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REVIEW PAPER

Applications of computer vision techniques in the agriculture and food industry: a review

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Abstract Over the last decades, parallel to technological development, there has been a great increase in the use of visual inspection systems. These systems have been widely implemented, particularly in the stage of inspection of product quality, as a means of replacing manual inspection conducted by humans. Much research has been published proposing the use of such tools in the processes of sorting and classification of food products. This paper presents a review of the main publications in the last ten years with respect to new technologies and to the wide application of systems of visual inspection in the sectors of precision farming and in the food industry.

Keywords Computational vision · Precision farming · Food industry · Food · Visual inspection · Image analysis

Introduction

The great concern with quality control due to new market restrictions in recent years has become so important that it has demanded a technology of process geared toward more reliable tests and new methods of monitoring product quality.

Over the past decade, significant advances in techniques of tests have been observed, while extraordinary resources in electronics and informatics were identified as important factors in this development. Automation has motivated the development of testing equipments in production lines, and the evolution of sensor technology has led to the establishment of new techniques of measurement of the products, thus allowing permanent monitoring during the process, with the implementation of visual inspection systems.

Systems of visual inspection are basically composed of a light source, a device for capturing the image and a computational system for the extraction of characteristics and processing. These systems are normally used in production lines where human activity is repetitive, products are manufactured very rapidly, and fast and accurate measurements are necessary for decision making during the process. Different from the problems present in visual inspection performed by people, these kinds of systems offer accuracy and repeatability in measurements without contact, especially due to the elimination of aspects such as subjectivity, tiredness, slowness and costs associated with human inspection.

The use of automatized inspections in agriculture and in the food industry has increasingly become an interesting solution for the final analysis of product quality, and the assessed values or characteristics involve not only dimensional aspects, but also characteristics of color, texture and shape.

Agricultural and food products present an incredible variety of shapes, sizes, colors and flavors, and as the market grows more demanding, food products are subdivided in

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various categories and are destined to different segments. The definition and the characterization of different attributes are very important for the business and for the consumer, making it necessary to establish norms of classification and standardization, thus making commercial trading more efficient and allowing for higher awareness on the part of consumers.

Moreover, with regard to obtaining measurements, even on the basis of images, it is necessary to have metrological rigor, which means having knowledge of the variables involved and of their contribution to error, and also to ensure that the process is replicable and that its results may be repeated, with measurements which are known and controlled within specific ranges. In this light, closer attention is needed to the standardization of measurements, and a higher emphasis on metrology in this sector becomes crucial, aiming to ensure repeatability of the results and the reproduction of the measurements employed, thus improving the reliability of this technique.

This paper reviews the main publications over the last decade with regard to the application of visual inspection systems in agriculture and in the food industry, demonstrating the diverse applications of computational vision in these industrial sectors. The papers were selected considering an exhaustive search in the main scientific database, in view of that they should use image processing and analysis to solve some agriculture and food problem. The purpose of the article is to present the tendency of the techniques and equipments used in the analysis of food and agriculture, and the great diversity of their applications, in order to subsidize new research in the area with image analysis. It also aims at highlighting the short amount of technical information regarding the measurements, which complicates the reproduction and comparison with other experiments, so as to validate the results obtained.

Automatic inspection systems

Computational vision is the science responsible for the study and application of methods which enable computers to understand the content of an image, and this interpretation involves the extraction of certain characteristics which are important for a given aim [1]. A system of visual inspection requires an entry of data (image) normally obtained by sensors, cameras or videos, and the further processing of these data in order to transform them into the information desired.

Stages of automatic inspection systems

Despite the fact that systems of visual inspection are organized according to a particular application, typical stages are observed in different computational systems which may be summarized as: image acquisition, pre-processing, segmentation, extraction of characteristics and processing.

The stage of image acquisition consists of capturing a real image and transforming it into a digital image using devices such as cameras, scanners, videos, etc. A digital image is a numerical representation of an image that can be computationally processed.

Pre-processing is the stage preceding the extraction of characteristics, which aims at improving the acquired image and highlighting the features or regions of interest, thus removing distortions and noise while not adding further information to its content. Pre-processing involves techniques to highlight regions and details and to remove any noise which may interfere in the analysis of objects and/or regions of interest. In this context, there is a great variety of techniques from which we can highlight the gray scale and color transformation, as well as thresholding and filtering [2]. This is an important stage in an automatic inspection system. The segmentation process can be based on the similarity of the color of each pixel and its neighboring pixels. Sometimes similar pixels, in terms of color, are not part of the same object or feature. The extraction of parameters enables the association between regions of the image and objects in the scene [3]. After these stages, the image should be ready for the extraction of important characteristics.

