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REVIEW

Machine Vision Applications to Aquatic Foods: A Review

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Abstract

Machine vision (MV) is a rapid, economic, consistent and objective inspection and evaluation technique. This non-destructive method has applications in the aquatic food industry. MV can perform many functions at once in an aquatic food processing line: sorting by species, by size, and by visual quality attributes, as well as automated portioning. In this review, the mode of operation and the components of a MV system are introduced, its applications to foods are briefly discussed, and the advantages and disadvantages listed. The literature in the MV applications to aquatic foods is grouped under the following topics: determination of composition, measurement and evaluation of size and volume, measurement of shape parameters, quantification of the outside or meat color of aquatic foods, and detection of defects during quality evaluation. Finally, brief examples from the industrial applications of this promising technology are given. Extensive bibliography is cited in this field.

Keywords: Computer vision, image analysis, seafood.

Bilgisayarlı Resim Analizinin Su Ürünlerine Uygulanması: Bir Derleme

Özet

Bilgisayarlı resim analizi (BRA); hızlı, ekonomik, tutarlı ve objektif olarak kontrol etme ve değerlendirme metodudur. Ürüne zarar vermeyen bu metodun, su ürünleri endüstrisine uygulamaları bulunmaktadır. BRA'nın otomatik porsiyonlama gibi, çoğu fonksiyonu veya ürünün türe, ağırlığa ve görsel kalite özelliklerine göre sınıflandırması su ürünleri işlemesinde, hızlı bir şekilde uygulanabilir. Bu derlemede, BRA sisteminin çalışma biçimi ve parçaları, kısaca gıdalara uygulanması, avantajları ve dezavantajları açıklanmaktadır. Su ürünlerine BRA uygulamalarının kaynakçaları; su ürünleri kompozisyonun belirlenmesi, ağırlık ve hacimin değerlendirmesi, şekil özelliklerinin ölçülmesi, su ürünlerinin et ya da yüzey renginin tanımlanması ve kalite değerlendirmesi sırasında istenmeyen kusurların belirlenmesi şeklindeki başlıklar altında gruplandırılmıştır. Sonuç olarak; gelecek için umut verici bu teknolojinin, endüstriyel uygulamalardaki bazı örnekleri verilmektedir. Bu konular derlemede kapsamlı kaynakça ile belirtilmektedir.

Anahtar Kelimeler: Bilgisayarlı resim analizi, resim değerlendirme, su ürünleri.

Introduction

Visual attributes are important quality parameters for foods in general and aquatic foods in particular. Consumer purchasing decisions, price, and eventual product forms are partly defined by these attributes. Increasingly tight requirements for quality and consumer expectations are forcing the evaluation of visual attributes to be more objective, more rapid, and more quantifiable. The traditional method of human subjective evaluation is being replaced by automated, camera / computer based systems. These systems known as machine vision (MV) or computer vision (CV) systems have been successful in objective evaluation of various food products (Gunasekaran, 1996; Brosnan and Sun, 2004).

Mode of Operation of Machine Vision Systems

MV technology aims to emulate the function of human vision by electronically perceiving and evaluating an image (Sonka *et al*., 1999). These systems work by capturing the image of an object, processing the image to measure the desired parameters, comparing these parameters with predefined inspection criteria, and then helping to make decisions / taking some type of corrective action on the object or the manufacturing process. One of the advantages of MV is the non-destructive nature of the process (Timmermans, 1998). Image processing and

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image analysis are the core of MV with numerous algorithms and methods available for classification and measurement (Krutz *et al*., 2000).

Components of Machine Vision Systems

A MV system consists of an illumination (e.g. a light box with fluorescent bulbs or other lighting sources), a camera, an image capture system, computer hardware, and software.

