Potato Sorting Based on Size and Color in Machine Vision System

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Abstract

Potato (Solanum tuberosum) is cultivated as a major food resource in some countries that have moderate climate. Manual sorting is labor intensive. Furthermore in mechanical sorting the crop damages is high, for this reason we must operate a system in which the crop damages would be diminished. For sorting of potatoes fast, accurate and less labor intensive modern techniques such as Machine vision is created. Machine vision system is one of the modern sorting techniques. The basis of this method is imaging of samples, analysis of the images, comparing them with a standard and finally decision making in acceptance or rejection of samples. In this research 110 numbers of potatoes from Agria variety were prepared. Samples were pre-graded based on quantitative, qualitative and total factors manually before sorting. Quantitative, qualitative and total sorting in Machine vision system was performed by improving images quality and extracting the best thresholds. The accuracy of total sorting was %96.823.

Keywords: Area, Color, Potato, Qualitative threshold, Quantitative threshold, Size, Sorting

1. Introduction

The potato (Solanum tuberosum) is an herbaceous annual that grows up to 100 cm (40 inches) tall and produces a tuber - also called potato - so rich in starch that it ranks as the world's fourth most important food crop, after maize, wheat and rice. The potato belongs to the Solanaceae - or "nightshade"- family of flowering plants, and shares the genus Solanum with at least 1,000 other species, including tomato and eggplant. S. tuberosum is divided into two, only slightly different, subspecies: indigene, which is adapted to short day conditions and is mainly grown in the Andes, and tuberosum, the potato now cultivated around the world, which is believed to be descended from a small introduction to Europe of andigena potatoes that later adapted to longer day lengths(FAO, 2008).

Potato consumption in any form as seed, using for human food, feeding animals or processing operations as chips, conserve operation and so on are dependent to special conditions which must prepare before those operations. The objective of sorting is preparation of these conditions.

By sorting we can grade crops based on size, shape, color, ripeness, damaging etcetera. The sorting operation by hand is time-consuming and its efficiency is low and sometimes its cost is high (Where the worker's wage is high). Mechanical grading can increase the sorting efficiency and the need for workers is decreased.

Technological advancement is gradually finding its applications in the field of agricultural and food, in response to one of the greatest challenges i.e. meeting the need of the growing population. Efforts are being geared up towards the replacement of human operator with automated systems, as human operations are inconsistent and less efficient. Automation means every action that is needed to control a process at optimum efficiency as

controlled by a system that operates using instructions that have been programmed into it or response to some activities. Automated systems in most cases are faster and more precise (Narendra and Hareesh, 2010).

By using machine vision systems and image processing techniques we can grade the crops by high precision and speed and diminish crop damages. Computer vision has been recognized as a potential technique for the guidance or control of agricultural and food processes. Therefore, over the past 25 years, extensive studies have been carried out, thus generating many publications (Narendra and Hareesh, 2010).

In this research we operated the image processing techniques and finally the program is tested.

Machine vision has been applied for sorting of a wide range of agricultural products. Some of theses researches are mentioned bellow:

Von Beckmann and Bulley in 1978 developed an electronic sorter for color and size grading of tomatoes. They used the ratio of surface reflectance in wavelength of 600 and 660 nm to sort tomatoes in 4 grades (Von Beckmann and Bulley, 1978).

Miller and Delwiche in 1989, developed a color vision system for detection and sorting of ripe peaches. For peach sorting their color was compared to color of standard ripe peach (Miller and Delwiche, 1989).

A prototype inspection station based on the United States Department of Agriculture (USDA) inspection standards was developed for potato grading. The station consisted of an imaging chamber, conveyor, camera, sorting unit, and personal computer for image acquisition, analysis, and equipment control. A sample of 9.1kg (201b) of pregraded potatoes was evaluated in three separate experimental runs to assess the system performance. The system correctly classified 80%, 77%, and 88% of the moving potatoes in the three runs at 3 potatoes/min, and 98%, 97%, and 97%, in three runs of stationary potatoes. Shape analysis was adversely affected by the potato motion, and this contributed to the misclassification error (Heinemann et al., 1996).