The final stage—processing—aims to recognize and interpret the images, seeking to make sense of the set of objects of the image, with the goal of improving human visualization and the automatic perception of data in a computer.

Types of characteristics analyzed

After the stages of pre-processing and segmentation, the image is ready for the extraction of important characteristics, where it is possible to obtain relevant data on the item to be analyzed. The characteristics most commonly extracted are number of objects, dimensions, geometry, luminosity and texture [1], and according to Rodenacker and Bengtsson [4], they may be grouped into four categories: morphological, chromatic, textural and structural.

The morphological characteristics, such as circularity, area, width, etc., consist in measuring the shape of the object that makes up the image, without considering the intensity of the pixels, and it can be calculated on binary images resulting from the processing of color images. The chromatic properties are those that describe the color or the spectral composition of the radiation emitted or reflected from objects, quantified by the intensity of pixels in different spectral bands. The textural characteristics consist in the measuring which characterizes the local variability of the intensities of pixels. And the structural or contextual characteristics describe the relationship between one or more objects that make up the image, such as the position of the defect in relation to the skin of the fruit [4].

With the evolution of techniques of process control and the need to increase efficiency in order to maintain competitiveness, the agricultural sector has been adopting these new technologies in what has been called 'precision farming', aiming to reach increasingly higher levels of control of the production line. Agriculture, together with the food sector, has become on the main applications of computational vision, since they require, in the analysis of the product, a reproduction of human perception with regard to the image of the product, involving the analysis of attributes, such as size, shape, texture, brightness, color, etc., which directly influence quality assessment. In this manner, food products are monitored from production in the fields to the final packing, after processing or not.

Vegetation and vegetables

Vegetation

One of the goals of precision farming is to minimize the amount of pesticides used in systems of pest control, and to this end, two main factors must be considered: the similarity in terms of shape and texture between pests and vegetation and the irregularity in the distribution of pests in the vegetation [5]. With that aim, much research has been conducted using computational vision in this area.

In plantations, one of the characteristics used in order to guide the robot vehicle through the crops is the contrast between green plants and soil background. Sogaard and Olsen [6] used an intensity indicator I [I = 2G-R-B], on the RGB system, in order to identify the plants in relation to other objects on the image, such as weeds growing in crops in rows like sugar beet. In 2008, Bakker et al. [7], with the same goal, used another normalized version from this indicator, concluding that it is safe to use this indicator in cases where there are changing levels of illumination.

Besides Sogaard [3], Ribeiro's group [5, 8–10] has been developing studies with the application of computational vision in pest control. Tellaeche et al. [5, 8] presented an automatic method for detecting weeds in barley plantations. The proposed method determines the amount and the distribution of pesticides and their method of application, using segmentation and fuzzy logic for decision making. It has been suggested that further work should consider the significant variation in natural light during image acquisition.

Burgos-Artizzu et al. [9, 10] presented several methodologies based on computational vision to estimate the percentage of crops, of weeds or of dirt present on the image of a field. The problems identified were the lack of control over the level of illumination and the different stages of plant growth. In this way, image processing was conducted in three stages where different elements were extracted. First, segmentation was performed by sorting vegetation from nonvegetation, followed by the extraction of the weeds. In each stage, different methodologies have been tested, in order to make processing faster and more accurate, showing an average of 95 % classification accuracy for pests and 80 % for vegetation under different levels of illumination, humidity and stages of plant growth.

In 2006, Cavani et al. [11] used techniques of computational vision in order to segment images and to identify elements of agricultural scenes, on the basis of images from orange fields. The segmentation of the images was conducted using the algorithm Jseg, and upon further assessment of multilayers of the segments extracted from the color space RGB and HSV, the latter has presented better results.

Potatoes

Much work has been published on the inspection of potatoes [12–14] where several analyses are conducted with regard to shape, size and color, aiming at the analysis of defects. In Noordam et al. [12] and Cabrera et al. [13] potatoes were analyzed as a whole, and, to this end, a camera with mirrors has been used in order to obtain a global image. Experiments with red and yellow potatoes were undertaken, showing that the system employed was robust for classification. However, Cabrera et al. [13] have not described the illumination used and its possible influence on classification. Noordam et al. [12] suggest that a model of correction should be developed in the future in order to reduce the differences in illumination on the images from the mirrors.

In 2010, Barnes et al. [14] developed a new method of detecting defects in potatoes using computational vision. In order to reduce shadow effects and changing conditions of illumination during image acquisition, the potatoes have been placed inside a white cylinder, with daylight lamps placed around the top of it, on a total of 4 lamps. After the segmentation of the potato on the bottom, a pixel classifier was trained to detect spots using extraction of characteristics of the image. Some parameters were used based on statistical information extracted from color and texture of the region surrounding the pixel, and then, an algorithm was used to automatically sort spots and not spots. The result showed that the method was able to classify and optimize the performance of classification with low computational cost, presenting levels of accuracy for white and red potatoes of 89, 6 and 89, 5 %, respectively.