Illumination is critical. The light source must have a defined energy distribution (e.g. D65) and its intensity must be even and controlled. Vision systems are affected by the level and quality of illumination. By proper lighting adjustment the appearance of an object can be radically changed with the feature of interest clarified or blurred (Sarkar, 1991). Illumination can influence the quality of image and the overall efficiency and accuracy of the system (Novini, 1995). Gunasekaran (1996) and Andreadis (1999) noted that a well-designed illumination can help the image analysis by enhancing image contrast. Good lighting can reduce reflection, shadow and some noise, resulting in less processing time. Various aspects of illumination including location, lamp type and color quality, need to be considered when designing an illumination system for applications in the food industry (Bachelor, 1985). Especially for generally wet materials such as aquatic foods, the problems caused by reflection can be minimized by using polarized light (Erdem *et al*., 2009). Use of infrared (IR) or near infrared (NIR), ultraviolet (UV), and X-ray sources enable possibilities not achievable by visible (VIS) light alone. Use of specific wavelengths or ranges of wavelengths (spectroscopy) has also been successfully applied to many foods (Heia *et al*., 2007; Yang *et al*., 2005).

With advances in digital cameras, the camera and the image capture system generally merge into one device. This device communicates with the computer via cables (e.g. IEEE 1394 or Firewire), or by wireless means. There can be 3 light detection sensors in the camera, dedicated to each primary color (red, green, blue), or one sensor can be selectively used to handle all three primary colors.

The software can control the camera settings, the timing of image acquisition, the light source, and can analyze the image to extract desired features to make decisions. These may include noncontact sensing, measuring object shape and dimensions, detecting product defects, providing process control feedback alerting production line operators for in-process system failures, and providing product quality statistics (Sarkar, 1991; Sun, 2004; Balaban *et al*., 2005; Balaban and Odabaşı, 2006).

Machine Vision Applications to Foods

Recent advances in hardware and software provided low cost and powerful solutions, leading to more studies on the development of MV systems in the food industry (Locht *et al*., 1997; Brosnan and Sun, 2004). Many applications have been developed, such as precision farming, postharvest product quality and safety detection, classification and sorting, and process automation. Many reviews exist in the literature that discuss the applications of MV to foods (Gunasekaran, 2001; Brosnan and Sun, 2002; Sun, 2004; Du and Sun, 2006; Zheng *et al*., 2006; Balaban *et al*., 2008a).

Image analysis can provide a wide range of information about a product from a single image in a fraction of a second, making it possible to analyze products as they pass on a conveyor belt (Storbeck and Daan, 2001). MV can play an important role in process control and robotic guidance in achieving more flexibility in manufacturing. It is a potential technique for the guidance or control of food processes (Tillett, 1990).

Quality assurance in the food industry is often subjective: traditionally, it has been performed by human graders. With high labor costs, the inconsistency and variability of human inspection accentuates the need for objective measurement systems. Promising superior speed and accuracy, MV has attracted significant research aimed at replacing human inspection. With increasing requirements of speed and tighter quality tolerances the use automatic systems for quality assurance / control becomes more beneficial.

MV systems are being applied increasingly to various foods for quality assurance purposes. Some examples of the MV applications are: poultry carcass inspection (Park and Chen, 1994; Park and Chen, 2001), detection of defects on chicken meat (Barni *et al*., 1997), beef marbling and color (Gerrard *et al*., 1996), prediction of beef qualities (Jackman *et al*., 2009), color grading of beef fat (Chen *et al*., 2010), the color of eggshells (Odabaşı *et al*., 2007), relative antibrowning potency of oxalic acid on banana and apple slices (Yoruk *et al*., 2004), color inspection of potatoes and apples (Tao *et al*., 1995a), shape grading of potatoes (Tao *et al*., 1995b) grading of mushrooms (Heinemann *et al*., 1994), quality inspection of bakery products (Abdullah *et al*., 2000), classification of cereal grains (Majumdar and Jayas, 2000), grading of lentils (Shahin and Symons, 2001) computer-assisted sensory evaluation of meals (Munkevik *et al*., 2007), and quantification of features of almonds (Varela *et al*., 2008).

Advantages and Disadvantages of Machine Vision

The advantages and disadvantages of MV were stated by various researchers (Sistler, 1991; Heinemann *et al*., 1995). Some advantages indicated were the generation of precise descriptive data, quick and objective operation, reduction of tedious human involvement and automation of many labor intensive processes, consistency, efficiency and cost effectiveness. The non-destructive and least intrusive natures, as well as the ease with which permanent records are kept are other advantages.

Disadvantages include the need for defined and consistent lighting, calibration requirements, the difficulties encountered with overlapping objects or objects that are difficult to separate from the background, speed of operations, and when both sides of a food need to be evaluated (Brosnan and Sun, 2004).

