Aquacultural Engineering 63 (2014) 62–71

Contents lists available at ScienceDirect

Aquacultural Engineering

journal homepage: www.elsevier.com/locate/aqua-online

Review

Visual quality detection of aquatic products using machine vision

Hanmei Hong, Xiaoling Yang, Zhaohong You, Fang Cheng*

College of Biosystems Engineering and Food Science, Zhejiang University, 866 Yuhangtang Road, Hangzhou 310058, People's Republic of China

ARTICLE INFO

Article history:
Received 5 May 2014
Accepted 14 October 2014
Available online 30 October 2014

Keywords:
Machine vision
Aquatic products
Visual quality
Detection
Image

ABSTRACT

Aquatic products are popular among consumers and their visual quality used to be detected manually for sorting, grading, species classification and freshness assessment. Machine vision, as a non-destructive method, has been used in external quality detection of aquatic products for its efficiency, objectiveness, consistency and reliability. Quite a number of researches have highlighted its potential for visual quality detection of fishes, fish filets and some other aquatic products (i.e. shrimp, oyster, and scallop). This review introduced detecting methods based on measurement of size, shape, and color using machine vision systems. Size measurement (i.e. length and area) was usually taken for sorting and grading, while shape was measured for species classification with the integration of size information. Color information was studied for analysis of fish filets, fish muscle, fish skin and shrimp, and for color changes of specially treated fish. Machine vision systems used for measuring size, shape, and color was described, including improvements of cameras, illumination settings, image processing and analysis methods, and experimental results as well. With the development in these areas, machine vision technique may achieve higher accuracy and efficiency, and wider application in visual quality detection of aquatic products. Besides, advantages and limitations of these machine vision systems were discussed, with recommendation on future developments.

Contents

1. Introduction

Nowadays, aquatic products have received great popularity because of their high nutritive value and delicious taste. When consumed, their quality would determine their value, price and "best-used-before" date (Sun, 2011). The quality may be presented

* Corresponding author. Tel.: +86 571 88982713; fax: +86 571 88982713.
E-mail address: fcheng@zju.edu.cn (F. Cheng).

http://dx.doi.org/10.1016/j.aquaeng.2014.10.003
0144-8609/

as appearance, odor, flavor and texture. Appearance attributes, such as size, shape and color, are assigned to visual quality (Alasalvar et al., 2011). These attributes directly influence the products' acceptance and thus affect most consumers' purchase trends consciously or subconsciously. Therefore, detecting these attributes is of great significance for better purchase decision and higher economic value.

Traditionally, visual quality detection is predominantly done by trained inspectors, which is labor-costing, time consuming, and difficult to quantify (Balaban et al., 2008). Manual processing and grading is inevitably influenced by human factors such as mistakes, occasional omission in processing as well as fatigue (Mathiassen et al., 2006). Alternatively, machine vision can provide fast, objective and robust measurement (Brosnan and Sun, 2002). Machine vision has been widely applied for quality assurance purposes in different industries (Gümüş et al., 2011). While, the aquaculture industry is a low technology industry for most activities started out in the natural way (Balchen, 1986). Machine vision still has not achieved a common utilization in aquaculture (Zion, 2012). This review described applications of this technology in visual quality detection of some aquatic products, including fishes, shrimp, oyster and scallop. These aquatic products have been studied by many researchers through measuring size, shape, and color parameters using various machine vision systems and methods. The objective of this review is to highlight development in detection methods, machine vision systems, image analysis and processing approaches, and analyzes its characteristics, so as to unlock the potential application of machine vision in aquaculture.

2. Machine vision system

Machine vision is a novel technology for recognizing objects, extracting and analyzing quantitative information from digital images. A typical machine vision system (MVS) often consists of an image acquisition system, image processing and statistical analysis procedures as shown in Fig. 1. Essential elements of an image acquisition system include: a camera, an illumination device, a frame-grabber, and a computer. Images are processed via pre-treatment, segmentation, and feature extraction (Gümüş et al., 2011; Sun, 2011). Then, statistical analysis is done using various methods for different purposes (Table 3). At last, output results work on the objects through a controlling module. Therefore, machine vision is a comprehensive technology, and requires coordinated application of several techniques (i.e. machinery, control, computer and image processing, etc.).