Grains

As presented by Davies [15], several types of food products have been inspected by computational vision techniques, including cereals, and in particular wheat, which is very important in the food industry. One of the main references on this application is Jayas, who has been developing studies on the sorting of grains from morphological characteristics. In 2001, Visen et al. [16] developed an algorithm of segmentation for the analysis of morphological characteristics of wheat grains, such as shape, size, etc., as well as physical characteristics, including area, perimeter, length, etc. For this characterization, the shape of an ellipse has been adopted, where the grain curvature was estimated on the basis of formulas developed by the author. However, problems have been found in the characterization of grains with irregular surfaces using segmentation on digital images. From 2001 to 2003, Jayas' team [17–20] developed several studies using neural networks for the sorting of grains, thus publishing a comparative study using neural network and a nonparametric classifier in the classification of grains. In this study, they have used an identical number of morphological parameters, color and texture, concluding that a backpropagation network is recommended for grain classification, leading to better results.

In 2007, Tahir et al. [21] presented a study analyzing the effect of humidity on the classification of grains from digital images. The grains were conditioned to different levels of humidity (12, 14, 16, 18 and 20 %) before image acquisition, and the classification of grains was conducted both by a statistical classifier and by a neural network. Both the texture and the color parameters have been affected by the humidity variation in the grains.

In 2008, Choudhary et al. [22] carried out a study of classification of cereal grains by analyzing morphological aspects, color and texture from the images. The linear classification showed the best result. However, the illumination influenced certain classifications of the study due to the reflectance of the samples. Therefore, Manickavasagana et al. [23] carried out a study for the classification of wheat using monochromatic images. Greyscale images were captured by a monochromatic camera, and an algorithm was developed in order to extract texture characteristics from the images. The use of monochromatic images pointed to a potential use in the sorting of wheat; nonetheless, further studies should be carried out for the characterization of impurities among the grains.

As a continuation of their research, Manickavasagana et al. [24] conducted a study in order to establish the best illumination to be used in the analysis of grains from monochromatic images. Incandescent and fluorescent lamps (ring and tube) have been tested. Mean gray values were significantly different for each kind of illumination, with a higher value for the fluorescent tube lamp and a lower one for the incandescent lamp.

In a recent publication [25], computational vision was used to analyze shapes and colors of seeds with the goal of finding parameters which could provide better classification of toxic contamination. Color analysis was performed using the L*a*b* system, calculated from the RGB channels, together with the analysis of shape (area, perimeter, etc.) of several types of seeds, with the conclusion that information on color is important in the analysis of the level of contamination of the seeds.

Effendi et al. [26] conducted a study with pine nuts. Recently, pine nuts have been widely used in biodiesel production, and its quality depends on the type and size of defects, as well as on the color of the coat (shell) and on the size of the fruit. In his study, Effendi presented the development of a classification system of pine nuts using color histograms in order to distinguish the levels of ripening of pine nuts based on color intensity (three levels of ripening). The system used the average intensity of the color to analyze the red, the green and the blue of the RGB system of the seed, concluding that the system is usual for the classification of the level of ripeness of this seed.

Fruits

The need for the characterization and the sorting of fruits for consumption has grown enormously in recent years, and one of the parameters used in this classification is appearance. This is due to the fact that it is a naturally used attribute in judging the quality, while it involves measurements such as size, shape, texture, brightness, color, etc. With this goal, several studies have been developed for the characterization and sorting of fruits, including tomato [27], apple [28], orange [29], olive [30], mango [31], pomegranate [32, 33], strawberry [34], tamarind [35], etc.

In the case of pomegranate, a fruit that has many nutritional properties, though it has a skin that is hard to be removed, a common system for its processing is the sorting of pieces of the skin and the healthy seeds for distinct applications. Blasco et al. [32] conducted a study on the development of a prototype for the sorting of pomegranate seeds, in order to assess the best color of the tray for image acquisition for further selection. The color blue showed the best performance as it presents higher B as opposed to the colors of the seeds to be classified (in the RGB system). Another study by Blasco et al. [33] consisted in sorting the seeds by color, using the ratio R/G, which presented better performance in the distinction between different colors of seeds than using R, G or B in isolation or grouped together.

Recent work has shown interesting studies on the external appearance of olives, considered as a decisive factor in the quality of this product, where computational vision becomes an important tool. Riquelme et al. [30] carried out a study on the detection of defects originating from different causes, where color and shape analyses were conducted from images in order to classify individual types of defects. This work, as is the case with many others on inspection in the food sector, presented as a limitation an insufficient number of samples tested in the classification of defects in order to allow for a reliable training of the classifier used.