The hygiene and safety risks, and high labor and social costs limit the use of human workers in the food sector, especially as food safety regulations are becoming more stringent. Recruiting, training and retaining skilled butchery or "slime line" (heading and gutting in fish processing) staff is becoming difficult and costly. Cost calculations can only be made on an individual basis, but many generic drivers are quoted by the food industry for the introduction of machine vision (Purnell, 1998).

The objective of this paper is to review the developments of MV technology as it applies to aquatic food products. It also provides a brief description of applications of this technology in the aquatic food industry.

Application of Machine Vision to Aquatic Foods

Visual quality of aquatic foods (size, shape, and color) has a direct influence on their value and acceptance. MV can evaluate all these attributes (Korel and Balaban, 2010). Nutrition can also be evaluated as far as some proximate composition components are concerned, such as moisture content and fat using e.g. near infrared (Wold and Isakkson, 1997). Direct measurement of safety (microbial, chemical, metal fragments, etc.) is currently difficult to measure using visible light.

Determination of Composition

Borderías *et al*. (1999) used image analysis to determine the fat percentage of Atlantic salmon (*Salmo salar*) fillets. Rønsholdt *et al*. (2000) scanned rainbow trout (*Oncorhynchus mykiss*) cutlets on a scanner to quantify the area of the cutlet, and the area of the fat stripes. Stien *et al*. (2007) also used the area of the white stripes on the salmon fillet's surface to compare it to its total area, thus automatically estimating fat content in fillets. Fifteen salmon fillets were sampled from an assembly line at a local fish-processing plant, photographed and analyzed for lipid content. The results obtained by the image analysis showed a good correlation (R=0.84) with those from chemical analysis.

Mohebbi *et al*. (2009) described a method based on MV to estimate shrimp dehydration level by analyzing color during drying. This can be applied for automated moisture content control in drying of shrimp, and has the advantage over conventional subjective and instrumental methods by being objective, fast, non-invasive, inexpensive and precise.

To investigate the impact of blood residues on the final quality of exsanguinated and unbled farmed turbot (*Scophthalmus maximus*), meat quality was evaluated using MV. Whiteness and redness were evaluated and were correlated with the blood residue in the fillet. Results showed that exsanguination was important in improving the visual appearance, and the blood residue could be quantified using MV (Roth *et al*., 2007).

Folkestad *et al*. (2008) analyzed Atlantic salmon live (VIS/NIR), after gutting (VIS/NIR and CT), and as fillets (VIS/NIR and digital photography). Chemical analyses (fat and pigment content) and computerized tomography, CT (fat content) were used as reference methods. Astaxanthin prediction error in whole salmon based on VIS spectroscopy had a root mean square error of prediction (RMSEP) of 0.9 mg/kg (r=0.85). Fat content in live fish prediction with VIS spectroscopy had RMSEP=1.0 fat%, and an r=0.94 correlation with chemical reference values. Fat predictions from NIR spectroscopy correlated well with predictions from CT analyses, r=0.95. VIS spectroscopy and DP were also well suited to determine pigment concentrations in salmon fillets, with prediction errors of 0.4 mg/kg astaxanthin, and a correlation with chemically determined pigment of r=0.92.

Size/Volume

Area, perimeter, length and width are the common features used to define the size of an object. Shape features can be used independently of, or in combination with, size measurements (Du and Sun, 2004).

