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COMPUTER VISION APPLICATION IN THE QUALITY EVALUATION OF CEREAL-BASED PRODUCTS

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Abstract: *Humans conduct the visual inspection and quality control of many bakery products relying on the use of the sense of sight. Human inspection is a slow process, has poor repeatability and result varies from person to person. Computer vision system (CVS) is becoming one of the most important non-destructive, rapid, economic, consistent and objective inspection and evaluation technique in the food industry. This inspection approach is based on image analysis and processing of many products from food industry for objective evaluation of quality parameters. Its speed and accuracy satisfy ever-increasing production and quality requirements, and offers the potential to automate manual grading practices thus standardizing techniques and eliminating tedious human inspection tasks.*

This paper is dealing with CVS application for quality inspection of the cereal-based product. This method is applied for the inspection and grading of cereal-based products based on shape, size, colour and internal structure. According to the obtained results, CVS can be successfully adopted for the quality analysis of many cereal-based products such as bread, cookies, crackers, pizzas, etc. Furthermore, the CVS method proved to be successful for examination of the wheat grain quality.

Keywords: *Non-Destructive Methods, Image Analysis, Computer Vision, Cereal-based Products, Physical Properties*

INTRODUCTION

Cereal products, especially bread, have been a major source of food for the human race since the commencement of civilization. There is a wide range of cereal-based products including bread, breakfast cereal, cereal bars, sweet bakery ware, pasta, and savoury snacks. Cereal products are based on different sources such as barley, wheat, corn, oats, rice, and rye. Raw materials derived from the grains vary from milled flours to grits semolina. There are some main groups of cereal-based product like bakery product, breakfast cereals of fermented cereals. *Bakery products* include different types of cereal-based products such as bread, cakes, cereal bars, wafers, and muffins. *Breakfast cereals* comprise corn flakes, muesli types, and expanded products. There are also *fermented cereal-based* (maize, sorghum or wheat) products eaten as non-alcoholic cold beverages (Gowé and Akpan), gruel (Kishk) or thick paste (Kenkey). To replace manual inspection performed by trained human inspector, automatic, objective, rapid and repeatable external quality inspection systems become very important and necessary. Researchers have been working to find techniques for evaluating external and internal quality attributes of cereal-based products nondestructively (Lukinac et al., 2018; 2013; 2009). Size, shape and colour of product are considered as external quality attributes. Internal quality attributes are texture (firmness, hardness, crispness, tenderness and juiciness), proximate composition and nutritive value (carbohydrates, proteins and vitamins) and defects like pest infestation internal cavity, frost damage, rotten, etc. While external quality attributes are evaluated by eye judgment, internal quality attributes are difficult to access by visual appearance and there is a need for technology that can determine them.

Instruments can be designed to imitate human testing methods or may be statistically related to human perceptions and judgments to predict quality categories. Because the most part of the external quality attributes evaluation is time consuming due to visual inspection, CVS provides a means to perform this task automatically. CVS is non-destructive and cost-effective technique, based on image analysis (IA) and processing. IA is used as a fundamental tool for recognizing, differentiating, and quantifying diverse types of images like grayscale, colour images, multispectral images or hyperspectral images.

Some of the devices or sensors used in generating images include CCD (Charged coupled device) or CMOS (Complementary metal-oxide semiconductor), scanners, and ultrasound, X-ray and near infrared spectroscopy. The colour image is analysed by a computer program/software and quantifies colour values in a relevant colour scale (Minz et al., 2013). In order to perform objective and reliable food inspection method suited for routine inspection and quality assurance tasks, the application of non-destructive optical devices is considered ideally (Lukinac et al., 2018; 2009). Non-destructive optical techniques includes CVS with online digital cameras/scanners, light and confocal laser scanning microscopes (CLS), the near-infrared (NIR) imaging systems, spectroscopy and hyperspectral imaging systems (HIS), X- ray imaging and ultrasonic devices (Lukinac et al. 2018). Over the past decades, CVS, including traditional CVS, hyperspectral CVS, and multispectral CVS, has been widely used in the food industry for the automatic external quality inspection of food and agricultural products (El Masry et al., 2016; Zhang et al., 2014). As consumers are demanding better quality and safer food products, there is an increasing need for rapid and non-destructive quality evaluation of foods. In recent years, new imaging-based inspection techniques, such as multispectral and hyperspectral imaging, have been developed for quality assessment of a variety of foods, which have overcome some of the drawbacks of traditional human and instrumental inspection techniques (Du & Sun 2004a,b). These methods, which are based on the automatic detection of various image features, correlate well with quality attributes of foods that are related to the sensorial, chemical, and physical properties. Computer vision has been successfully adopted for the quality analysis of pizza and bread, and quality of grain.

