Machine-vision based quality evaluation of meat and meat products- a review

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Abstract

The increasing demands for meat and meat products of high quality and safety standards has led to the development and search of technologies with accurate, fast and more objective quality determination. Machine vision provides an alternative for an automated, non-destructive and cost-effective technique on long run to accomplish the present requirements. The technology matches the function of human vision by electronically perceiving and evaluate into an image. Considerable research has highlighted its potential and already been successful in the inspection and grading of meat and meat products. The significant components of a computer vision system are introduced listed with advantage and disadvantage. The image processing technique coupled with a review of the most recent developments and possible application in quality evaluation of meat and meat products are discussed in this review paper.

Key words: Machine vision; automation; non-destructive; quality evaluation; meat and meat products

Introduction

Global demands for meat and meat products are ever increasing mainly due to increase in per capita income, awareness on nutritional values of meat and changing life style. The main driver for ensuring consumers satisfaction is the quality and safety. However food safety is a growing challenge and concern all over the world, and the recent pandemic (Covid-19), threw light on how crucial it is, for the very existence of a healthy life and environment. Ensuring food safety is the most important and critical requirement of any food industry, considering the increasing food-borne illness globally over the years. Despite of the extensive scientific progress and technological developments achieved in recent years, microbial food borne illness remains a global concern. There are various sources that contribute contamination of meat and meat products and repeated human handling in the production line increased the risk of contamination. And the most effective way to overcome these problems is to introduce automation. Automation may be applied through artificial intelligence, machine learning, deep learning, computer vision and robotic technologies (Bukhari et al., 2021). The growing demand for high quality and safety products on the market necessitated the development and adapting of advanced new technologies in evaluation of quality. These rising demands have promoted the quality evaluation methods progressively shifting from its conventional invasive testing methods to newer non-destructive, more accurate and quick techniques. Evaluation of food quality can be investigated by their changes in the visual properties like colour, shape and texture (Wu et al. 2013, Valous et al. 2010). Conventionally sensory analysis is often implemented by professional panelist, which is subjective, laborious, time-consuming and inconsistent. At the same time chemical procedures and instrumental methods have been used in detecting quality attributes for a long time, which are more convenient, precise and more effective compare to sensory analysis. However the main drawback of chemical methods is long time consumption and destructive nature of the sample. In most of the cases the sample used for chemical analysis cannot be used for further human uses. For example estimation of protein is analyzed by the Kjeldahl method and the method of choice for fat analyses is a solvent-based method for measuring the total fat content in meat. In terms of instrumental methods, pH is traditionally measured by pH meter by inserting the probe into the muscle directly after incision of the muscle, and colorimeters are commonly utilized for meat colour evaluation. However, most of the above-mentioned techniques are destructive, tedious, time consuming and requires lengthy sample preparation. Therefore, these traditional methods have limited applicability and are not suitable for quick analysis and early detection of quality attributes in industrial and large scale processing line.

Therefore more recently in contrast to the conventional methods, many novel, automatic and highly advanced technologies based on optical, X-rays, spectroscopy, nuclear magnetic resonance and near-infrared spectroscopy have emerged for detecting the quality and safety attributes of food products. The former invasive tests predicted food quality only in statistical terms due to their destructive nature and their consequential limited sample counts, whereas non-destructive methods now test every sample in an on-going and continuous manner in the production line. Machine vision is one of the most widely used methods for studying the meat colour characteristics (Wu,X. et al., 2020.) Quality evaluation based on machine vision is discussed in this content with an objective to bring the subject into the public domain by identifying its possible use, advantages-limitation, and introducing new concepts used for evaluation of meat and meat products.