Fish is sorted according to species, size and quality after harvesting. Sorting can be done automatically using MV systems (Korel and Balaban, 2010). Since image analysis is nondestructive, size features can be used for the online sorting of fish, or even live fish (Lauth *et al*., 2004). Arnarson (1991) described a system to sort fish and fish products by MV. The difficulties of sorting fish were listed as: fast speed requirements, number of species, the variation of the size and shape of each species, variation of the optical characteristics of each fish, the elastic nature of fish, and the harsh environment for MV systems in factories. 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 grabbed. Using fish length-to width ratio flat and round fish were differentiated, and using the shape and color features mentioned by Strachan and Kell (1995), 12 fish species were sorted 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. Odone *et al*. (1998) developed a "support vector machine" combined with a vision system to estimate fish weight from sets of morphometric measurements. The method was tested on 99 trouts between 300 and 600 g showing good accuracy and reliability. An image processing algorithm based on moment-invariants coupled with geometrical considerations for discrimination between images of three species of fish was developed (Zion *et al*., 1999). Correct identification reached 100%, 89% and 92%, respectively, for grey mullet, carp and St. Peter fish for 124 samples examined at different orientations. Storbeck and Daan (2001) measured a number of features of different fish species as they passed on a conveyor belt at a speed of 0.21 m/s. A neural network classified the species from the input data with an accuracy of 95%. Clausen *et al*. (2007) developed a method to extract weight distribution of the fish within fish cages from captured images. They reported that lighting was critical and resolution of overlapping objects depended on the density of the fish. Sorting of Atlantic salmon (*Salmo salar*) and Atlantic cod (*Gadus morhua*) fillets with MV system has been used (Misimi *et al*., 2008a), and was found suitable for industrial purposes. Balaban *et al*. (2010a) developed equations to predict the weight of four species of whole Alaskan salmon by measuring their view area, with r^2=0.987. The same method was applied to rainbow trout (Gümüş and Balaban, 2010) and Alaskan pollock (Balaban *et al*., 2010b) with good accuracy (r^2=0.99 in both cases). The effect of fins, and/or the tail on the accuracy of the weight prediction was found to be not significant.

A machine vision system has been developed to determine the count and uniformity ratio white shrimp (*Paneus setiferus*) and tiger shrimp (*Paneus monodon*) (Balaban *et al*., 1994). Shrimp area viewed by a camera was used to estimate weight after calibration and count and uniformity ratio was accurately calculated (Luzuriaga *et al*., 1997).

Oysters are mostly sold by volume and grading is important for pricing. They are typically graded and sorted by humans before and after shucking. Oyster shells are very irregular and very significantly from oyster to oyster in size, strength, shape, location of the center of gravity, and geometric center. Fouling and boring organisms on the shell exterior add to the variety of shell shapes. The wide variability in the oyster's shape and size is the main reason why commercial automatic shucking equipment is not widely available (Little *et al*., 2007a). Tojeiro and Wheaton (1991) developed a system based on a black-and-white video camera and a mirror to simultaneously obtain top and side views of an oyster, and then developed the software to determine the ratio of thicknesses about 1.5 cm from each end to locate the hinge side. The method correctly oriented 233 oysters in 98.2% of the trials. Li and Wheaton (1992) obtained images using a video camera in a Wheaton shucking machine to trim the hinge-ends of oysters. A pattern recognition technique was used to locate oyster hinge lines with an error rate of 2.5%. Parr *et al*. (1994) developed a raw oyster meat grading and sorting machine consisting of a vision system, a conveyor, a micro computer, and sorting stations where meats were ejected into containers. It was capable of sorting oyster meats into 3 sizes with an accuracy of 88% at a rate of 1 oyster every 2 seconds. Lee *et al*. (2001) used a laser line-based method to predict the volume of oyster meat. Thickness was deduced by the shape of the laser line on the meat. The predicted and experimental volumes were compared, with a correlation coefficient of 0.955. So and Wheaton (2002) published the results of their software development efforts to automate oyster hinge line detection using MV with a color camera. They determined circularity, rectangularity, aspect ratio, and Euclidian distance to recognize the hinge from other dark objects on the hinge-end of the oyster. Lee *et al*. (2003) developed a 3-D oyster meat volume measurement method that truly measured the volume instead of estimating oyster volume from 2-D image. None of these existing systems measure oyster shape quality. To estimate the volume of oysters, a method based on cubic splines was developed. Fifty oysters each from Florida, Texas and Alaska regions were used to test the method that predicted volume and weight for oysters. Good correlations between predicted and measured volumes were found (Damar *et al*., 2006).

Balaban *et al*. (2011) used the cubic splines method to predict the volume of whole Alaskan pollock with good accuracy (r^2=0.99). They took top view and side view images of whole fish. The effects of fins and tail did not significantly affect the results.

