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Trends In Automatic Quality Inspection And Grading Of Food And Agricultural Products By Machine Vision –A Review

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Abstract: This paper describes the fast growing aspects of computer vision in automatic inspection of food and agricultural product. Quality inspection of food and agricultural product is very time consuming, labor intensive and costly. Besides all these, safety standards are very important which requires high accuracy. Manual inspection is not that much fast and reliable. A vision based control strategy is always required to fulfill the increased expectation of high quality and safety standard. Machine vision is based on image analysis and results in highly automated, non-destructive and economical inspection. This paper basically highlights that how in short span of time machine vision has find wider application in food industry. Recent works going on inspection and grading of fruit, vegetables, packed product like bakery, pizza, aquatic material has been reported.

Keywords: Machine vision, image analysis, food and agricultural product, quality inspection, grading.

I. INTRODUCTION

By giving a vision to computer, its application has extended in various fields where significant information is extracted automatically from images and it has also provided necessary theory and example for a practitioner in field of multimedia, art and design, geographic information system, image database, medical imaging, remote sensing, computer cartography, autonomous vehicles and robot sensing [1].

With advancement of methodologies in machine vision human endeavor is replaced by automatically perceived image which are obtained by combination of physical image sensor, dedicated hardware and software instruments [2]. The principle energy source for image is electromagnetic energy spectrum. In EM spectrum X-ray imaging and images in visual band of spectrum are quite famous. For ex Jamison found that detection of bones in fish and chicken can be done with the help of X-ray imaging with accuracy of 99% [3]. Major area of visual processing is remote sensing, which usually includes several bands in the visual and infrared regions of spectrum is represented in table1. Several bands with its characteristics and uses are shown in this table. This table is also called thematic bands in NASA’s LANDSAT satellite [4]. Computer vision system consists of five basic elements camera, optics, illumination, and Image acquisition hardware and machine vision software. Mostly solid state cameras are used in machine vision applications.

Type of solid state camera used are 1. CCD (camera coupled device), 2. CID (charge injected device) and 3. CPD (charge priming device). CCD, CID, CPD are compared in Galbiati[5]. Fuqiang Zhou, Yi Cui, Bin Peng, Yexin Wang developed an optimization method of camera parameter in 3D coordinate [6].Illumination : Illumination technique consideration include whether the object is dull or reflective, flat or complex in shape, if through holes are to be deflected or to find if there is surface defect. Five categories of lighting can be distinguished for machine vision 1.front lighting, 2.Back Lighting, 3. Side lighting, 4.Structured lighting, 5.Strobe lighting. They are classified on the basis of position of light source relative to the camera. Lighting technologies include incandescent lamps, sodium vapor lamp and lasers the paper reviews the existing trend in machine vision for automatic inspection of food products.

This attempt not only reduces the total cost but also increase the quality assessment of fruit product. Vision based sorting system consists of different subsystem. These components has been shown in fig 1.for increasing the speed of sorting scaled image is used .The small sized image is processed faster than main image. Accuracy is not affected by this size reduction. However some noise can be detected in background but that can be discarded easily [7].

Machine vision stages are image acquisition, image processing, image enhancement, image restoration, image segmentation, image analysis, model matching. Components and stages of machine vision are shown in fig 2.

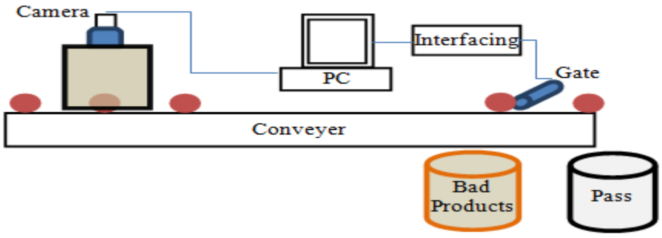

Figure-1: sorting system [7]

Table -1: thermal band in NASA’S LANDSAT satellite [4]

band no.	name	Wavelength (micron)	Characteristics and uses
1	Visible blue	0.42-0.52	Maximum water penetration
2	Visible green	0.52-0.60	Good for measuring plant vigor
3	Visible red	0.63-0.69	Vegetation discrimination
4	Near infrared	0.76-0.90	Biomass and shoreline mapping

5	Middle infrared	1.55-1.75	Moisture content of soil and vegetation
6	Thermal infrared	10.4-12.5	Soil moisture; thermal mapping
7	Middle infrared	2.08-2.35	Mineral mapping