Machine vision (MV) systems

In recent years the uses of MV in meat processing industries are significantly increasing mainly for quality control and quality assurance purpose. Machine vision is a technology which deals in automatic extraction of information from images with the help of computer. Machine vision is synonym with computer vision, which is recognized as the use of device for non-contact optical sensing and computing then process to receive and interpret the captured image of a real scene automatically. The aim of the technology is to match the function of human vision by electronically perceiving and evaluate into an image. The MV system offers high potential to automate manual grading practices, thus standardization of techniques and eliminating tedious human inspection tasks. Computer vision has been successfully used for the objective; online measurement of several food products ranging from routine inspection to the complex vision guided robotic control (Gunasekaran, 2001). These systems works by capturing the image of an object like the pieces of meat, process the image to measure the desired parameters and compare these parameters with predefined inspection criteria then helps to make decisions / taking some type of corrective action on the object or the manufacturing process. The most important advantage of meat inspection through MV system is its non-destructive nature on the sample. The core of the system consists of image processing and image analysis with numerous algorithmic methodologies available for classification and measurement (Krutz et al., 2000). Recently there is significant increase in application of MV in various fields like; inspection of poultry carcass, prediction of weight, measurement of beef colour, prediction of tenderness and chemical constituents of meat and meat products.

Components of MV systems

An MV system consists of an illumination source, a camera, an image capturing system along with a computer hardware and software device. The appearance of an object as desired can be radically changed just by proper adjustment of the illumination system. Illumination influences the image quality and the overall efficiency and accuracy of the system. Image processing and analysis are considered as the core of computer vision (Krutz et al., 2000). The main tasks of MV are image acquisition, processing or analysis, and recognition processes. Various properties of the objects are obtained from the acquired images during the analysis phase, and the final decisions are made in recognition process by using various image processing techniques and algorithms (Mery, et al. 2013). Image analyzer can provide a wide range of information about the product/sample in a fraction of second, making it possible to analyze as the product passes through the conveyor belt (Storbeck and Daan, 2001). MV can play an important role in process control and automatic guidance in achieving more flexibility in manufacturing. It is a potential technique for the guidance or control of food processes.

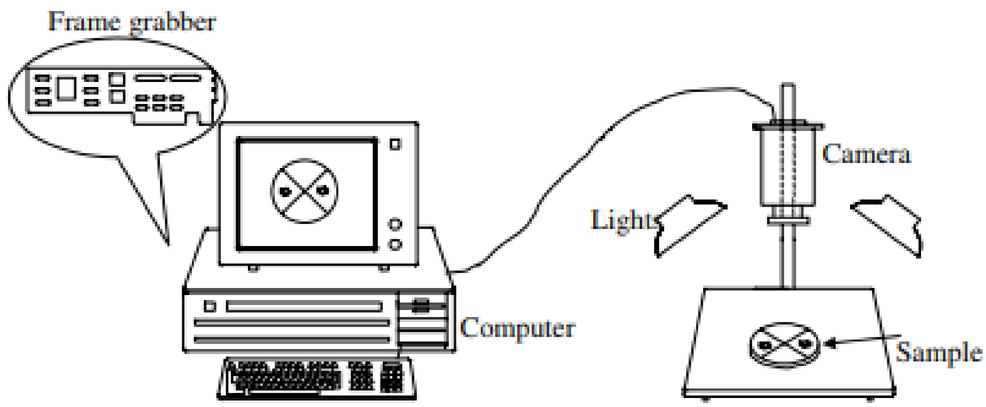

Fig.1. Component of computer vision (Wang & Sun 2002a)

