Automation of Chestnuts Selection Process using Computer Vision in Real Time

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***Abstract*—Nowadays, chestnuts selection process in Peru is done by hand, therefore some important problems occur. People who work in this area could make a lot of mistakes because their personal situation or environment variables influence them. Fatigue, feelings, light conditions or working comfort are examples. For this reason the production may become slow and/or imprecise and think about increasing production needs to hire more employees and spend more money. In that sense, it is proposed the automation of the chestnuts selection process for industrial scale, where real time computer vision techniques are applied in order to detect products defects, that are analyzed by some external characteristics: Oval shape to detect the chestnut product and the same descriptor with color and size descriptors to detect the chestnut defects and their types. In this way, this approach allows to improve and increase the quality of the chestnuts selection for its exportation, reducing errors in the process operations. Experimental results show that the performance achieved in each chestnuts selection is 86.78 %**

***Index Terms*—Chestnuts selection; Automation; Computer vision; Color Spaces.**

I. INTRODUCTION

Nowadays, an important economic activity of the forest of Perú [1], Bolivia and Brazil [2] is the production and commercialization of chestnuts and other types of dry fruits. However, before to the exportation process is necessary a set of selection operations, which commonly are done by hand. This selection process is based on the chestnuts grouping according to defect types that they could present.

So, the quality of exportation product is based on flawless products (are marketable products of first quality), *eyes* (the eyes are removed and are marketable products of second quality), *husk* (will be re-processed after removal of the husk), *chipped* or *cracked* (marketable products of third quality) and *rancid-stained* (will be discarded to the human consumption).

Actually, many researches have tried to automate the classification process, based on external damages and features such as color, size, shape or weight, all of them using computational vision and image analysis [2], [3], [4], [5]. For example, in Spain a study was presented by Lopez et. al. [6], showing the use of computer vision for classification of damage and defects in fruits. The result of this research works with human inspection.

In the same way, Castelo et al. [7] classified Brazil-Nuts according to size (Large, Medium, Small and Tiny) considering that there is a direct relation between the weight and size of a Brazil-nut. They used color spaces YCrCb for the segmentation and a dynamic threshold for the binarization, obtaining a yield of 99.7 %.

Similarly to previous studies, the main proposal described in this paper is the automation of the Chestnuts Selection Process for industrial scale, where the selection is according to the defect type (quality, *eyes*, husk, rancid/stained, chipped/cracked) in the chestnut, for its exportation.

The work is organized as follows: section II describes the proposed approach for automation of the chestnuts selection process by defect type. Section III shows experiments and results. Finally, in section IV conclusions of the work are presented.

II. DESCRIPTION OF WORK ENVIRONMENT (SELECTION MACHINE)

To achieve better understanding of the proposal, it is necessary to describe how images of chestnuts were obtained and in what context they were processed . Thus, a sorting machine was built and its part were:

- A personal computer with a real time configuration.
- A special visualization area to take chestnuts images in a set of production lines.
- A set of special rollers to rotate chestnuts.

The real-time computer was configured with a GNU - Linux distribution and the application of special techniques of processes affinity in the CPU cores. These settings are not described in this paper because it does not represent the main objective of the work performed.

[1]http://www.promamazonia.org.pe/
[2]http://www.ccbolgroup.com/brasilnuts.html

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The visualization area is composed of three cameras VIVOTEK - FD8161 [3], each of them captures two production lines. This area must have constant and uniform brightness in all the environment. To achieve this feature, the area was covered by a fully enclosed inox box to keep out any light beam that could damage the chestnut image.

The machine also has two rollers for each production line in order to rotate the chestnut while the camera take photos. These features are displayed in figure 1.

Fig. 1. Visualization Area for the Chestnuts Selection Process - Industrial Machine Prototype

III. AUTOMATION SELECTION PROCESS

The first step of the chestnuts selection process, is to take a set of 360 degree chestnuts and its areas images as shown the figure 2. Then, image processing is started.