Laykin in 2002, used three methods for sorting of tomatoes. These methods were: Mean-Standard deviation, Slide Blocks and Quad tree (Laykin et al., 2002).

Deck in 1995 compared the color segmentation results of a Multilayer Feed Forward Neural Network (MLF-NN) and a traditional classifier for the color inspection of potatoes (Deck et al., 1995).

Tao et al., in 1995 represented a method for sorting of green and good potatoes. They used HSI color system. Samples of potatoes were sorted by experts and farmers. They used 40 numbers of green and good potatoes in training phase and 20 numbers for each grade in test phase. In training phase all 40 good potatoes and 38 numbers of 40 green potatoes and in test phase all 20 good potatoes and 18 of 20 numbers of green potatoes were sorted correctly. The results of human and machine detection were close (Tao et al., 1995).

A high speed machine vision system for the quality inspection and grading of potatoes has been presented by Noordam et al. in 1995. The vision system graded potatoes on size, shape and external defects. For color grading of potatoes they used Linear Discriminate Analysis (LDA) and MLF-NN techniques. Results of LDA and MLF-NN sorting techniques implementing for different variety of potatoes were respectively 86.8%- 98.6% and 88.1% - 99.2% (Noordam et al., 1995).

Zhou et al. (1998) evaluated weight, cross-sectional diameter, shape, and color of three cultivars of potato using a computer vision system which was able to classify 50 potato images per second. An ellipse was used as the shape descriptor for potato shape inspection and color thresholding was performed in the hue-saturation-value (HSV) color space to detect green color defects. The average success rate was 91.2% for weight inspection and 88.7% for diameter inspection. The shape and color inspection algorithms achieved 85.5% and 78.0% success rates, respectively. The overall success rate, combining all of the above criteria, was 86.5%.

Rios-Cabrera et al. (2008) determined potato quality evaluating physical properties using Artificial Neural Networks (ANN's) to find misshapen potatoes. The results showed that FuzzyARTMAP outperformed the other models due to its stability and convergence speed with times as low as 1 ms per pattern which demonstrates its suitability for real-time inspection. Several algorithms to determine potato defects such as greening, scab, cracks were proposed.

Barnes, et al. (2009) introduced novel methods for detecting blemishes in potatoes using machine vision. The results show that the method is able to build "minimalist" classifiers that optimize detection performance at low computational cost. In experiments, minimalist blemish detectors were trained for both white and red potato varieties, achieving 89.6% and 89.5% accuracy respectively.

2. Materials and Methods

2.1 Sorting Mechanism

The sorting mechanism was consisted of:

1) Lighting chamber

2) Lighting source

- 3) CCD camera
- 4) Personal computer

The lighting source selection is a key factor in image processing operation. In designing the lighting chamber the outer light must be eliminated. In this research we used four florescent lamps by lateral positions in chamber and camera lens was entire to lighting chamber by a hole which was only entrance to outer which was covered by camera lens. Potatoes were placed under camera lens in the center of lighting chamber. A camera which was selected for image capturing was CCD camera. The software of this system was MATLAB (R2008a).

2.2 Quantitative Sorting Procedure

2.2.1 Transformation of RGB to Gray Scale Image

When a RGB is transformed to gray scale image, the image size is decreased and the image processing is accelerated.

2.2.2 Calculation of Threshold

Threshold extraction is the best way for image segmentation. If the image is consisted of a light object in a dark background, the grayscale pixels are placed in two modes.

2.2.3 Image Noise Elimination

In this research for elimination of some noises and reaching the best boundary, we used 25 by 25 Gaussian Low-pass Filter by standard deviation of 15. The way which we selected was the Replicating method. In this method size was developed by replication of values in outer boundary.