COMPONENTS OF CVS

CVS is the automatic extraction of information from digital images. Computer vision includes several operations: image capturing, processing and image analysis. After image capture, there is a process of digitization (transformation images into numbers). Basic components of CVS are illumination device (lights), a device for image acquisition (digital camera/scanner), frame grabber (in the case of an analogue camera), and computer hardware and software (algorithms for image analysing and pre-processing).

Image illumination: Image analysis can be easier with good illumination by reducing noise, shadow, reflection, and enhancing image contrast. To view an object, it is necessary for it to be illuminated by a light source. Light sources may be either natural (sunlight) or artificial (incandescent, halogen, fluorescent, compact fluorescent, LED, metal halide, Xenon, High Pressure Sodium, lasers, and infrared lamps). There are many properties of illumination that must be selected in such a way that a perfectly evaluable image is generated in combination with the material properties of the object under inspection (Moeslund, 2012). Factors that influence on choosing suitable illumination are object geometry under inspection, nature of object surface and the nature of the object feature to be imaged in comparison with the background (Abdullah et al., 2008; Zuech, 2004).

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Image acquisition: This is a very important step because a poorly acquired image cannot provide useful results even with best image processing infrastructure. Image acquisition encompasses images capturing, with digital camera or scanner. There are three basic elements in image capturing: energy, the lens (optical system) and the sensor. According to the operating range of the spectrum, we distinguish different type of cameras: CCD camera (400-700 nm), near-infrared (NIR) camera (900-1700 nm), near-ultraviolet (UV) camera (300-369 nm). Cameras that operates in visible part of the spectrum are analogue and digital cameras. Digital cameras can be equipped with CCD or CMOS sensor arrays (Waltham, 2013). Furthermore, important components of CSV are computer hardware and software, providing storage space for images and computing capacity with specific software applications. Visualization of images and results of the image analysis process, are enhanced by high-resolution monitors.

Image analysis: Image analysis is the process of discriminating the objects (regions of interest) from the background and producing quantitative information, which are used in the subsequent control systems for making decision. Image processing and analysis steps can be divided into three levels: low, intermediate and high (Patel et al., 2012; Sun, 2000). The core technique in computer vision is always related to image processing and analysis. Primary types of object measurements (size, shape, colour and texture) can be acquired from any image (Du & Sun, 2004a,b). In computers, images are stored and processed in the form of matrices whose elements are pixels. Two types of information are stored in pixels, geometry information (location of pixels in image) and surface information (intensity values associated with pixels). From the geometry information, size and shape of the object can be obtained. Colour and texture can be extracted from the object surface information (Fig. 1).

Fig. 1 The image analysis procedure

APPLICATION OF CVS IN THE ANALYSIS OF CEREAL-BASED PRODUCTS

The physical properties such as colour, size, and shape are three important quality attributes of most baked foods. Large variability in these attributes can affect the visual perception of customers.

Shape and size inspection: The variability of size and shape are due to many factors such as inferior dough formulation, overbaking, and mishandling. In order to ensure that baked foods are compliant with production standards, shape inspection is widely used for food quality evaluation.

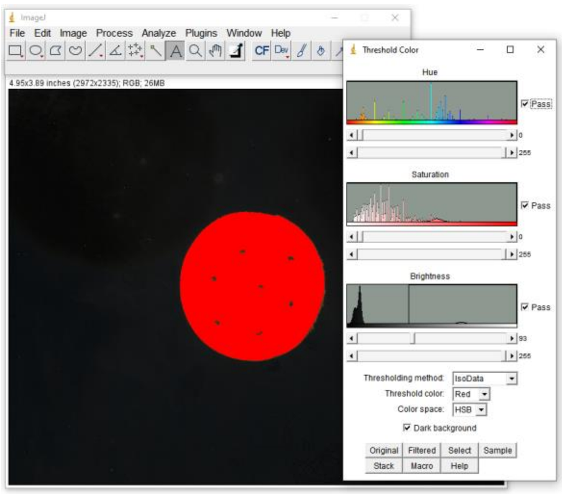

Fig. 2 The cracker size and shape measuring using CVS

The CVS can be used to analyse the colour and geometric features of the crackers before and after the baking process (Fig. 2). Gunasekaran and Ding (1994) described a machine-based learning system, which was trained to distinguish between whole and broken crackers. Their method relies on the assumption that all crackers in the production line were supposed to have the same size and shape. Scott (1994) described a system, which measures the defects in baked loaves of bread, by analysing its height and slope of the top. Nia (2012) investigated the physical characteristics of bread using CVS. Abdullah et al. (2000) developed a prototype-automated system for visual inspection of muffins, and they reported that it was able to correctly classify 96% of pre-graded and 79% of ungraded muffins with an accuracy of greater than 88%.