As is the case with other fruits, the appearance of the tomato is one of the important parameters to estimate its internal quality and, for that, some characteristics should be analyzed, such as size, tridimensional shape, color and color uniformity, as well as the observation of possible defects. In 2006, Louro et al. [36] presented a study with the goal of classifying tomatoes using artificial neural networks and of assessing its performance by comparing the results with information from an expert. Image processing techniques and neural networks were applied to classify tomatoes in four different classes, based on their size and color. In image acquisition, Louro has initially used a black background, though this has proved to be inadequate, having been changed to a white background, which, according to Louro, has substantially facilitated the segmentation phase. Louro has also concluded that the RGB space used has not been efficient, suggesting the use of the L*a*b* system in further work.

In 2008, Lino et al. [37] presented a study aiming to classify the shape, volume and color of fruits, applied to tomatoes and limes. According to Lino [37], the technological implementation of sophisticated systems of classifying fruits is of difficult access to small and medium producers, given the high cost of software, equipments, as well as the high operational costs.

Research work has been developed with the aim of improving the processing of citrus fruits, which are widely consumed internationally. Recent work has been conducted by the same group of authors [29, 38–41] on the selection of fruits according to defects, such as spots, damages, bruises, etc. These studies are interesting due to the use of multispectral images. The study conducted by Gómez et al. [40] relates to this recent technology, which permits the analysis of an image with different wavelengths, and the spectral result may be used to help identify types of defects which are already known.

In 2008, Gómez-Sanchis et al. [41] suggested that some of the problems arising from the inspection of images of certain products are due to their spherical shape, as is the case with oranges, pears, tomatoes, apples, etc. The methodology presented uses a hyperspectral computational vision system (spatial and spectral information of the scene), based on harmonious liquid crystal filters which minimize the effect produced by the curvature of the fruit on the intensity of radiation captured by the camera.

Apple is one of the fruits most widely consumed in the world, and therefore, it is the fruit that presents the highest number of articles related to its processing systems, in terms of checking its growth and ripening rate [42, 43], as well as on sorting through certain characteristics, such as size, shape, color, etc. [28, 44–47].

Apples are very susceptible to damage and the presence of bruises on the apple skin affects not only the appearance of the apple, which is an important indicator of quality, but also accelerates its deterioration. Therefore, an effective system of removing damaged apples allows the maintenance of the quality of the other products in a tray, and it is one of the essential stages in the processing of apples. Several studies use the color of the apple as an important characteristic of its quality, as well as on the characterization of defects. However, certain types of apples show a bicolored characteristic, that is, they exhibit two colors on their appearance, which makes their sorting in processing very hard to meet European requirements with regard to classification. According to Madieta [48], it is necessary to know the interval in the color variation of the apple skin in order to decide the best manner of measuring it. Based on the type of color distribution on the skin, the apple may be classified as homogenous, heterogeneous or bicolored. In this way, many studies are carried out with the goal of reaching better performance of visual systems with a view to meeting these requirements, seeking improvements in the localization of defects [49–53].

Yimyam et al. [31] described a technique of visual processing for detecting, segmenting and analyzing physical properties of mango, such as size, shape, surface area and color from images. Firstly, the images of the mangos were obtained by a digital camera, then analyzed and segmented. Segmentation was done by building a *hue* model of the samples of mangos, and some morphological and filtering techniques were applied in order to eliminate the noise. From the segmented and clean image, the area of the mango was computed and the shape was analyzed using structure models. Color was also analyzed and indexed in the database for future classification. The image in RGB was transformed in values of hue by the equation, $\cos H = (2R\text{-}G\text{-}B)/(2*(\mathrm{root}(R - G)2 + (R - G)*(G - B)))$. The result shows that the technique is a good alternative and that it has practical application for sorting mangos, compared to manual sorting.

Kang et al. [54] investigated the use of a system of color digital measuring in order to obtain values of hue, chroma, laboratory, of heterogeneously colored fruits, adopting mango as an example. The goals of the study were to establish the effect of the fruit curvature on the measurements of laboratory in a large color interval, to quantify the effect of the curvature in the calculation of the hue and of the chroma, and to demonstrate the way in which the obtained data on hue may provide quantitative values for the description of the color profile and color changes in heterogeneously colored fruits.

In order to minimize the problems found in supermarkets, in the identification of fruits and vegetables at the point there they are to be weighed and priced, Rocha et al. [55, 56] proposed a system using characteristics of color, texture and structural appearance from images of vegetables and fruits. The images were obtained on a white background and under different types of illumination (natural and artificial). The vegetables and fruits were classified and identified from previously obtained images. Good results were observed in the classification.