2.2.4 Extraction of Boundary

Boundary extraction is a major technique in image pre-processing and is used in the most algorithms. Boundary detection is the basic process for extraction of image information. We must select one method which its sensitivity to image noises is the least and can extract continuous boundary in a simple and fast way. We used Sobel estimate which its sensitivity to horizontal and vertical boundaries is higher than others. Sobel extracts boundary by non-linear calculation and it isn't dependant to point value.

2.2.5 Calculation of Area

By labeling the extracted boundary we can calculate quantitative parameters such as max diameter, min diameter, equivalent diameter, area, and perimeter and so on. We can use all these parameters to grade potatoes based on size. In this research we employed the area. The area was calculated by counting the number of pixels in the labeled region.

2.3 Qualitative Sorting Procedure

2.3.1 Evaluation the Combination of Intensity Transformation Functions and Color Spaces

The various combinations of intensity transformation functions and color spaces were implemented on images and by detection the pixels that belong to health class and numbering them, by dividing them to the total number of pixels the percentage of health class was calculated. By comparing the percentage with the percentage that specified by experts, the R^2 of them was calculated. The best combination which has the highest R^2 is 0.989 that belongs to the combination of HSV color space and logarithmic transformation (figure 1).

3. Results and Discussion

3.1 Threshold Extracting and Evaluating in Quantitative Sorting

For calculation of area threshold, we divided each grade to training and testing groups. In training group the numbers of Small, Medium and Large groups were respectively: 12, 20 and 23.

For extracting the proper threshold, the tubers were pre-graded by experts in classes of Small, Medium and Large sizes. Thereafter each class was divided to phases: Training and Testing. In Training phase the threshold was extracted according to table (1), relations (1), (2) and (3). For evaluating the accuracy of this threshold to

classify the samples based on size, it was operated on the samples of Test phase. This process is represented in table (2). As represented in this table the accuracy of this threshold on sorting test samples based on size was 100%.

$$\begin{cases} d_1 = \frac{(a_2 + b_1)}{2} \\ d_2 = \frac{(b_2 + c_1)}{2} \end{cases}$$
(1)

$$\begin{cases} Small < d_1 \\ d_1 \le Medium \le d_2 \\ d_2 < L \text{ arg } e \end{cases}$$
(2)

$$\begin{cases} Small < 995.577 \\ 995.577 \le Medium \le 1472.393 \\ L \ arge > 1472.393 \end{cases}$$
(3)

3.2 Threshold Extracting and Evaluating in Qualitative Sorting

110 numbers of potatoes were pre-graded by experts into 19 numbers of Grade1, 37 numbers of Grade 2, 33 numbers of Grade 3 and 21 numbers of Rejected groups. For extraction of appropriate threshold the samples were divided into two groups of Training and Testing. In Training phase the threshold was extracted by implementing the qualitative algorithm based on combination of logarithmic transformation with coefficient of 0.5 and HSV color space. The extracted threshold was implemented on the testing phase to identify accuracy of qualitative sorting. The process of threshold extraction is represented in table (3) and relations (4), (5) and (6). The evaluating of the extracted threshold is represented in table (4).

$$\begin{cases} e_{1} = \frac{(a_{1} + b_{2})}{2} \\ e_{2} = \frac{(b_{1} + c_{2})}{2} \\ e_{3} = \frac{(c_{1} + d_{2})}{2} \end{cases}$$
(4)
$$[e_{1} < Grade]$$

$$e_{1} < Grade 1$$

$$e_{2} < Grade 2 \le e_{1}$$

$$e_{3} < Grade 3 \le e_{2}$$

$$e_{3} \le \text{Re jected}$$
(5)

$$\begin{cases} Grade1 > 95.515 \\ 86.2 < Grade 2 \le 95.515 \\ 60.4 < Grade 3 \le 86.2 \\ \text{Re jected} \le 60.4 \end{cases}$$
(6)

3.3 Threshold Extracting for Total Sorting

For total sorting, at first the threshold was extracted. This threshold was based on the considerable sorting factors in quantitative and qualitative sorting. For example the factors of small size and rejected qualitative were combined to create the total sorting threshold in Rejected group and so on. These factors are represented in table (5).