Colour inspection: Several different systems are used to represent colour images. The most common are RGB (additive colour system), CMYK (subtractive colour system), HSV and the CIELAB colour space. RGB is a colour model that uses the three primary (red, green, blue) additive colours, which can be mixed to make all other colours. Digital cameras produce RGB images, and monitors display RGB images. In food research, colour is frequently represented using the CIELAB or L*a*b* colour space since results closely match those of the human perception of colours. Mathematical conversions between different colour spaces for analysis and special visualizations are also possible. As a decisive and informative quality indicator, colour measurement using non-destructive computer vision-based image analysis offers great advantages as an online process control tool. In fact, computer vision-based image analysis has been widely established in the food industry for a rapid inspection of quality defects by means of colour differences. One potential application of the computer vision-based image analysis for this purpose could be online monitoring of thermal processing contaminants in bakery products. Nowadays, thermal processing contaminants, such as acrylamide, are one of the major concerns for consumers from a food safety point of view.

Arabi & Ardebili (2020) monitor the Acrylamide (AA) contents in biscuits produced on the industrial scale. Effect of sugar types, inverted sugar syrup and sucrose, and baking conditions including time and temperature on the AA formation were studied in rotary moulded biscuit at the industrial scale. The AA content and the correlation between AA concentration and CIE colour space parameters of L*a*b* and C index was studied. Colour was measured using the CVS. The results of the colour analysis of biscuit samples revealed that a significant correlation was observed between AA concentration and brightness parameter L*, while parameters a*, b* and C did not show significant differences. Davidson et al. (2001) measured the physical features of chocolate chip biscuits, including size, shape baked dough colour, and fraction of top surface area that was chocolate chip using image analysis. Four fuzzy models were developed to predict consumer ratings based on three of the features. Automated visual inspection of muffins has also been performed by use of a system developed by Abdullah et al. (2000). Colour of 200 muffins were examined using the vision system with a classification algorithm used for separating dark from light samples using pre-graded and ungraded muffins. Visual features such as colour and size indicate the quality of many prepared consumer foods (Fig. 3). Sun (2003) investigated this in research on pizza in which pizza topping percentage and distribution were extracted from pizza images. Combining three traditional segmentation algorithms to segment many different types of pizzas were found to be inadequate for this application. Therefore, they developed a new segmentation algorithm.

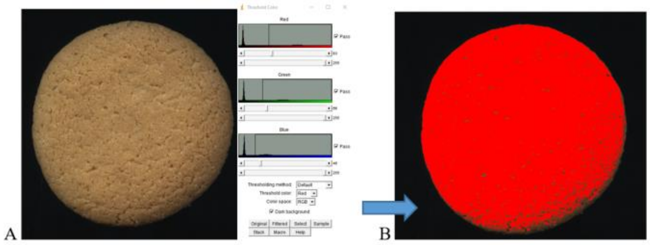

Fig. 3 Application of CVS in determining the colour of biscuits: A) original image; B) image after colour processing

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Gallagher et al. (2003) studied the effects of baking on colour values and other quality parameters of gluten-free breads, which were supplemented with seven dairy powders at four inclusion rates based on flour weight: 0%, 3%, 6%, and 9%. Crust and crumb colour were obtained through a software in terms of CIEL*a*b* values. Since it is desirable to have a bread showing dark crust and white crumb characteristics, it can be concluded that the presence of protein rich powders such as smr, nac, and mpi helped improve the quality of baking.

Crack inspection: In addition to colour, shape, and size, another test that needs to be carried out on most biscuits or baked products is the inspection of cracks (Fig. 4).