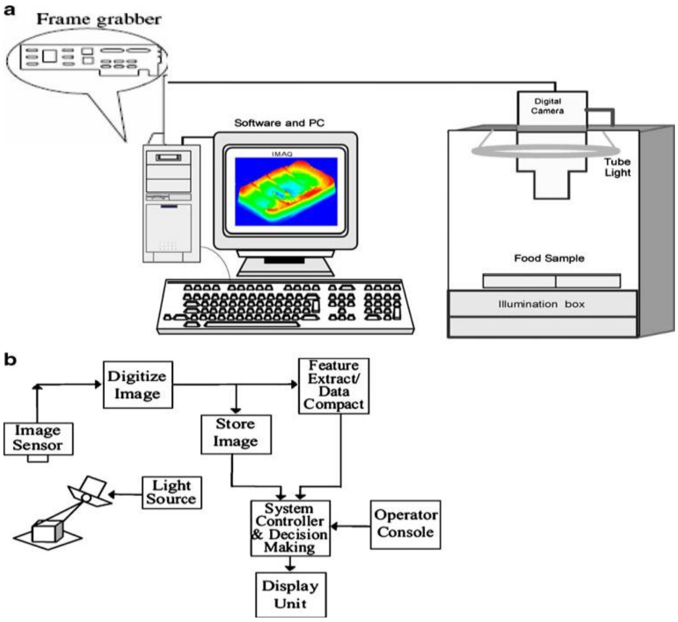

Figure-2: a) principal components of machine vision. b).block diagram of machine vision [32].

Computer vision systems are being used increasingly in food and agricultural industries for grading and quality assessment. Some of the food industries, were its applications has increased in just few decades have been discussed in following paragraph.

II.FRUIT AND VEGETABLE

For providing consistency in product quality and to handle large varieties of vegetables and fruits automation via computer vision is required. The united states of department of agriculture (USDA) has classified five grades of potatoes. The attributes for deciding these grades are size, shape, external defect. The system correctly classified 80%, 77% and 88% of moving potatoes in three runs at 3 potatoes per minute and 98%, 97%, 97% in three run of stationary potatoes [8]. In 2012 computer vision system was developed for detection of irregular potatoes in real time, with the help of four shape descriptor and two shape feature, roundness and extent. Experiment showed that it is very fast and accurate method where inline classification of moving potato was 96.2% [9]. Fruits and vegetables are presented in batches to consumer. From consumer point of view its presentation and quality are two important factors.

The project ESPRIT3, “SHIVA”: is an integrated system for handling, inspection and packing of fruit and vegetables, in which robotic system was developed for doing these tasks, and efficiently measured qualities such as color, size, stem location and detection of external blemish. [10]. With the help of multispectral machine vision bi-colored apples can be graded in fully automatic way. Grading can be done by either of two ways one is two category methods while other one is multi-categories method. Two category grading improved the accuracy compared to state of art while varieties of architectural approaches are proposed by multi-category. It was observed that if computational resources are limited single classifier architecture should be given priority. Cascaded classifiers are very précised with better recognition rates [11]. Yousef al Ohali in 2011 successfully implemented date grading and sorting system. Fruit placer at the beginning placed dates on conveyor belt, which were driven by motor. From there they were carried to imaging chamber and finally placed at image processing and classification unit. These dates are graded in three categories manually by visual inspection based on external features. After that dates are classified by two BPNN model (back propagation neural network).

In preprocessing module from date image binary image is obtained, than from that binary image edges are extracted by applying sobel edge operator. The corresponding date image, its binarised image and extracted edges are shown in figure 3. Several mathematical relations have been derived for checking these external features [12].Indonesia oil palm research institute (IOPRI) has developed automatic grading machine for oil palm fresh fruit bunch (FFB) based on machine vision principles. From 7 to 20 years of tenera varieties fruit bunches were used as samples. These machines successfully performed on more than 12 tons FFBs grading per hour which is not at all possible with manual grading. Success rate for background removal was obtained 100% using adaptive threshold algorithm and also the region of interest lied in intensity within digital number (DN) value from 100 to 200. Two classification methodologies were developed. They were Group class and fractional class. Group classification of FFBs resulted average success rate of 93.53% while fraction classification showed 88.7% of success rate using Euclidean distance analysis [13].

