surface structure which provided spatial stability. Fish nose and tail points in image pairs were located manually, and fish length calculated between these points was accurate to approximately 96.5%. Beddow et al. (1996) used a stereo-camera system to predict the mass of individual Atlantic salmon and the biomass of a group of fish. They used fin-to-fin length, and body depth and length dimensions visible from side views and achieved a high accuracy of 99.6% in the biomass estimation. Tillett et al. (2000) segmented fish images by means of a modified point-distribution model (PDM) which considered the strength of an edge and its proximity to attract landmarks to edges. They trained their 3D PDM on a set of salmon stereo images acquired in a tank and thus avoided the arbitrary setup of initial values required by other methods. They estimated fish length with an average accuracy of 95% relative to manual measurement. Their procedure required manual placement of the PDM in an initial position close to the center of the fish, thereby affecting the accuracy of the final fitting. Neighboring fish images forced the PDM away from the correct edges, and fish whose orientation was very different from the initial PDM or were smaller than the initial values could not be correctly fitted. Later, Lines et al. (2001) modified their method by detecting the fish's head using the difference between two successive frames and an *n*-tuple binary pattern classifier to locate the initial fish image. They fitted the PDM to a presumed fish image in this location. They estimated the mean mass of 70 dead salmon hanging in a tank with an accuracy of 98%. Estimation errors for individual fish mass reached 20%. Estimation accuracy was poorer for live fish images and it was assumed that the results could be degraded when images were acquired in commercial fish cages due to poorer imaging conditions and larger fish population density. Martinez-de Dios et al. (2003) used an underwater stereovision system to estimate the mass of adult fish in sea cages from their length, and an over-the-water stereo system to estimate fish mass in a nursery. Fish segmentation was based on finding points of interest on the fish image and linking them with real-world coordinates "using a priori knowledge of the species". Matching with several templates was used to find caudal-fin points. Details of methods for finding other points, such as the tip of the head, were not provided. From the length of 120 correctly segmented images, they estimated fish mass, using length-to-weight ratio, with an accuracy of 95% and 96% for the underwater and over-the-water systems, respectively. No data were provided on false fish-detection ratios or on how the accuracies were figured out as the analyzed fish were among many other fish. Costa et al. (2006) used a submersible dual camera module connected through two frame grabbers to a PC. They filtered and segmented images using a fixed threshold to obtain binary images. Image segments were analyzed for area, major axis length and circularity, and the segments which "fit into appropriate ranges" were considered to belong to fish. Landmark points in stereo image pairs were then located (no procedures were described) and the geometry was calculated. The boundary of the fish was located in 3D and distances between key points were calculated. Fish-length estimation error, based on a single measurement of a model fish, was approximately 2%. Costa et al. (2009) tested a dual parallel camera module for counting and estimating northern bluefin tuna (*Thunnus thynnus*) length while they were being transferred from a purse-seine to a cage. They reported length-estimation calibration errors of less than 13%. When tested with transferred fish, the biomass estimation error was 50.6%. Torisawa et al. (2011) used a stereo-video system positioned 2, 4, 6, 8, 10 and

12 m deep in a 30-m diameter commercial cage to estimate the length of Pacific bluefin tuna (*Thunnus orientalis*). From multiple images of the same fish, they calculated the repeatability, as a measure of accuracy, of their method and concluded that the fish-length error ratio was 5% if the tuna were up to 5.5 m away from the cameras. However, snout and tail points were manually marked.

The commercial optical ''Biomass Counter'' (Vaki Aquaculture Systems Ltd.) is a 0.6×0.65 m frame suspended in the water. Fish voluntarily swim through it and interrupt a set of infrared light beams, their silhouettes are generated and their sizes are calculated. It is not known whether the device's frame influences the sample of fish swimming through it, thereby introducing a bias into the biomass estimation. However, it offers a technological alternative to physical sampling and weighing of fish in cages.