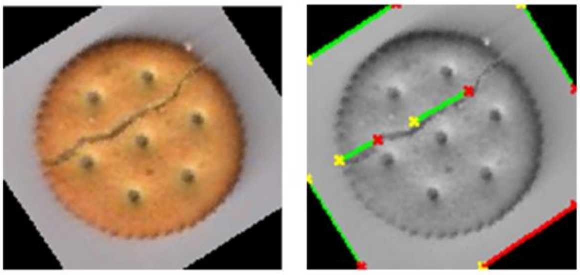

Fig. 4 The crack detection of biscuits using CVS

In image-based quality inspection and diagnosis of food products, Davidson et al. (2001) implemented a vision system to measure the physical features of chocolate chip cookies such as size, perimeter, and fraction of the chocolate top surface area. Nashat et al. (2014) developed an automatic machine vision system for the crack inspection of biscuits featuring a pyramid detection scheme. The main objective was to detect a small and minute crack of biscuits with nonuniform colour distributions and textured background. In their study, the popular Cannye Deriche filter was used to emphasis the crack whereas an advanced unimodal thresholding (Nashat et al., 2012) technique was employed to segment minute crack pattern with less noise.

Internal structure (texture) inspection: Image texture is an attribute representing the spatial arrangement of the grey levels of the pixels in a region (Anon., 1990). The computer inspection of texture can be categorized into four groups: (1) statistical texture, (2) structural texture, (3) model-based texture, and (4) transform-based texture. Features such as coarseness, regularity, presence of privileged direction, size, and colour are all important for texture analysis. Almost all of these attributes can be analysed by means of digital image processing. The first application of computer vision analysis to describe the textural appearance of baked goods, such as bread crumbs, was performed by Bertrand et al. (1992). They analysed bread crumb texture using two-dimensional Haar transform together with the canonical discriminant analysis.

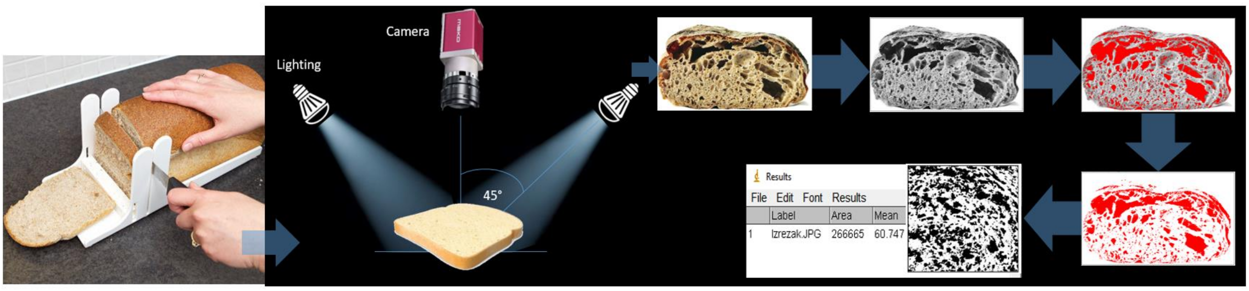

Fig. 5 The procedure of bread crumb analysis using CVS

Furthermore, Zayas & Chung (1996) categorized bread crumbs into five classes, ranging from the best or outstanding category (grade 5) to the worst or “questionable” category (grade 1). The grading was based on the bread crumb textures, in which the superior category contains bread crumbs exhibiting very fine and elongated cells, uniformly layered with light, lacy, and very thin cell walls, while the inferior categories are bread crumbs having cells which are coarser and extremely irregular in both shape and size. The internal structure (crumb grain) of bread and cake was also examined by machine vision (Sapirstein, 1995). Several image texture techniques have been used to quantify various crumb grain structures, including first-order statistical measures (Zayas, 1993), the grey level co-occurrence matrix method (GLCM) (Gonzales-Barron & Butler, 2008), transform-based methods such as Fourier transform (Rogers et al. 1995), Haar transform (Bertrand et al., 1992) and fractal dimension (FD) (Gonzales-Barron & Butler, 2007). The usefulness of the application of digital image processing is thus demonstrated by these examples, leading to a more reliable and objective evaluation of bread crumb texture (Fig. 5).