Meat and fish

Color evolution is the main characteristic used by consumers in the perception of food quality, particularly for different kinds of meat, where it constitutes an indicator of its stage of degradation. Meat undergoes various processes before being commercialized and consumed, and during these stages, computational vision has been an important tool for ensuring its final quality. In this way, several authors have investigated techniques for analyzing the quality of meat using computational vision, such as beef, pork, fish, etc.

O'Sullivan et al. [57] studied the degradation of pork on the basis of color, with variations from red to brown. The main goal of the study was to compare instrumental measurements with the digital image in order to determine the effective identification of the meat color by the system of visual inspection. The analysis was performed using the L*a*b* system, which showed excellent correlation with the digital measurements.

In 2008, Jackman et al. [58] examined the quality of beef using computational vision to analyze the color and the texture of the meat, as well as the amount of muscles observed. Different background colors were used during image acquisition, with the black background showing the best results.

Much work has been developed on the implementation of automatic systems to estimate the composition of ham on the basis of the analysis of the area of fat and the muscles, as well as an estimate of weight, which are characteristics that influence the quality of the product. Researchers have concluded that the RGB and the L*a*b* systems provide important information which may differentiate between the distinct types of ham surface. Valous et al. [59] conducted several studies on this topic, applying new techniques for the characterization of the quality of ham. In 2010, Valous et al. [60] presented a summary of the distinct techniques used in the characterization of these products, showing the main advantages of the computational vision method on this area, which are identified as: rapid and objective generation of data, consistency, effectiveness, low cost, low human involvement, besides being a robust and competitive technique.

Louka et al. [61] conducted a study on the variation of the color of fish after its desiccation. The drying process of fish has been used to increase its conservation period. However, this process changes the original color of the fish, making it look brownish. This study analyzed the variation of the final color of the fish, after three different drying processes. The whiteness of the meat was measured in an automatic system, varying in a scale of 0 to 4. Different background colors were used during image acquisition, with the black background showing best results. From the four color spaces used, L*a*b* was chosen for presenting better results.

Misini et al. [62] developed an automatic system of classification of salmon based on the external geometry of the fish analyzed from images, reaching 90 % of accuracy when compared to the manual system of inspection.

Industrialized products

Several other computational vision applications on the food sector have been studied, including the analysis of ham, bread, chocolate, potato chips, wine, etc.

Bread and potato chips

In 2006, Pedreschi et al. [63] presented a study using computational vision for the characterization of the color of potato chips. The goal of the research was to project and implement a computational vision system in order to measure the high heterogeneity of shape and color of potato chips, using the laboratory system from images obtained in the RGB system. The background color used on image acquisition was black, in order to avoid reflections of the incident light. The methodology presented was considered easy, accurate, representative, objective and economical.

In 2009, Jusoh et al. [64] developed a study of characterization of the thickness of the edge of bread through color, using computational vision. In order to distinguish between the crust and the crumb of the bread from the image, the laboratory system was used in the characterization of the brown color on the edge of the bread, thus making it possible to determine the thickness of the crust.

Cheese and wine

The cheese production industry has undergone constant innovation as a consequence of competition in the sector. One example of this innovation is the production of pasteurized cheese with vegetables to be used in sandwiches, salads, pizza, etc. In order to ensure the quality of this new product, new techniques of monitoring using computational vision are being developed. A study has been presented by Jelinski et al. [65] aiming at the inspection of two main characteristics of pasteurized cheese: the amount and the distribution of ingredients. An algorithm for pre-processing the image was developed in order to extract the area of the edge of the cheese and then to extract the ingredients, using, for that purpose, the quantification of color and localization of the ingredient. The amount and distribution of each ingredient were automatically calculated for two types of pasteurized cheese, cheese with garlic and parsley on the one hand and cheese with pepper and parsley on the other hand, showing 88 % accuracy for the first type and 81 % for the second. The results found in this study were promising, and the algorithms developed may be applied in the inspection of different kinds of cheese with ingredients. Different backgrounds were tested, with the black background presenting best results. It should be highlighted that, for the image acquisition of the analyzed cheese, a scanner was used rather than a camera, the latter being the most usually used equipment in similar studies.

The color is one of the main parameters of the quality of wine, having an important influence on consumers' receptivity. According to Martin et al. [66], the color also provides information about defects, types and conservation during storage. Martin et al. [66] developed a study in order to quantify the relation between visual observation and a physical measurement of the color in a selection of wines. Four types of samples were used in the analysis of the visual color appearance of the wine. Observers were asked to estimate the brightness, colorfulness and hue of each test sample, and the results were compared with two instrumental measurement techniques, using a telespectroradiometer and using the image acquired by a calibrated digital camera. The correlation between visual assessment and instrumental color measurement of wine is not very high, and some discrepancy occurs with averaged hues, particularly at greenish-yellow colors. Both the spectroradiometric and the camera measurements are in good agreement with each other. Recent advances in image acquisition technology offer the possibility of using this technique available at low cost. The results showed that the measurements obtained from image acquisition with no contact may be rapidly acquired and present accurate results.