3.4 Total Sorting

For total sorting the samples were pre-graded by experts then the total sorting threshold was implemented by applying the total sorting algorithm. The result of total sorting was based on the comparison between pre-graded and algorithm graded samples. The result is shown in table (6).

4. Conclusions

For total sorting of potato (Agria variety), the quantitative and qualitative sorting was performed. At first step, in the quantitative sorting experts pre-graded the samples and those were divided into two groups of training and testing phases. In the training phase the threshold was extracted based on applying area calculation algorithm. For evaluating the quantitative algorithm, it was evaluating in the domain of testing phase.

For extraction of qualitative threshold, experts pre-graded potatoes based on health percentage. The pre-graded samples were divided into two groups of training and testing phases. The threshold was extracted in training and evaluated in testing phases. Accuracy of threshold evaluating in quantitative sorting based on Area in all three groups of Small, Medium and Large was 100%. The accuracy of qualitative threshold evaluation in groups of Rejected, Grade3, Grade2 and Grade1 was respectively: 100%, 96.97%, 89.19% and 100%.

For total sorting the quantitative and qualitative thresholds were combined. Potatoes were pre-sorted by experts based on both quantitative and qualitative factors. Then the accuracy of total sorting was obtained by comparison between pre-graded and Machine vision grading. The accuracy of total sorting was 96.823%.

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		1747 505212	
		c ₂	
		1634.317731	
	1310.468393	c ₁	
	b ₂	56.63879032	
	1144.331607	Standard deviation	
	b ₁	1690.956522	
	83.06839287	average	
	Standard deviation	1668	
	1227.4	1822	
	average	1651	
846.8224074	1214	1691	
a ₂	1208	1615	
720.1775926	1244	1700	
a ₁	1235	1662	
63.32240735	1239	1642	
Standard deviation	1260	1697	
783.5	1316	1769	
Average	1312	1744	
713	1172	1660	
754	1405	1677	
904	1124	1756	
912	1104	1769	
790	1350	1731	
769	1104	1662	
767	1157	1717	
728	1152	1607	
789	1271	1632	
791	1276	1613	
752	1143	1674	
733	1262	1733	
area(pixel)-small 733	area(pixel)-medium 1262	area(pixel)-larg	

Table 1. Threshold extraction of quantitative sorting (Training phase)

U			
area(pixel)-Small	area(pixel)-Medium	area(pixel)	
< 995.577	995.577 ≤ Medium ≤ 1472.393	Large> 1472.393	
751	1187	1821	
768	1131	1667	
898	1176	1906	
906	1171	1759	
902	1142	1757	
746	1133	1842	
880	1296	1884	
722	1139	1771	
846	1132	1728	
876	1151	1751	
858	1189	1672	
863	1404	1715	
Accuracy = $(12/12) * 100 = 100\%$	1315	1843	
	1261	1849	
	1162	1647	
	1170	1686	
	1138	1694	
	1177	1686	
	1206	1642	
	1188	1653	
	Accuracy = (20/20) *100= 100%	1637	
		1867	
		1769	
		Accuracy = (23/23) *100= 100%	

Table 2. Threshold testing of quantitative sorting (Testing phase)