Shape

Morphological and spectral features of shrimp can be determined to find the optimum location for removal of shrimp heads (Ling and Searcy, 1989). Prawns can be automatically graded and packaged into a single layer with the same orientation by combining machine vision and robotics (Kassler *et al*., 1993). Fish species can be sorted according to shape, length and orientation in a processing line (Strachan *et al*., 1990). Tayama *et al*. (1982) described a method for sorting species based on shape and achieved a sorting reliability of 95% for four species of fish. Loy *et al*. (2000) compared geometric morphometrics, elliptic Fourier analysis and Bezier functions to determine size-related shape change of Sparidae. They found that Fourier methods performed the best, and Bezier functions performed poorly. Wagner *et al*. (1987) used simple shape features of fish to sort them using linear discrimination functions and achieved a sorting accuracy of 90% for nine species. Utilizing color and shape parameters to sort fish by species, reliabilities of 99% for 23 species of fish have been achieved (Strachan, 1993a). CV systems that can automatically measure the length of fish in the laboratory have been described (Arnarson and Pau, 1994; Strachan, 1993b) with errors less than 1 cm. Arnarson and Pau (1994) developed an algorithm that used structuring primitive shape elements to describe fish shape features, which were then fed to a neural network for species classification. Classification rates of 100 and 94.6% were achieved with a training set of 29 fish and a test set of 928 fish (three species: cod, flounder and redfish). CV systems automatically measured the length of fish in a research vessel with a standard deviation of 1.2 mm and with up to 99.8% sorting reliability for seven species of fish (White *et al*., 2006).

MV systems allow for high speed shellstock grading. A system allowing the flexibility for the operator to teach the grading system, the sizes needed for different grades on different days based upon sizes/volume of shellstock supply, and sizes/volume of customer shellstock demand would simplify operations. The MV system could allow counting and boxing or bagging of graded oyster shellstock. Currently bagging and boxing are in separate areas increasing labor and operational costs. Lee *et al*. (2004) developed a shape analysis method for an automatic oyster grading system. The system first detected and removed poor quality oysters such as banana shape, broken shell, and irregular shapes. Good quality oysters moved further into grades of small, medium and large. The contours of the oysters were extracted for shape analysis. Later, Xiong *et al*. (2010) improved the method by using a shape similarity measure called turn angle cross-correlation. Incorporating a machine vision system for grading, sorting and counting oysters results in reduced operating costs. The savings produced from reducing labor, increasing accuracy in size, grade and count and providing real time accurate data for accounting and billing would contribute to the profit of the oysters industry. A system was designed to handle wild, single oysters having widely variable shapes from the Chesapeake Bay. The initial target speed was 60 oysters/min. An algorithm was developed for orientating oysters and transfers them onto an exit conveyor without losing their orientation (Little *et al*., 2007b).

Color

Color is a major quality attribute of aquatic products (Francis, 1991) and is used as a predictor of quality, composition, and standards of identity. Consumers initially accept or reject a food based on its color and other visual attributes. These can be measured by visual, instrumental, and machine vision methods (Balaban and Odabaşı, 2006). The human eye can discern thousands of color shades and intensities compared with approximately only 24 shades of gray. In machine vision an image of the sample is digitized into pixels containing levels of the three primary colors (red, green and blue = RGB color system). By using image processing techniques one can identify and classify colors quantitatively and describe all the colors of the sample. With this procedure samples with varying colors, different shapes, sizes, and surface textures can be easily analyzed (Luzuriaga and Balaban 1999).

Muscle color is an important factor in consumer perception of fish quality. Consumers mostly associate color with freshness, better flavor, and high product quality (Gormley, 1992). Strachan and Kell (1995) used ten 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.