3. Visual quality detection based on size and shape measurement

Visual quality detection, for the seek of sorting, grading, counting and species classification of aquatic products, was mainly based on measurement of size (i.e. length, area, volume, width, height and so on) and shape. In this section, methods and systems for size and shape measurement were reviewed for several application fields including fishes, shrimp, scallop and oyster.

3.1. Fish

According to commercial requirement, sorting, grading and classification of fish are important processes during fish farming and processing. Typical demands include more precise weight class distribution and less damaged fish. This creates incentives to find more accurate methods for weight and quality grading (Mathiassen et al., 2006). Sorting and grading of fish are mainly based on size information, consisting of length and area. Usually, length and area of fish are measured and then related to weight, because weight is often used in trade or to estimate load in production systems (Zion, 2012). Fish species classification was achieved mainly on shape measurement, sometimes with a combination of size information.

3.1.1. Length measurement

The Length-weight relationship of different fish species has been investigated by some researchers (Aguirre et al., 2008; de Ciencias Marinas and de Matanchen, 2010; Froese, 1998). The most typical mathematical model characterizing fish length (L) and weight (W) is the power model $W = aL^b$, where a and b are empirically characterized species- and strain-dependent parameters (Zion, 2012). Therefore, the determination of fish length L was the crucial process of this algorithm. Development of the length measurement methods and systems during the last decades were summarized as follows.

In the early 20th century, a machine vision system was described to sort fish and fish products (Arnarson, 1991). The length was determined by measuring the distance between the middle of the tail and the top of the head of a straight fish. The accuracy was tested by measuring 50 fish twice, resulted in a standard of 0.5 cm and a mean of 0.4 cm. And the accuracy of length measurement was 0.9 cm when compared with manual measurement. For the machine described by Strachan (1993), the error in length measurements of fish was ±1% when samples were machine oriented to a minimum distance. And this increased to ±3% when the fish were randomly oriented. The machine got a throughput of greater than one fish per second. Later in 2002, Martiínez-Palacios et al. (2002) used a simple video system to measure length of larval and juvenile fish with minimal handling. A specific length/weight relationship was prepared where length and dry weight of 170 larvae were measured manually. Then the regression equation was used to calculate the weight of larvae from video estimates of body length from 17 individuals, and the error was −2.05%. Analysis was on one-way analysis of variance (ANOVA). Mean values were compared using Turkey's test. The results showed that the above equation was particularly useful and extremely linear ($R^2 = 0.99$). Mortality due to handling was extremely lower than the earlier work.

These simple systems could only provide two dimensional (2D) information, which was impossible to furnish the spatial distribution of fish or deduce the size of a fish from its image. Three dimensional (3D) measurement emerged with the technological progress. As far back as 1991, Frisby and Mayhew described the stereo image analysis technology that required two views of an object, which contributed to the 3D development (Frisby and Mayhew, 1991). Based on earlier studies, Ruff et al. (1995) developed an arrangement for the 3D measurement. The arrangement consisted of two charged-coupled device (CCD) cameras which were set to form a working volume where the subject was visible from the field of view of both cameras. Stereo calibration was a necessity for accurate estimation (Ruff et al., 1995; Williams et al., 2010). Here, the calibration of the stereo optical system was completed using the Tsai calibration procedure. Two views of an object were required for stereo image analysis. To perform accurate stereo image analysis, it is thus vital that the data produced by the cameras is recorded digitally. Finally, they obtained initial results that fish dimensions might be measured to millimeter accuracy and that fish might be tracked over limited time intervals to observe detailed movement. Then 3D technique was widely used in the subsequent researches.

Improvement focused on illumination systems was also studied to enhance image quality and speed up the process for weight estimation. Mathiassen et al. (2006) developed a multi-modal machine vision system combined with robotized sorting for weight and quality grading of pelagic fish. The illumination system consisted of a diffuse illuminator, a laser to the camera and a second laser at