4. Gender identification and quality assessment

Identification of fish gender by rapid optical technology could be of high economic value. For example, sturgeons for caviar are grown for a few years (typically 3–4) before males are separated from females, which are kept for a few more years before their caviar is harvested. In most sturgeon species, there are no phenotypical differences between the sexes before sexual maturity. However, in a few species, the morphological shape of the urogenital opening and pectoral fins can be used to distinguish the genders (Di Marco et al., 2011). Tilapia growers are interested in males since their growth rate is higher than that of females. In ornamental fish farms, gender determination is important for breeding programs and for marketing. The males of most tropical ornamental fish are more colorful and considered of superior quality. Edible fish quality in terms of appearance (shape and color) is almost exclusively tested postharvest, before or after processing. This could be due to the lack of sensing technologies for in situ (underwater) applications and/or lack of intervention methods (e.g. means for removal of fish of inferior quality from a large population) during the growout period.

Morphometric features are good indicators of gender in many species. For example, Merz and Merz (2004) showed that morphometric-discriminant functions could be used to determine the sex of adult Chinook salmon (*Oncorhynchus tshawytscha*) with an accuracy of over 90%. Odone et al. (2001) presented a system which takes top- and side-view images of live fish as they slide along a transparent channel and analyzes shape features. They used it to predict fish mass, but the features could potentially be used for quality grading in some cases. Such a physical structure could be used in some intensive or semi-intensive systems, where fish are transferred between pools or containers.

Detection of gender and quality of ornamental fish is crucial during the growout period and before marketing. Breeding and production of high-quality fish is based on selection, by repeated sorting and grading of many fish according to gender and quality (Gomelski et al., 1995; Wohlfarth and Rothbard, 1991), a labor-intensive operation. Wallat et al. (2002) used a machine vision system to quantify the development of goldfish (*Carassius auratus*) skin color in response to different feeds. They compared pixel colors to 64 color standards, generated color histograms and used them as an objective measurement of skin color. Zion et al. (2008) developed image-processing algorithms for sorting guppy fish (*Poecilia reticulata*) by gender, to be used by a system for sorting and grading ornamental fish (Karplus et al., 2003, 2005). An algorithm for the detection of landmarks on side-view image contours was developed and enabled extraction of specific shape and color features of the fish's tail and body. Gender identification accuracy was approximately 90% using shape features, approximately 96% using color features, and was slightly improved when both color and shape features were used.

5. Species and stock identification

In polyculture fish farming, where several species are grown together in ponds or reservoirs, it is necessary to sort harvested fish according to species and size for optimal marketing. A common practice (called 'decimation') is to harvest, at specified intervals during the season, fish that are ready for marketing, usually the larger fish of a species. Pond decimation increases overall fish production by decreasing population density, and reduces growth disturbances caused by competitive interactions between big and small fish. However, this is a labor-intensive and expensive operation and it is harmful to the fish. Development of means and methods for continuous, automated, underwater selective fish harvesting would be of interest to this sector.