Marty-Mahé *et al*. (2004) constructed a light tent for imaging of brown trout (*Salmo trutta*) cutlets. Images of 48 cutlets were made using a digital camera and image analysis methods were developed to quantify the color and fat stripes. Various color spaces such as L*a*b* color space can be used. Features obtained from the L* component and the combination of a* and b* components can predict lipid levels of fish flesh with a correlation coefficient of 0.75. Furthermore, after drying different groups of fish could be better discriminated by using color features measured by L*a*b* space from images than by sensory panelists (Louka *et al*., 2004). MV systems can determine L*, a*, and b* values for each pixel of an image and analyze the entire surface of homogeneous and nonhomogeneous shapes and colors of samples. MV also provides the color spectrum and other visual attributes of the sample (Balaban, 2008; Balaban *et al*., 2008b). The performance of a Minolta colorimeter and a machine vision system in measuring the color of Atlantic salmon (*Salmo salar*) fillets was compared (Yağız *et al*., 2009a). The average L*, a*, and b* values measured by MV were very close to that of the original sample. Results from Minolta were significantly different. Color MV was used to determine color of rainbow trout (*Oncorhynchus mykiss*) cutlets. Automated image analysis methods were tested on a total of 983 scanned images for quality traits such as fat percentage, flesh color and the size of morphologically distinguishable subparts of the cutlet. A sub-sample of 50 images was randomly selected for manual segmentation of the cutlet, the dorsal fat depot, the red muscle and morphologically distinguishable subparts. The identification of these regions by manual and automatic image analysis correlated strongly (r=0.97, 0.95 and 0.91, respectively). The estimated fat percentage obtained from image analysis, based on the area of visible fat and the color of the cutlet flesh, correlated well with chemical fat percentage measured by mid-infrared transmission spectroscopy (MIT) (r=0.78) (Stien *et al*., 2006b). Processing techniques and packaging conditions affect aquatic food color. High pressure processing (HPP) could extend the shelf-life of seafood; however, this process causes a change in the color of rainbow trout (*Oncorhynchus mykiss*) and mahi mahi (*Coryphaena hippurus*) (Yağız *et al*., 2007). HPP in combination with cooking was also found to affect the color of Atlantic salmon (*Salmo salar*) (Yağız *et al*., 2009b). Changes in the color of salmon fillets have also been investigated during thermal sterilization processes (Kong *et al*., 2007). MV systems could be used for automated quality control and grading of salmon fillets based on color. The changes in skin and fillet color of anesthetized and exhausted Atlantic salmon after killing, during rigor mortis, and after seven days on ice storage have been investigated (Erikson and Misimi, 2008). Atlantic salmon (*Salmo salar*) fillets have been sorted based on their color using CV (Misimi *et al*., 2007). Korel *et al*. (2001a) used a color MV system to monitor the changes in the color of tilapia (*Oreochromis niloticus*) fillets dipped in sodium lactate solutions. In another study (Korel *et al*., 2001b), raw and cooked catfish (*Ictalurus punctatus*) fillets were evaluated with MV and electronic nose throughout storage. Luzuriaga *et al*. (1997) objectively measured the percent area with melanosis on white shrimp (*Penaeus setiferus*) stored on ice for up to 17 days using a MV system. Melanosis was quantified and correlated with the grading of a trained inspector. Yağız *et al*. (2010) measured the surface color of treated and untreated Atlantic salmon muscle with different irradiation doses during storage by MV. As irradiation dose increased, the samples discolored compared with untreated samples. Color evaluation was performed using a color MV system during 6 days of storage at 4 °C. At the beginning of the storage study, it was found that increasing the level of irradiation dose from 1, 1.5, 2 and 3 kGy for fresh light muscle resulted in a decrease in a* values of 12%, 27%, 41% and 56%, respectively. Balaban *et al*. (2005) analyzed the color of fresh tuna treated by 4% carbon monoxide+20% carbon dioxide+10% oxygen, or irradiated at 1 KGy or 2 KGy, or first gas treated then irradiated, using the R, a* and hue parameters in a MV system. Hue was selected as the best representative of the red color of tuna. A method was suggested to select the threshold value of this parameter. Irradiation did not change the color of fresh tuna. Exposure to CO increased the redness, and preserved it for up to 12 days in refrigerated storage.

Color of food products changes as the components of food products are restructured during processing. Therefore, evaluation of these color variations instantly during processing is important as these changes can reflect the reconstruction of components of food products caused by processing (Zheng *et al*., 2006). Köse *et al*. (2009) quantified the color of whiting burgers affected by the method of mincing.

Defects/Quality

Kohler *et al*. (2002) developed a method for sorting quality classes of cod fillets. A method for quality grading of whole Atlantic salmon (*Salmo salar*) has also been developed using CV systems (Misimi *et al*., 2008b). Shrinkage of pre-rigor filleted rainbow trout (*Oncorhyncus mykiss*) was analyzed by MV. An economical and efficient online image analysis method for registering length changes in these fillets during rigor contraction was developed. It measured not only contraction in whole fillets but also in their parts, provided the fillet was complemented by morphological location markers. The method could be improved by a hardware upgrade, particularly of the image-acquisition equipment. The method is also better suited to measuring length contractions in parts of the fillet than methods based on excised muscle samples, since the surgical removal of the muscle strip, in itself, causes tissue trauma that in turn affects the rigor process (Stien *et al*., 2006a). Kong *et al*. (2008) used a MV system to quantify shrinkage and collagen solubility in pink salmon due to thermal processing.