Advantage of Automation and Machine vision

Automation and machine vision have transformed food packaging, improving efficiency, extending shelf life, and enhancing quality. Automation has been applied in various tasks like filling, sealing, labeling, and palletizing with precision and speed. Automation increase throughput, ensuring higher production volumes. Automation reduces product damage, contamination risks, and integrates quality control. It extends shelf life through controlled packaging processes and customization for consumer convenience. Machine vision systems integrated with robotics do not care about the comfort of their environment and do not get tired. These advantages allow robots to work in different areas, from slaughtering of meat animals to evaluation of meat quality through estimation of various components of meat quality traits. Another important advantage of machine vision system is the non-destructive nature in which the information's are collected making inspection process unique with the potential to assist humans involving visually intensive work. The system can be used to create permanent record of any measurement at any point of time, allowing further analysis later (Tarbell and Reid, 1991). It generates precise descriptive data, reducing tedious human involvement, consistent, efficient and cost effective in long run (Lu, Tan, Shatadal and Gerrard, 2000)). Automation of many labour intensive processes is possible with the help of machine vision technology (Gunasekaran, 2001). The technology proved to be more quick, objective, flexible and accurate. Such advantages have encouraged food manufacturers to adopt machine-vision methods (Sylla, 2002). Computer vision is a promising technology for food safety and quality assurance applications, because of having advantages such as much higher operating speed, consistency, reliability, objectivity and applicability to industrial environments (Park 2016). Automation is the best solution to reduce cost of production in the long run. Progressive growth in production have been reported by use of automation instead of human labours (Mahalik and Nambiar, 2010) because meat processing industries are highly labour-intensive and the labour cost is sometimes reported to be 50% of total production cost (Meshram, et al. 2018).

Disadvantage and challenges

MV technology requires a defined consistent lighting and calibration. Overlapping objects are often difficult to separate from the background, when both sides of a food material need to be evaluated (Brosnan and Sun, 2004).

Unexpected or erroneous results may be produced due to improper lighting in the MV system (Vithu and Moses 2016). High-resolution is required to provide better performance and accuracy, however providing sufficient image resolution is a challenge in the technology (Zhang, et al. 2014). Examination of rounded objects by considering all their surfaces is another challenge, as a regular camera captures images that represent only a portion of the surface, which is a projection of the object (Misimi, et al. 2016).

Recent advances on Quality evaluation of meat and meat products through imaging technique/machine vision

Color characteristic is considered as one of the most important attributes of quality appraisal of meat and meat products. The first and foremost quality evaluation done by any consumer before buying a food commodity is the inspection of colour (Rahman, et al. 2020). studied the ability of computer vision technology to predict the quality attributes of beef and concluded that highest prediction accuracy was found for colour lightness (L*), medium accuracy was found in redness (a*), pH, drip loss, crude protein and ash content in the beef sample. Liu, et al. (2014) predicted porcine meat colour with 72.6 % and pH with 86% accuracy using near infrared hyperspectral technique. Chmiel, et al. (2016) detected pale soft exudative in pork successfully by using image analysis technology. Kamruzzaman, et al. (2013) predicted tenderness in lamb with 84% accuracy by hyperspectral technique. Mortensen, et al. (2016) predicted weight in broiler chicken with an accuracy of 92.2% with the use of 3D camera. Del Moral et al., (2007) studied the application of image analysis for automatic quantification of intramuscular connective tissue in meat and found that image analysis application permits the automatic, accurate, objective and reliable quantification of intramuscular connective tissue in meat and fibre retraction in muscle. The software design by them can analyze 20 images per minute and offers more precise measurements compared with conventional morphometric methods. The study concluded that changes in the physicochemical properties of meat have a histologic basis. Basset et al., (2000) applied texture image analysis for the classification of muscle type, breed and age of bovine meat. (Tan et al., 2000; Lu et al., 2000) developed software to segment pork loin images into background, muscle and fat. They employed both statistical and neural network models to predict colour scores by using the image features as inputs and then compared to the sensory scores of a trained panel. Result showed 90% agreement between the vision system and the panelists. Jamieson (2002), investigated the use of X-ray for detection of bones in chicken and fish. The system works 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%. Cluff, et al. (2013) classified the tenderness of cooked-beef based on hyperspectral optical scattering imaging, and the accuracies were found to be 83.3% and 75.0% for tough and tender samples respectively. Similarly, Wu, et al. (2010) predicted colour, pH value and tenderness of beef with a correlation coefficient of 0.86 for Warner-Bratzler shear force by using hyperspectral scattering techniques. Park et al (2001), investigated the technique of spectral image characterization of poultry carcass for separation of tumorous, bruised and damaged skin carcass from normal carcass. For the purpose the carcasses were scanned by an intensified multi-spectral camera with wavelength range from 542–847 nm. The study indicated that the optical wavelengths of 542 and 700 nm were the most useful for the desired classification. The neural network performed with 91% accuracy for separation of tumorous carcasses from normal ones. Co-occurrence matrix texture features of multi-spectral images were used to identify unwholesome poultry carcasses (Park & Chen, 2001). Ziadi, et al. (2010) developed a non-destructive method using computer vision using NIR light in transmission mode to estimate the volumetric marbling percentage in beef. The study revealed that, it was possible to detect not only the visible fat on the meat surface but also underneath the surface. The results obtained are in agreement with the samples AAA grade and with similar studies. Hence they concluded that the proposed method could be a potential attractive alternative method to the cumbersome traditional chemical (destructive) method for meat evaluation.