Current commercialization sorting based on machine vision can solve many problems and require less computing time. Sometime in order to achieve high speed they work with low resolution image. This approach is good for sorting based on sizing or classification of color. This approach reduces accuracy when system estimates the size of fruit and defect on skin surface. With the help of multispectral camera those wavelengths which are outside the visible spectrum can be used to determine skin defect. Thus both visible as well as infrared image can be achieved from same scene. Here to save the processing time whole inspection is divided in different processor with the help of specific algorithm and two DSPs working in parallel. With the minimum rate of 5 fruits per second, size, color and presence of defect in citrus can be estimated with this model. Lemon and Mandarine can also be correctly classified having external defects with appreciable percentage of 93% and 94% respectively. With proper hardware improvement inspection rate can be increased from 5% to 10% [14]. One of the major reasons for decreased commercialization of pomegranate is the problem associated in its peeling. However this problem can be sorted out by marketing arils of pomegranate in ready to eat form. This paper suggests that very tough task of removing defective arils and internal membrane from good arils can be made simpler with the application of computer vision.

Figure-3: Figure shows an original date image, its binarised image and edges which surrounds this binarised image. [12]

Average success rate of 90% was achieved with both methods. First one is however more instinctive, faster and easy to apply. Thus whole setup can successfully classify arils in four groups and can automatically sort more than nine tons of arils [15].In 2015 problems of uneven lightness distribution on surface of apples has been solved to some extent. Novel automatic defective apple detection method by using computer vision system was presented, which combined automatic lightness correction, number of the defect candidate (including true defect, stem and calyx) region counting, and weighted relevance vector machine (RVM) classifier. Automatic lightness correction was used to solve the problem of the uneven lightness distribution, especially in the edge area of the apples [42].

III. AQUATIC FOODS

Machine vision can help in finding several characteristics of aquatic food like its shape size color, moisture content; freshness etc [16]. One of the important parameter is freshness of fish, which can be calculated using techniques of machine vision. Here a digital color imaging system was applied to provide accurate CIELAB color measurement of eyes and gills. Thus the total color change of eyes and gills has been calculated as, lightness [L*], redness[a*], yellowness[b*], chroma[c*] and total color difference[E] . It was observed that in case of fish eyes, color parameter L*, b*, E increases with storage time while c*, decreases. However a* didn’t show any clear trend with storage time. In case of fish gills L*, b*, E increases while a* and c* decreases. Through Matlab program, particular area of interest for color determination can be selected.

Regression analysis and artificial neural network showed that there is strong correlation between color parameter and storage day. However results showed that color parameter of fish eyes for fast and online freshness assessment is comparatively cheap and simple[17]. Hong-ju, Di wu, and Da-wen Sun in year 2012 developed a strategy for determining spatial distribution of moisture content in salmon fillets using hyper spectral imaging technique. Here salmon fillets were graded according to their moisture content and thus accordingly three spectral ranges were defined. PLSR (partial least square regression) was used to develop a relation between moisture content and spectral data obtained [18]. For any salmon product PH and drip loss are two great significant characteristics. Rapid and nondestructive determination of drip loss and PH distribution was carried out using VIS-NIR hyper spectral imaging technique by same publishers Hong-ji, Di wu and Da-wen in 2014 [19]. Hyper spectral imaging techniques divides object into bands that can be extended beyond the visible range. PH and drip loss was calculated using near infrared hyper spectral imaging. After obtaining hyper spectral imaging for salmon fillet samples, their spectral signature in 400-1700 nm range were extracted. Here with the help of PLSR calibration reference drip loss and PH values were matched up with calculated spectra. After that using regression coefficient method important wavelength were selected to decrease redundancy of hyper spectral

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IV. BAKERY PRODUCTS

An automatic and intelligent system has been developed by S.Nashal, A.Abdullah, S. Armvith, M.Z Abdullan [2011] for classification of biscuit products according to their color. Here biscuits were classified in 4 groups basically under baked, moderately baked, over baked, considerably over baked based on two analysis support vector machine (SVM) and wilk’s λ analysis .Results showed that radial basis SVM followed by wilk’s λ gave more précised and accurate results compared to other. They found that compared to non touching biscuit touching biscuit are substantially slower for image processing. Average rate taken by image processing for touching and non touching biscuit were 36.3ms and 9.0ms respectively. Also classification rate for stationary biscuits as well moving biscuit at 9m/min was found correct in more than 96% cases[20]. Chemical and physical properties of bakery product such as lipid oxidation, loss of weight, water activity, dry matter and moisture were monitored for 12 weeks by testing PPTH (polypropylene) and lacquered acrylic on muffins. In these 12 weeks of storage sensory profile method and image analysis measurement were performed regularly. Sensory changes were investigated by panel of 12 judges these changes declined at 3rd evaluation and it was observed that the shelf lives of both muffins packed in films were same [21]. With the help of support vector machine (SVM) and color vision the automatic classification of pizza sauce spread was achieved and resulted in classification accuracy of 96.67%