Pizza

An important work has been conducted by Du and Sun [67] in order to classify pizza using color features to quantify the distribution of ingredients for quality classification using computer vision. Five transformations for the RGB system were done in order to verify the best performance in relation to other color systems in the classification of pizza. The following systems were examined: NRGB (normalized RGB), HSV (hue, saturation and value), I1I2I3 (OHTA), L*a*b* and YCbCr. Using these five transformations of the color space, the performance of three classifiers (linear, polynomial and RBF) were compared. Du and Sun concluded that the classifiers SVM and the SVM polynomial combined with the HSV space proved to be a good approximation for the use of computational vision in pizza classification.

Ready meal

Consumers seek practicality as well as quality. Therefore, the food industry has been searching for innovation in the sector, aiming to meet consumers' need to have fast and practical meals with quality. In this way, there is now the need to develop systems to classify, monitor and sort the components of a ready meal so as to make it similar to the meal prepared by consumers during a meal. Munkevk et al. [68] developed a study to introduce an automatic method to describe a meal (ready meal) using a computational vision system, employing algorithms for the analysis of images, including segmentation and extraction. For image acquisition, a white plate and a red tray were used as background and the results were promising.

Overview

Precision farming has significantly grown in recent years, and computational vision has been the main actor in this process. As presented, much work has been developed to increasingly improve systems of production and the quality of products, both in agriculture and in the food industry. Most of the systems proposed present, in general, four well-defined stages, which are image acquisition, segmentation, extraction of characteristics and comparison with standards. However, the adequate tools and strategies both for image acquisition as well as for their processing are not straightforward.

Image acquisition

The stage of image acquisition is a physical process which depends on a large number of parameters for the final achievement of a good image. Some parameters influence the quality of the image to be obtained, such as the device used for image acquisition, the illumination system employed and the background color.

Several devices are used in image acquisition such as digital cameras, scanners, videos, thermal cameras, etc. Considering the articles examined, most authors declare the device used in image acquisition, although around 6 % of authors do not show this concern, not mentioning the device used in the study. The devices most frequently used are digital cameras (58 %), video cameras (8 %), scanners (3 %) e thermal cameras (2 %). Several systems used colored image acquisition (53 %), though the need for colored image depends on the characteristics to be analyzed in the object and on the type of processing to be used. Another aspect to be analyzed regarding the image acquisition device is the detection system, which may be CCD (charge coupled device) or CMOS (complementary metal oxide semiconductor), since this influences the speed of image acquisition and considering also that both present advantages and disadvantages.

Another parameter that influences image quality is the type of illumination. Considering the articles examined, most authors declare the type of illumination used, although around 25 % do not show this concern, not mentioning the type of illumination used in the study. It is worth highlighting that some features of the source used, such as the correlated color temperature (CCT) and the color reproduction index (CRI) alter the final perception of the image and they should be defined according to the goal of the study. The types of illumination most commonly used are fluorescent lamps (65 %), incandescent lamps (10 %), natural light (19 %) and LEDs (2 %). Clearly the natural light would be the best option, although it presents a large variation in its characteristics, depending on the inclination of the sun, on the hour of the day, on weather conditions. Incandescent lamps present a high value of IRC, though they show high energy consumption and their use should be avoided. Fluorescent lamps have been replacing incandescent ones; however, their characteristics vary in terms of composition (amount or kind of phosphorus) and they present mercury in their composition. Nonetheless, their use has risen significantly, mainly with the use of compact lamps, due to their low energy consumption level and reasonable lifespan.

Another important parameter to be considered in image acquisition is the background color, which directly influences color analysis. In the studies presented, different background colors have been tested, with the black and the white background colors being the most commonly used, which, according to the authors, facilitate the stage of segmentation. Blasco et al. [33] presented a study with different background colors for the selection of pomegranate seeds, concluding that the blue background contributes toward better segmentation. In this way, the characteristics that are to be analyzed must be examined in order to define the parameters to be used in image acquisition, so as to obtain the best image possible.

Pre-processing

Pre-processing is an important stage of computational vision, as it aims at improving the acquired image as a means to facilitate the stage of segmentation, by removing distortions and noise without adding further information to the content of the image. Pre-processing involves techniques to highlight contrasts, remove noise and isolate regions of interest, and may be conducted manually or automatically, depending on each system.