Tayama et al. (1982) developed an optical sensor which acquired binary images of four fish species. They employed various dimensions to produce shape descriptors that were then used to discriminate between the species with 95% accuracy. Wagner et al. (1987) used simple shape features (cross-section and length dimensions) of side-view images of dead fish to show that it may be possible to sort them using linear discrimination functions. Strachan and Kell (1995) used 10 shape features and 114 color features to discriminate between haddock fish stocks from two different fishing regions. Using canonical discriminant analysis and the 10 shape features, they achieved 72.5% correct classification for a calibration set of 100 fish and 71.7% for a test set of 900 fish. With the color features they achieved 100% classification of the calibration set and 90.9% and 95.6% correct identification of fish from the two stocks. Strachan (1994) tested a prototype system at sea for sorting fish by species and size. Fish were placed manually on a conveyor belt and their image was acquired. Using fish length-to-width ratio, he differentiated between flat and round fish, and using the shape and color features mentioned by Strachan and Kell (1995), he managed to sort 12 fish species (9 round fish and 3 flatfish) with an accuracy greater than 99% at a rate of 40 fish/min. The system required color calibration every 3 h to correct for lighting changes and camera color drift. Arnarson and Pau (1994) developed an algorithm that used structuring of primitive shape elements to describe fish-shape features, which were then fed to a neural network for species classification. Classification accuracies of 100% and 94.6% were achieved with a training set of 29 fish and a test set of 928 fish (consisting of three species—cod, flounder and redfish), respectively. Zion et al. (1999) used moment invariants to extract typical features from side-view images of dead fish tails and used them for species identification. Species identification accuracy was 99%, 93% and 93%, respectively, for grey mullet (*Mugil cephalus*), St. Peter's fish (*Sarotherodon galilaeus*) and carp (*Cyprinus carpio*). The method was later tested with live fish swimming in clean water (Zion et al., 2000), and species identification accuracies were 100%, 91% and 91%, respectively. However later, the moment-invariant features proved to be sensitive to water opaqueness and fish motion, which strongly affected the appearance of the fish tail in the image. White et al. (2006) used 10 shape features (grid-line lengths) and 114 color features (average RGB values of 38 grid elements) to sort trawl-catch fish by species while being conveyed on a belt. Their system was 99.8% accurate at classifying 7 species and measured fish length with a standard deviation of 1.2 mm. The system required hourly color calibration and background measurements.

Most of the studies discussed above dealt with dead fish, which are easier to handle and inspect than live ones. Castignolles et al. (1994) developed a method for off-line detection of live fish on

S-videotapes recorded by a camera facing an observation window. The window was mounted on the side of fish passages constructed in dams to allow migratory fish to swim upstream for spawning. They used background lighting to enhance image contrast and static thresholds to segment fish silhouettes. Twelve geometrical features were extracted from fish images and a Bayes classifier was tested for species recognition among six species. A perfect classification was achieved by analyzing multiple images of each fish as it swam across the passage. However in real-time applications, where fish are lined up close to each other, multiple imaging tends to be impractical. Cardin and Friedland (1999) reviewed morphometric analyses with regard to fish-stock discrimination. They claimed that discrete juxtapositions of fish tissue types are the most useful homologous landmarks for biometric interpretation and that external points (such as tips of the snout or fins) are not satisfactory because their locations are subjective. However, they did not refer to algorithms for determining landmarks or external points. Cardin (2000) reviewed various morphometric methods used for stock identification. He discussed outline and shape landmark methods. Points of attachment of fin membranes were found to be more effective for fin-fish group discrimination than landmarks located on extremities (Winans, 1985). Homologous landmarks were found to be more effective in describing shape than other arbitrarily located landmarks (Bookstein, 1990). Feature selection should consider fish sample size, life history, stage of development and the feature's discriminating power. Algorithms for image processing and morphometric-feature extraction were beyond the scope of that review.