Private sector, start-ups working in the field of Automation and machine for meat industry

The use of robotics and automation assisted by machine vision in the food industry is increasing at a robust pace. Manufacturers are increasingly turning to robotic automation to help keep up with the rapidly changing consumer habits around food consumption. Automation with the help of machine vision has already occupied and established in various range of tasks in meat industry. In many modern poultry processing plants its application are increasing in various field like carcass grading, automatic live bird counting, metal detector, detection of defects on chicken meat and grading of marbling, colour and fat in beef. Robotics is another technology which used combined technology that has found application in the meat industry. Robot named 'Robo Butcher' uses a lifting arm to pick up meat cuts from a moving conveyor belt and arrange them on trays. The system pre-measures the weights of incoming portions, optimizes the best combination to achieve a specified package weight. Deboning processing robot (developed by Canadian meat researchers in 2001), Robotic pig scribbing system (developed by KUKA Robotics, 2002), Robotic butcher named 'Robochop' (designed by Kram and Wasshaer, KUKA Robotics) and 'Gribbot' - remove breast fillet from chicken automatically. (Developed by Elling Ruud, Ekram Misimi and Aleksander Eilertsen at SINTEF, Norway). A new technology of X-ray robots detects location, length and joints of bones (Ollinger, M. 2005). This system dismantles rather than cutting the meat off the bone, which prevents knife damage and improves final product quality and better yield. RND Automation Pvt. Ltd. design and manufacture customized Poultry and Meat Processing Equipment. The company manufactures complete range of semi-automatic to automatic plant equipment's for processing between 500 to 4000 birds/hour, which is extensively used by both small scale and large scale processors and integrators. To date, automatic carcass-cutting technology have been commercialized by Marel (Gardabaer, Iceland), Frontmatec (Kolding, Denmark), Scott (Dunedin, New Zealand), and the Danish Meat Research Institute (Taastrup, Denmark). Marel M-line neck cutter and AiRA RNC Neck Clipper were developed by MNC, Marel, Gardabaer, Iceland to remove head from carcass of pigs. These automatic devices can cut off the head just above the ears of the carcass and can processs up to 650-750 pork carcass per hour (de Medeiros Esper, et al. 2020). The technology used in the system is a 3D image vision technology for object recognition.

Conclusion

This review over view the recent developments, its possible applications, the concepts and technologies associated with computer vision to assist in automation process. The implications of these applications are vast. Machine-vision can provide fast identification and measurement of selected objects; perform quality evaluation of meat and meat products. Automated, objective, rapid and hygienic inspection of diverse products in a flexible and non-destructive manner maintains its attractiveness. Viewing the practical importance and advantages, it is expected that the machine-vision technology will find more real-world applications. Its applications will improve overall productivity of industry and will help to provide better quality to consumers.

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