Histogram alteration is one of the most frequently used tools in this stage, since the histogram allows a graphic visualization of the distribution of hues of the image pixels, making it possible to observe and change characteristics of contrast and levels of illumination of the image.

It should be highlighted that the choice beforehand of a region of interest, in the stage of pre-processing, may simplify or even eliminate the stage of segmentation. In general, this technique is performed manually by an operator, which may bring disadvantages to the system as it increases the possibility of errors during selection. In some cases, the manually performed selection of a region of interest does not translate into errors, such as when used in the selection of fruits, where one manually isolates the fruit where it stands. However, when this technique is used in decision making about which region of the fruit corresponds to the defect, manual selection may result in errors, since it depends on the perception and judgment of the operator. Automatic computational methods should be therefore preferred, as they aim at particularly reducing these kinds of error (of the operator), thus consequently improving reproducibility and repeatability [69] of the inspection process.

Segmentation, feature extraction and comparison with standards

After image acquisition, three further stages are required in computational vision, which are segmentation, feature extraction and comparison with standards. These stages belong to the field of processing and computer science and diverse techniques may be employed, according to the goals of the study.

One of the goals of segmentation is to separate the object of interest from other objects in the image, using techniques such as binarization, treshholding, etc., and the better the quality of the image obtained, the better the performance in this stage.

After segmentation, the image is ready for the extraction of the relevant features, such as shape, dimensions, number of objects, color, etc. The kinds of features to be extracted are usually grouped in four categories: morphological, chromatic, textural e structural.

Table 1 lists the main characteristics extracted by systems of visual inspection utilized in precision farming and in the food industry from the items analyzed.

Among the studies examined, the RGB is the color system most commonly used in feature extraction, due to the fact that they are, most of the times, the components of the images acquired by most image acquisition systems. Often, from the RGB system a conversion is carried out to other color systems, such as the laboratory system and HSI (around 30 %), since these systems present characteristics closer to human perception of color. However, around 41 % of studies only use the RGB system for feature extraction.

Several authors use more than one kind of characteristic in order to conduct the classification of their product. The use of morphological and chromatic features together (33 %) is the most employed combination. It is worth of mention that the use of texture analysis in computational vision systems (19 %) is still small in comparison with morphological and chromatic features. The use of this feature may contribute toward object identification, especially in the food area, whose objects of analysis present varying characteristics in terms of their appearance.

Conclusions

Despite the numerous studies developed in this area, there is still no standardized method which could be proposed for the assessment of the quality of different types of food. The great diversity of products and their characteristics often impose that the inspection system be customized, resulting in a higher investment than the simple purchase of an equipment, as well as the demand for specific knowledge of the system in order to perform adjustments which are adequate to the problem.

The difficulty and the complexity of the studies on the assessment of food using computational vision are due to the fact that it is hard to establish an optimal method of extraction of certain image characteristics. Besides, as discussed by Simões and Costa [70], the automation of processes based on digital images presents as main difficulties: "(1) the nonexistence of a formal description of patterns; (2) the nonexistence of computational tools and consolidated models for classification; (3) dependence on the conditions of illumination of the environment".

It is observed that several methodologies have been proposed with the goal of characterizing distinct types of food through computational vision, aiming at optimizing the process of inspection and minimizing losses. Each of the technological options presented shows a particular behavior in terms of its results. However, there is an increasing need to improve these methodologies in order to meet the large demand observed currently, and to contemplate the requirements and restrictions of the existing

Table 1 Main characteristics extracted by systems of visual inspection in precision farming and in the food industry

Characteristic	Category of the product	Product	References
Morphological	Vegetable and vegetation	Plantation	Søgaard et al. [6], Tellaeche et al. [5, 8]
		Potato	Noordam et al. [12], Cabrera et al. [13]
	Grain	Seeds	Dana and Ivo [25]
		Wheat and cereals	Visen et al. [16], Paliwal et al. [17–20], Tahir et al. [21], Choudhary et al. [22]
	Fruit	Olive	Riquelme et al. [30]
		Citrus fruits	Blasco et al. [39, 44], Gómez et al. [40], Gómez-Sanchis et al. [41]
		Apple	Stajnko and Emelik [42], Stajnko et al. [43], Kleynen et al. [51], Throop et al. [52], Bennedsen et al. [50], Unay and Gosselin [49], Zou et al. [45]
		Mango	Yimyam et al. [31]
		Strawberry	Liming and Yanchao [34]
		Tamarind	Jarimopas and Jaisin [35]
		Pomegranate	Blasco et al. [32, 33]
		Tomato	Jahns et al. [27], Louro et al. [36], Lino et al. [37]
		Vegetables and fruits	Rocha et al. [55, 56]
	Meat and fish	Fish—salmon	Misimi et al. [62]
		Ham	Valous et al. [59]
	Industrialized product	Ready meal	Munkevik et al. [68]