Parasites can be automatically detected by MV. Heia *et al*. (2007) used imaging spectroscopy to detect parasites in cod (*Gadus morhua*). Wavelengths from 350 to 610 nm and 530 to 950 nm were used. Spectral resolution of the system was approximately 2 to 3 nm. Parasite detection at 0.8 cm below the fillet surface was possible, which was 2 to 3 mm deeper than what can be found by manual inspection of fish fillets. Sivertsen *et al*. (2009) used a ridge detection method in image analysis to locate the centerline of a fillet to eliminate artifacts interfering with nematode detection.

Some Alaskan pollock roe quality attributes was evaluated by image analysis (Chombeau *et al*., 2010b). Size, greening level, and color uniformity could be quantified using MV. Herring roe quality was automatically determined using an integrated system (Croft *et al*., 1996).

Jamieson (2002) used an X-ray vision system for the detection of bones in chicken and fish fillets. This commercial system depended on the principle that the absorption coefficients of two materials differ at low energies allowing the defect to be revealed. The developed system had a throughput of 10000 fillets/hour and can correctly identify bones with an accuracy of 99%.

Industrial Applications in Aquatic Foods

The food industry ranks among the top 10 industries using CV technology (Gunasekaran, 1996). MV systems promise faster, cheaper and more consistent operations than manual methods. Since the aquatic foods industry requires skilled seasonal workers to perform repetitive and arduous tasks, automation is desirable. Considering the limited existing labor pools, the current congressional reduction in foreign temporary labor supply, a MV system could be an alternative for high speed grading.

R&D for automatic fish processing equipment is increasing. Marel (Reykjavik, Iceland) produces intelligent portioning machines with vision control for fixed weight slicing of fish sections. The system takes a 3 dimensional representation of the fish and adjusts the cut position to give constant weight portions. Up to five portioning cuts per second can be achieved (Purnell, 1998). In the area of shrimp processing, once calibrated, the Marel Model L-10 “Vision Weigher” estimates the weight of a shrimp from its view area.

Precarn (Ottawa, Canada) has developed “the Parasensor system” to improve productivity and reduce costs in fish processing. The system automatically inspects and classifies fillets using an intelligent camera system that emulates aspects of human eye peripheral vision and scanning (Balaban and Odabaşı, 2006).

SINTEF (Oslo, Norway) developed a system for objective visual inspection of split cod, by detecting overall color, liver stains, blood stains, deformation, and ruptures/splitting in the cod meat (Balaban and Odabaşı, 2006).

A European Union funded project ‘Robofish’ involves robotic handling of the slippery and flexible fish to be feed into a deheading machine (Buckingham and Davey, 1995). Accurate deheading is important to maximize yield. A special purpose robot was constructed by Oxim (Oxford, England) that utilizes a continually rotating motion rather than the normal back and forth action used in other robotic machine loading applications.

Development of integrated grippers with tactile and visual feedback specifically for the fish industry is under way in Canada. This work will connect the appropriate sensors to cutting devices such as water jets and artificial intelligence to replicate the yields that can be achieved by skilled manual fish cutting methods (Purnell, 1998).

Automation of fish processing with MV, apart from savings in labor costs, can also bring an overall improvement in the product quality (Arnarson *et al*., 1988). Although a large variety of examples of using CV in food industry have been reported (Panigrahi and Gunasekaran, 2001), the use of MV in automation of fish processing industry is still limited.

Conclusion

MV has the potential to become a vital component of automated aquatic food processing operations, with increased computer capabilities and greater processing speed, and with new algorithms that are developed to meet the real-world requirements. MV can provide fast identification and measurement of selected objects, perform quality evaluation of aquatic foods, and their classification into categories based on shape, size, color and other visual attributes. Automated, objective, rapid and hygienic inspection of diverse raw and processed aquatic foods in a flexible and non-destructive manner maintains the attractiveness of MV for the aquatic food industry. As data and methods from more research accumulates, it is expected that MV will find more real-world applications.

Applications of MV will improve industry’s productivity, and will also help to provide better quality aquatic foods to consumers.

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