Cadieux et al. (2000) developed an automated imaging system for counting fish by species as they cross fishways mounted next to river dams. The hardware was based on Vaki's commercial biomass counter—a set of infrared diodes and sensors that generate silhouettes as the fish swim between them. They calculated seven moment invariants (Hu, 1962), the Fourier descriptors of the silhouette contours, and the geometric features described by Castignolles et al. (1994). A majority vote of three classification methods was used to classify images of five fish species with an overall accuracy of 78%. Tidd and Wilder (2001) designed a machine vision system for the detection and classification of fish in an estuary. They used strobe lighting driven by a video sync signal and directed through a fiber bundle into a $300 \times 300 \times 300$ mm field of view in a water tank. They also applied a window-based segmentation algorithm to segment fish images, and an aspect ratio to eliminate partial fish segments. Water currents were employed to direct fish perpendicular to their camera, and they considered eliminating overlapping fish images by means of the segment aspect ratio and a length test. They extracted fish image area and aspect ratio to classify three fish species using a Bayes classifier. The system was tested on only 10 images of each species, but they concluded that the system and method have the potential for operation in situ. Storbeck and Daan (2001) used structured light and a camera mounted on top of a conveyor to measure the width and distorted width (by the length of the light line) of a dead fish at points along its length. The data were fed into a neural network which differentiated among sole (*Solea solea*), plaice, whiting (*Merlangius merlangus*), dab (*Limanda limanda*), cod (*Gadus morhua*) and lemon sole (*Microstomus kitt*) with an overall accuracy of 98%. Zion et al. (2007) improved their species-identification methods (Zion et al., 1999, 2000) and showed that fish could be sorted according to species while swimming in pond water containing algae and suspended sediments. Fish images were acquired while swimming with their sides to the camera. Background illumination was used to overcome water opaqueness and to generate high image contrast. Size- and orientation-invariant features were extracted from the fish silhouettes and processed by a Bayes classifier, which classified grey mullet, St. Peter's fish and common carp to accuracies of 98.9%, 94.2% and 97.7%, respectively. A real-time underwater computer vision system was tested in a pool in which fish swam through a narrow transparent unidirectional channel. Two sets of 1701 and 2164 images were analyzed with overall species recognition accuracy of 97.8% and 98.9%, respectively. Aguzzi et al. (2009) analyzed video footage acquired by a permanent deep-sea (1100 m) observatory in Japan, using a video camera and constant white lighting. Subtracting the background image from an image and using fixed segment area and gray-scale thresholds, they selected suspected image segments for further identification. The segment contour was Fourier-transformed and 20 normalized descriptors were used by a K-nearest-neighbors (KNN) classification algorithm to classify the segment into three species classes. The RGB components of the segments were also used by a KNN classifier. Results were compared to decisions made by a trained operator: 78%, 43% and 63% of Zoarcid fishes (eelpouts), red crabs (*Paralomis multispina*), and snails (*Buccinum soyomaruae*), respectively, were correctly classified.

6. Monitoring welfare

Farmers' attention has been drawn to animal welfare by public awareness and by the potential economic impact of stressed animals. When fish are stressed, they undergo various metabolic changes, all of which are expressed externally by variations in their behavior. Similarly, a change in fish feeding behavior, swimming behavior or skin color is a sign of unfavorable conditions, stress, distress or pathogenic conditions (Conte, 2004). For example, swimming depth and behavior of Atlantic salmon in sea cages is strongly influenced by environmental factors such as temperature and light (Oppedal et al., 2001). Fish under continuous stress are known to stop feeding (Love, 1981). The characteristics of the aquatic environment and the impact of cultural practices on fish have forced the industry to develop monitoring tools. Various sensors (e.g. for temperature, oxygen, nitrogen, etc.) are implemented to monitor water quality and alert the user when predetermined extreme conditions are approached. Deviations beyond acceptable ranges of water-quality indices lead to stress, impaired health, and even mortality. However, fish might be stressed by factors such as presence of predators near the cages, which cannot be sensed by these sensors. Such behavioral traits could potentially be monitored by computer vision systems, as already noted some 20 years ago. However, aquaculture poses a special challenge to developers. The wide variety of growing methods and species, the fact that the environment is under water, uncontrolled (e.g. lighting, turbidity) and very crowded by fast-moving animals make the challenge far more difficult relative to other animal husbandries.