with polynomial SVM classifier. A sequence of image processing algorithm was developed to obtain HSV (hue, saturation and value) color space from RGB color space. Then this HSV space was quantified to 256 dimensions with the help of vector quantifier. Then quantified color feature was represented by histogram. 256 dimension vector was reduced to 30 dimension vector by PCA (principal component analysis) [22]. Among SVM classifier (polynomial, linear and RBF) approach, polynomial SVM classifier combined with HSV color space transformation proved to be a good approach for the classification of pizza topping using computer vision [23]. In other experiment it has been shown that linear SVM classifier, polynomial SVM classifier and Gaussian radial basis function SVM in case of pizza base gave classification accuracy of 86.7%, 95.0% and 98.3% respectively [24].

V. GRAINS

Algorithm based on computer vision techniques, novelty detection and principal component analysis(PCA) is combined to work in line and identify damaged kernels of corn. 450 dent corn which were previously classified by expert were taken and experiment was carried out on them in three color spaces. Visual difference between good and bad kernel is very minor and thus very difficult to analyze. This method automatically detects if corn is defective or not. It gave 92% successful result [25]. Grain qualities (such as physical attributes, safety, composition factor) evaluation is very important for any nation, accordingly some changes can be brought in agricultural methodology. For bringing automation in these evaluation techniques several computer vision technologies such as color imaging, hyper spectral imaging, x-ray imaging, and thermal imaging have been employed and found that they are giving best results[26].

Orthogonal length and width of singled particle can be obtained from its digital image with help of machine vision plug-in developed in java; this plug-in method was validated using digital calipers used for actual dimension measurement. Pixel-march method utilized image fitted ellipse centroid coordinate and major axis inclination for determining particle boundaries. This method was applied to 8 food grains and gave overall accuracy greater than 96.6% with speed of 254+_125 particles/sec [27]. Grains having slight color differences or small defects can be detected by a device that combines CMOS color image sensor with a FPGA. This device doesn't need external computer for image processing in real time. The throughput rate was also very high compared to other image inspection system, which was 75 kernels/per channel. Inspection rate was approximately 8kg/hr for wheat and 40kg/hr for popcorn.

System showed 74% accuracy in removing blue eyed damage from good popcorn and 91.5% accuracy at recognizing good popcorns [28]. In 2012 a technique was invented for automatic detection of various contaminants such as rodent dropping, a poisonous mold called ergot and larger insect of cereal grain, in which morphological filters were used along with large median based filters. Small insects were modeled as small linear features and determined by isotropic laplacian type operator. Dark contaminants were determined by thresholding operation [29]. Fast and reliable identification and classification of seeds on basis of seed size, shape, color and texture is very important.

Naïve bayes classifier identified optimal set of 12 seed characteristics which were 6 morphological, 4 color and two textures based. Bayesian approach is very beneficial when applied. Classification based on artificial neural network is only slightly better than this simple Bayesian approach and also it uniquely identified seeds of 57 weed species [30]. In other research work barley kernels were analyzed for its quality assessment and classification with help of its digital image. The algorithm identified wrinkled and smooth region of individual kernel with mean accuracy of 99%[31]. Another technique of stereovision can help in measuring thickness and crease detection of wheat grain. Stereovision extracts 3D information from its digital image [32].

VI. CONCLUSION

This paper reviews the existing trends and application of machine vision for automated quality inspection and grading of food and agricultural product. By reviewing papers especially from 2010 onwards it can be concluded that computer vision has all the capability to become a vital component of automated food processing. Now we will end the discussion with the advantage and disadvantage of machine vision as described by Bronson and sun in year 2004 in table 2.

Table -2: Benefits and drawbacks of machine vision [Bronson and Sun][16].

Advantages	References
Generation of precise and descriptive data	Saperstein(1995)
Quick and objective	Li, Tan, and Martz(1997)
Reducing tedious human involvement consistent, efficient and cost effective	Lu, Tan, Shatadal, Gerrard (2000)
Automating many labour intensive process	Gunasekaran (2001)
Easy and quick, consistent	Gerrard, Gao, and Tan (1996),
Robust and competitively priced sensing technique	Gunasekaran and Ding (1993)
Permanent record, allowing further analysis later	Tarbell and Reid (1991)
DISADVATAGES	
Object identification being considerably more difficult in unstructured scene.	Shearer and Holmes(1990)
Artificial lighting needed for dim or dark conditions	Stone and Kranzler (1992)

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