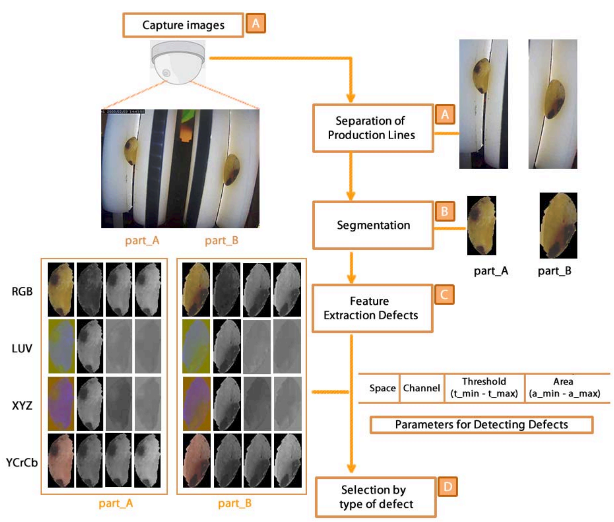

Fig. 2. Computing Vision System for the Selection of Chestnuts, using Color Spaces and multi-threshold binarization

After the image is captured by the camera (Fig. 2_A), it proceeds to the segmentation of the Chestnuts using the color space RGB, specifically the R channel. Then the image is binarized with a threshold (Grey image level) with a value of 100 achieving the background removal. However, this method could not remove the thick line between the rollers. This line causes some errors because its dark color could be confused with some defects like *eye* or spots. To solve this problem, the operation of aperture and closing was used with values of 5 and 1 respectively to delete the rollers gaps. This technique fill the regions of the thick line located between the rollers.

Then, the oval shape technique and an area discards (smaller detected areas for the commons chestnut are deleted) were used to delete undesirable image-noise. Finally a segmented image with a chestnut and a only-black background is obtained (fig. 2_B).

After obtain the segmented image, the next step is the detection of defects of the chestnut (Fig. 2_C), where the most significant features of the image are extracted. To achieve this, 3 manual (visual tools were used) steps were applied for each defect to find:

- Find a correct color space.
- In this space, find the correct channel.
- Find the correct threshold (channel level).

Searching in a color space and its respective channels, some important dark or bright regions are segmented in order to establish a correct relation between the color space and a chestnut defect.
Color spaces like HSV, HLS, YCrCb, Lab, Luv, RGB and XYZ were used and Luv, XYZ, YCrCb and RGB color spaces showed better results for all the defects.

For example, the figure 3, shows two cases for the detection of the color space and its respective channel in order to detect the *eye* defect.

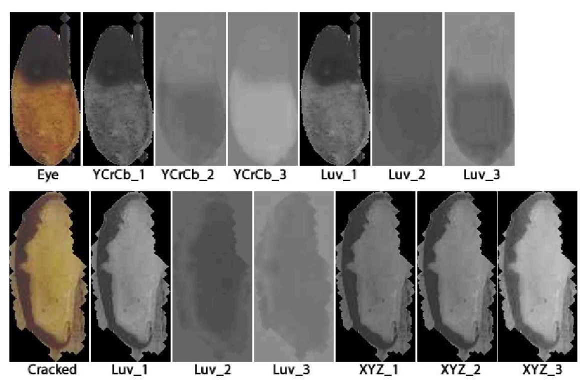

Fig. 3. Show Detect Eyes and Detect Cracked with their respective color space and channels

In the first case, eye defect was detected with the YCrCb and Luv color spaces using the YCrCb_Y and Luv_v channels; however an image could have an other dark sections very similar to the defect (simple visual detection). This may cause confusion in process time. For that reason, when the multi threshold binarization was applied unwanted results were obtained (non *eyes* defects segmented). For that reason, YCrCb_Y color space and threshold binarization were

[3]http://www.vivotek.com/

applied showing better results.

In the second case, for the *cracked* defect Luv and XYZ color spaces were applied. A very dark region is obtained in the defect area using the Luv_v channel. This fact may cause confusion in process time, so the XYZ_X threshold binarization showed better results.