Savage et al. (1994) tested edge-detection techniques on video recordings of Chinook salmon (*Oncorhynchus tshawytscha*) stocked at 8–20 kg/m^3 in 3.3-m diameter tanks, and Chinook and Atlantic salmon (*Salmo salar*) stocked at 4–8 kg/m^3 in various sea cages. Their project objective was to develop automated monitoring systems. They concluded that several edge-detection methods perform well with backlit fish images. However, they did not complete the segmentation or identify procedures required for further analysis of fish movement and behavior. Foster et al. (1995) used an underwater video camera, pointed downward in a sea cage, to detect uneaten feed pellets. They used a fixed gray-scale threshold to segment objects from the background and the curvature of the segments was used to distinguish a single pellet from two overlapping ones. They tested their methods in a sea cage with and without fish and with 9.5-mm diameter pellets. Counting errors varied, reaching 33%. The methods were further improved and tested under various conditions (stocking density, visibility, cage size and camera depth) but false-positive and negative errors were still considerable (Parsonage and Petrell, 2003). The purpose of the work was to develop a sensor to feed back to a controller which could potentially manage feeding quantity and rate. However, such a concept could also be used to monitor changes in feeding behavior. Israeli and Kimmel (1996) monitored the swimming behavior of a school of 40 goldfish (*Carussius auratus*) in a small tank by two cameras which provided side- and top-views. They calculated the school's center of gravity (in 3D), mobility and density under various oxygen levels and were able to characterize well-known behavioral patterns—upward school motion and reduced swimming speed—during hypoxia. Similar methods were later used to monitor the response of koi (*Cyprinus carpio*) to sublethal concentrations of ammonia (Israeli-Weinstein and Kimmel, 1998). However, exporting the methods to larger tanks or cages is not straightforward due to dimension and visibility complexities. Xu et al. (2006) monitored the response of tilapia (*Oreochromis niloticus*) to dissolved oxygen levels in a small 300-l aquarium. The aquarium was painted for enhancement of image contrast and stocked at a low density (12 fish of 80 g) to minimize fish overlap. They estimated fish swimming speed by subtracting successive images and calculating the distance change made by the fish, and they calculated the center of the fish school using the procedure described by Israeli and Kimmel (1996). They found that swimming activity increased slightly as the oxygen level decreased and concluded that the activity and location of the fish can be used to indicate severe hypoxia conditions. Stien et al. (2007) marked dark vertical lines on a 3-m diameter, 0.75-m deep tank and used the percentage of line sections hidden from the camera's view by fish to calculate their vertical location. However, under real conditions, fish closer to the camera hide a longer section of these lines than fish closer to the line. Duarte et al. (2009) monitored the movements of Senegalese sole (*Solea senegalensis*) stocked at two densities in small white tanks using a camera pointing downward from above the water. They used red lights to enable imaging at night due to the nocturnal nature of the fish, and used simple frame subtraction to quantify fish movement. However, this method does not provide details of movements and is limited to small-size tanks and a single layer of non-overlapping fish. Rodriguez et al. (2011) developed a method and algorithms to characterize the behavior of fish in fishways, where water turbidity and image noise may resemble aquaculture systems. A self-organizing-map neural network was used to segment objects from the background and noise was removed using temporal and spatial filtering. From calculated positions in successive images, velocities and accelerations were calculated and compared to numerical models known for the tested species and fish size (medium-size trout). Pinkiewicz et al. (2011) calculated average swimming speed and direction of fish from successive frames of video footage. They used adaptive thresholding and edge detection to segment objects from the background and the eccentricity of the segments to differentiate between fish and noise. A Kalman filter was used to assign new track estimates from previous estimates for a few segments and the system calculated swimming speed averages and direction every 30 s. They validated their method in a square commercial sea cage (25×25 m) with Atlantic salmon (*Salmo salar*), in which a camera was mounted at a depth of 6 or 8 m and directed upward. They compared the image-processing results to manual measurements from the video footage and found that the median differences in swimming speed and direction were 0.1 body lengths per second and 14°, respectively.

7. Discussion and conclusions

This review presents the evolution of computer vision technologies in the context of aquaculture in the last 25 years, from simple measurements of fish length out of water to sophisticated systems, such as underwater stereo imaging for various applications. The main motivations for this progress have been the rapid growth of aquaculture into a powerful industry, the problems identified by growers that require technological solutions, and the rapid developments in hardware and software which have enhanced the capabilities of cameras and peripheral equipment, reduced their cost, and enabled rapid image processing and accurate data interpretation.