Grain inspection: Quality inspection of cereal grains and pulses like rice, corn, wheat, gram, beans, etc., can be performed based on size (length/width) and colour quantification of samples. Grain quality attributes are very important for all users and especially the milling and baking industries. Computer vision has been used in grain quality inspection for many years. An early study by Zayas et al. (1989) used machine vision to identify different varieties of wheat and to discriminate wheat from non-wheat components. In later research Zayas et al. (1996) found that, wheat classification methods could be improved by combining morphometry (computer vision analysis) and hardness analysis. Hard and soft recognition rates of 94% were achieved for the seventeen varieties examined. Twenty-three morphological features were used for the discriminant analysis of different cereal grains using machine vision (Majumdar et al., 1997). Image analysis has also been used to classify dockage components for CWRS (Canada Western Red Spring) wheat and other cereals (Nair et al., 1997). Ng et al. (1997) developed a machine vision algorithm for corn kernel mechanical and mould damage measurement, which demonstrated a standard deviation less than 5% of the mean value of the 250 grains examined. They found that this method was more consistent than other methods available. Steenhoek & Precetti (2000) performed a study to evaluate the concept of two-dimensional image analysis for classification of maize kernels according to size category. Wan et al. (2000) employed three online classification methods for rice quality inspection: range selection, neural network and hybrid algorithms. The highest recorded online classification accuracy was around 91% at rate of over 1200 kernels/min. The range selection method achieved this accuracy but required time-consuming and complicated adjustment.

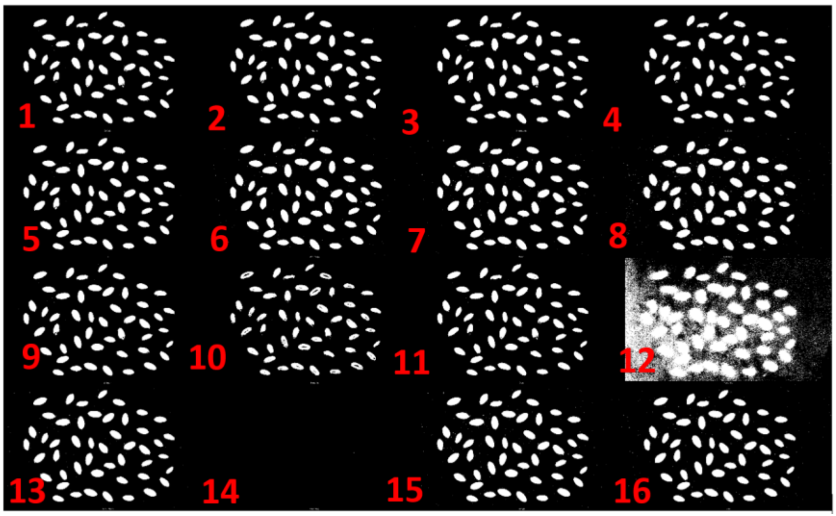

Fig. 6 Segmented wheat grain samples using 16 different segmentation methods

In a comprehensive study Majumdar and Jayas (2000 a, b) investigated the use of morphology models, colour models, texture models and a combined model of all three for the classification of cereal grains. 23 morphological, 18 colour, 25 textural features were tested on the training data set of 31,500 kernels. Narendra and Hareesh (2010) used CVS to identify different variety of wheat and to discriminate wheat from non-wheat components. They developed the CV algorithm for corn kernel where mechanical and mould damage measurement and whiteness of corn has been measured by on line CV approach, measuring the degree of milling of rice. The brightness, cell density, cell area and uniformity of the grain analysed indicated that even the minor deviations from the required specifications could be identified through CVS, allowing corrective

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measures in the bakery to be taken sooner. Using CVS and digital image analysis the geometric features of wheat grain can be inspected using different image processing algorithms and different segmentation methods (Fig. 6).

CONCLUSION

The physical properties such as colour, size, and shape are three important quality attributes of most baked foods. For bakery products, the superficial appearance and colour are the first parameters of quality evaluation by consumers. Nonvisual inspection, such as touching the edge of the product, may damage delicate foodstuffs and introduce bacteria. The automated, objective, rapid and hygienic inspection of diverse raw and processed foods can be achieved by the use of CVS. The need for visual quality control with the increasing scrutiny of hygiene standards and factory automation leads to a demand for automatic and objective evaluation of visual parameters. CVS in the form of cameras, illumination, frame grabbers, and computers provide a solution that may satisfy this demand.

The application of the state-of-the-art technology from processing down to the proportioning of ingredients enhances the baker's ability to produce a quality product and reduce material waste. The movement toward automation in the bakery industry reflects the industry's goal of producing quality products while simultaneously preparing to meet the competition of tomorrow. CVS is the upcoming field with lot of scope for improvements with advancements in the computer hardware and software. It offers enormous opportunity because it is applicable in both food industry and in research field.

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