(human view)-rejected (health percentage)	(human view)- Grade3	(human view)- Grade2	(human view)-Grade (health percentage)
	(health percentage)	(health percentage)	
25	80	90	99
10	80	95	99
20	80	90	99
20	70	90	98
10	65	90	99
25	82	90	97
5	75	90	96
60	70	90	97
60	75	92	96
5	85	90	99
5	70	95	99
5	70	95	98
5	85	90	96
5	78	90	98
50	80	90	99
60	75	95	99
45	85	90	96
45	80	87	99
50	69	95	99
50	65	90	
40	75	90	average
average	65	92	98
28.57142857	75	95	std
Standard deviation	75	90	1.247219129
21.45593491	85	95	a ₁
d_1	85	90	96.75278087
7.115493662	75	90	a ₂
d ₂	85	95	99.24721913
50.02736348	80	95	
	80	90	
	80	95	
	80	90	
	80	90	
	Average	95	
	76.93939394	95	
	Standard deviation	90	
	6.174237777	95	
	c ₁	average	
	70.76515616	91.78378378	
	c ₂	Standard deviation	
	83.11363172	2.495942654	
		b ₁	
		89.28784113	
		b ₂	
		94.27972644	

Table 3. Threshold extraction of qualitative sorting (Training phase)

(health percentage)-rejected	(health percentage)-	(health percentage)-	(health percentage)-	
(Number of Health pixels/	Grade3	Grade2	Grade1	
Total number of pixels)	(Number of Health	(Number of Health	(Number of Health	
	pixels/	pixels/	pixels/	
	Total number of pixels)	Total number of pixels)	Total number of pixels)	
20.1553	83.5431	87.1497	99.0986	
13.0995	86.1749	94.645	99.77	
18.211	80.6414	87.4319	96.9561	
25.1762	65.9125	87.3727	98.56	
11.5349	64.946	90.3589	99.9294	
23.0401	82.6749	93.334	98.3951	
6.551	74.1197	91.0322	98.6167	
58.8319	63.4823	93.6128	99.4219	
53.9572	75.3461	93.3604	98.0658	
4.8508	85.0422	89.7911	99.9364	
7.2305	70.8654	94.597	95.8273	
7.51	70.3478	89.2337	99.8734	
5.9045	85.1685	95.0175	99.3953	
6.2938	78.427	90.7863	96.4363	
50.2566	85.4629	93.3224	96.916	
59.5977	76.7409	97.788	97.4325	
43.284	86.8638	95.2524	98.2297	
44.2339	82.932	95.5812	97.2447	
41.9844	66.3643	94.0955	97.8712	
49.0085	63.1006	89.1813	Accuracy=	
			(19/19)*100=	
	- / 00-1		100%	
38.6844	74.9371	90.047		
Accuracy = (21/21) * 100 -	68.9122	95.6853		
(21/21)*100=				
100%	70.0004	02 2227		
	70.9904	95.5557		
	/2.80/0	90.8269		
	84.1387	94.1113		
	85.7621	95.5555		
	/ 5./0/5 0/ 5//C	92.7041		
	82,7207	94.2933		
	02./20/	91.0/9		
	80.4023 01.9617	91.1989		
	01.0017	92.7999		
	/ 0.403	91.4339		
	05.0554	02 8017		
	(32/33)*100=	72.071/		
	96 97%			
	70.7770	94 0328		
		01 8102		
		94 9083		
		$\Delta coursev=$		
		(33/37)*100=		
		89 19%		
		07.17/0	l	

Table 4. Threshold testing of qualitative sorting (Testing phase)

Table 5. Extracting of total sorting threshold

Quantitative Grade	Qualitative Grade	Total Grade
Medium	Grade 1	Grade 1
Medium	Grade 2	Grade 2
Large	Grade 1	
Medium	Grade 3	
Large	Grade 2	Grade 3
Large	Grade 3	
Small	Rejected	
Medium	Rejected	
Large	Rejected	Rejected
Small	Grade 1	
Small	Grade 2	
Small	Grade 3	

Table 6. Total sorting result

	Grade 1	Grade 2	Grade 3	Rejected	(%) Accuracy
Grade 1	12	0	0	0	100
Grade 2	1	21	0	0	95.454
Grade 3	0	4	45	0	91.837
Rejected	0	0	0	27	100
					96.823



Figure 1. The best combination of color spaces and intensity transformation functions