Inspection of agricultural products requires gentle handling to avoid damage. In the case of fish, handling has to be far gentler, and sometimes becomes the limiting factor in sensor development. Since the focus of this review is the use of computer vision systems for various sensing tasks required before harvest, the animals are alive and in most cases, should not be removed from their environment. Thus, the sensing technology has to overcome limited visibility, temporal and spatial variations in lighting, varying distances and relative orientations between cameras and objects, motion and density of the monitored targets, and even lack of physical stability. These are extremely challenging conditions for sensor development, and are likely the main reason for the limited commercial solutions available for aquaculture systems relative to other industries.

A variety of commercial devices for counting fish, fingerlings and eggs are available. They are designed for various ranges of fish sizes and their accuracy is good. However, simple and accurate devices for counting larvae (small quantities in the thousands and large quantities in the millions) are greatly needed. Limiting factors include the huge counts involved and handling, because the larvae are very sensitive. Sampling and estimating the count of small quantities is currently the common practice.

Fish dimensions can be closely estimated by computer vision in various settings (e.g. laid on a conveyor belt or while swimming in a cage). The relationships between dimensions and mass are quite solid and have been used to estimate fish mass from length and/or image area (both side and top views). In sea cages, where object-to-sensor distance varies, visibility is limited and fish occlusion and sensor's physical instability are common problems, directing fish through passages (either frames such as the biomass counter or transparent channels) is a way of bringing the fish to the cameras (or other optical sensors) and overcoming poor water transparency, as well as varying distances and orientations. However, this concept could introduce a bias into the estimate because there has been no confirmation that fish that tend to swim through a passage are representative of the whole population. Recent advances in underwater stereo imaging of live fish could potentially lead to the development of systems capable of estimating biomass and monitoring fish welfare.

Morphometric and color features are good indicators of gender in many ornamental fish species. They have also been successfully used in edible fish species identification. In polyculture of several fish species in extensive and semi-intensive freshwater systems, methods and systems for in situ selective fish harvesting are needed. Such systems are required not only to identify species and/or size but also to physically separate the fish into groups (by size and or species). One of the possible ways of performing such a task is to attract fish to swim through a transparent narrow channel on the side of which a computer vision system is mounted and at the end of which fish are directed according to the inspection. The main challenge in such a project would likely be the fish handling and not the image processing. From the literature described in this review, it seems that fish identification (species, size, gender) has been quite extensively dealt with and that there are satisfactory general solutions. The attraction of fish to and through passages has to be developed, and behavioral conditioning using lights or acoustic signals should be tested. Alternatively, feeding fish in a location which tempts them to swim through a passage to get to the food might be feasible.

Welfare of fish in aquaculture systems can be monitored by changes in their behavior (e.g. swimming depth or speed), or by an excess of feed pellets sinking under the net pens. However, the environmental conditions under which potential computer vision sensors must operate (underwater, uncontrolled lighting, turbidity, crowded fast-moving animals) make the challenge far more difficult relative to other animal husbandries and as yet, no commercial applications are in wide use. In edible or ornamental fish farms which use a recirculated aquacultural system (RAS), water depth is relatively shallow, feeding location can be adjusted if needed and lighting can be controlled. In such systems, monitoring fish size and health while they are being transferred between pools and monitoring feeding behavior seem to be worth looking at for developers of computer vision systems. Since feed represents a major portion of the cost of aquaculture production and since feeding behavior is an indicator of welfare, it is well worth following up on initiatives (or initiating new ideas) for monitoring excess feed in sea cages (and other systems) as an indirect way of monitoring health and welfare and of pursuing direct monitoring of fish behavior. There has been quite a lot of preliminary work in these directions. The needs of the aquaculture industry and the commercial potential are significant, and a tight collaboration between engineers, fish physiologists and ethologists could contribute to the search for viable solutions for the benefit of aquaculture.

Acknowledgment

Contribution from the Agricultural Research Organization, Israel, No. 736/12.

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