Table 1 continued

Characteristic	Category of the product	Product	References
Chromatic	Meat and fish	Beef	Jackman et al. [58]
		Fish	Louka et al. [61]
		Pork	O'Sullivan et al. [57]
		Ham	Valous et al. [60]
	Fruit	Olive	Riquelme et al. [30]
		Citrus fruits	Blasco et al. [44]
		Apple	Madieta [48]
		Mango	Kang et al. [54], Yimyam et al. [31]
		Strawberry	Liming and Yanchao [34]
		Pomegranate	Blasco et al. [33]
		Tomato	Jahns et al. [27], Louro et al. [36], Lino et al. [37]
	Grain	Cereal	Choudhary et al. [22]
		Seeds	Dana and Ivo [25], Effendi et al. [26]
		Wheat	Manickavasagan [23, 24]
	Ready meal	Ready meal	Munkevik et al. [68]
	Industrialized product	Potato chips	Pedreschi et al. [63]
		Bread	Jusoh et al. [64]
		Pizza	Du and Sun [67]
		Wine	Martin et al. [66]
	Vegetation	Beetroot plantation	Bakker et al. [7]
		Barley plantation	Burgos-Artizzu et al. [9, 10], Tellaeche et al. [5, 52]
		Orange plantation	Cavani et al. [11]
		Plantations	Søgaard and Olsen [6]
	Vegetable	Potato	Barnes et al. [14], Cabrera et al. [13], Noordam et al. [12]
		Vegetables and fruits	Rocha et al. [56]

Table 1 continued

Characteristic	Category of the product	Product	References
Textural	Meat and fish	Beef	Jackman et al. [58]
		Fish	Louka et al. [61]
		Pork	O'Sullivan et al. [57]
		Ham	Valous et al. [60]
	Fruit	Olive	Riquelme et al. [30]
		Citrus fruits	Blasco et al. [44]
		Apple	Madieta [48]
		Mango	Kang et al. [54], Yimyam et al. [31]
		Strawberry	Liming and Yanchao [34]
		Pomegranate	Blasco et al. [33]
		Tomato	Jahns et al. [27], Louro et al. [36], Lino et al. [37]
	Grain	Cereal	Choudhary et al. [22]
		Seeds	Dana and Ivo [25], Effendi et al. [26]
		Wheat	Manickavasagan [23, 24]
	Ready meal	Ready meal	Munkevik et al. [68]
	Industrialized product	Potato chips	Pedreschi et al. [63]
		Bread	Jusoh et al. [64]
		Pizza	Du and Sun [67]
		Wine	Martin et al. [66]
	Vegetation	Beetroot plantation	Bakker et al. [7]
		Barley plantation	Burgos-Artizzu et al. [9, 10], Tellaeche et al. [5, 8]
		Orange plantation	Cavani et al. [11]
		Plantations	Søgaard and Olsen [6]
	Vegetable	Potato	Barnes et al. [14], Cabrera et al. [13], Noordam et al. [12]
		Vegetables and fruits	Rocha et al. [56]
Structural	Fruit	Apple	Stajnko et al. [42]
	Ready meal	Ready meal	Munkevik et al. [68]
	Industrialized product	Cheese	Jelinski and Jaisin [65]

procedures given the specificity of each product, with the further goal of standardizing these new technologies.

A great increase in the use of computational vision systems in the food industry has been observed. However, the industry has been generally employing closed systems, with no concern for the reproducibility and repeatability of the results obtained. On the most part, the systems are not validated, thus not offering guarantee of the quality of the results. It is known that, in some applications, the margin of error acceptable is large, and as a consequence, the lack of validation of the results does not have a significant impact on the final result. However, it should be highlighted that a validated system of measurement (or inspection) means: control of the variables, definition of standards, identification of errors, possibility of comparison, provision of traceability, etc. Due to the great variation of their aspects, (of color, texture, shape, etc.), it becomes difficult to establish standards for the element itself, but it is possible to standardize the conditions of measurements, such as standardization of the type of illuminant, of the equipment for capturing, of background, of the reference standards (length, color, roughness), etc.

Several techniques of computational vision have been studied, considering the wide scope of activities related to the food segment, from the cultivation on the fields to the manufactured food products, encompassing the use of several aspects of vision through the computer in a wide variety of conditions for the acquisition of data and processing. Besides, the main problems related to the techniques of computational vision have been clearly identified, demonstrating that there is still much work to the done, in order to obtain more reliable results.

In this light, this bibliographic review aims to summarize the methods already employed and their specific applications with a view to encouraging new research to be developed.

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