After finding the channel that shown the defects in the best way, the next step is to apply the multi threshold binarization. This was determined using a visual Slider in order to get the corrects minimum and maximum channel values. As shown in figure 4, this allows to get more defect area and delete image-noise in a efficiently and accurately way.

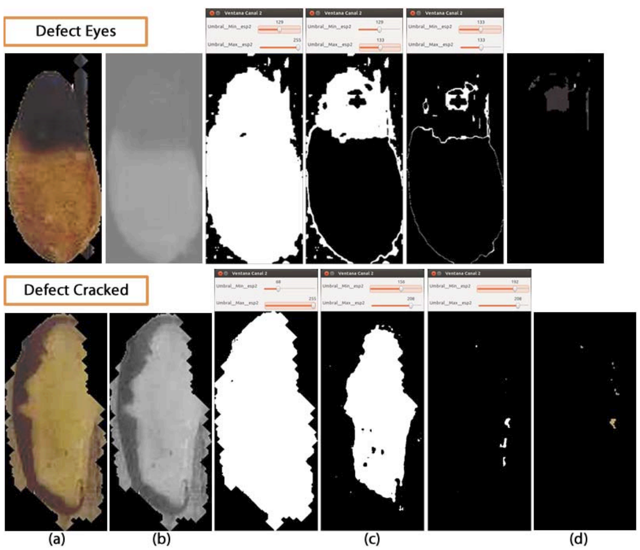

Fig. 4. Multi threshold binarization. Where (a) Original Image, (b) Channel Image, (c) Multi threshold binarization and (d)Fusion Image. For defect *eyes*, with channel (Y) of the color space YCrCb, with binarize t_min= 133 and t_max=133, and defect *craked* with channel (X) of the color space XYZ, with binarize t_min=192 and t_max=208

After the threshold binarization, a maximum and a minimum possible defect area were established. Small detected areas (image-noise) and large detected areas (shadows) were discarded in order to obtain the correct defect image.

Algorithm 1 details how to detect defects in chestnut, depending on the established parameters (Table I).

IV. EXPERIMENTS AND RESULTS

The chestnuts selection machine for industrial purpose, as it said in the first section, has six production lines which are observed by three cameras. Each camera works with two production lines; so, each processed image represents two chestnuts to be selected according to the defect founded in them. This feauture shown in Fig. 5.

Algorithm 1 Defect Detection

Given an image *img*
Given an image *imgDefect*
vector<int> *vector* //characteristic vector where fill defects found
//Obtain the specified channel for obtain the defect, where X is the color space (YCrCb, Luv, XYZ, RGB) and X_i is the channel (canal_1, canal_2, canal_3) the color space
imgDefect = **imgChannel_SpaceDeter** (*img*, X, X_i)
//Binarize the image with a multi threshold (t_min and t_max) with show figure 4
binarize(*imgDefect*, t_min, t_max);
//Elimination of noise or small areas in the image imgDefect
discardAreas(*imgDefecto*,a_min, a_max);
//defect detection
if discardAreas then
    //I can find defect
    //fusionImage, showing the defect in its original color
    fusionImage(img, imgDefect);
    vector.push_back(1);
else
    //I do not find defect
    vector.push_back(0);
end if

Fig. 5. Where (a) Automatic Selection of Chestnuts Industrial Machine and (b) Image taken by VIVOTEK - FD8161 camera

The images of the database (Fig. 6) were taken by VIVOTEK - DF8161 camera, these images have JPG/JPEG format, with a resolution of 640 x 480 pixels.

For each defects in chestnuts several parameters were calculated. The table I show the parameters that performed the process in a successful way. The figures 7 and 8 show the defects present in chestnuts.

After obtaining all defects of chestnuts, the proposed technique continues with the selection (based on priority defined by human experts). First, chestnuts with *eyes* are separated, if there isn't *eyes*, this will continue with husk, if there isn't husk, this will continue with rancid or stained, if there isn't rancid or stained then the system verifies if chestnut is chipped or cracked and if there isn't chipped or cracked (no defects were detected), the products are classified as first quality.

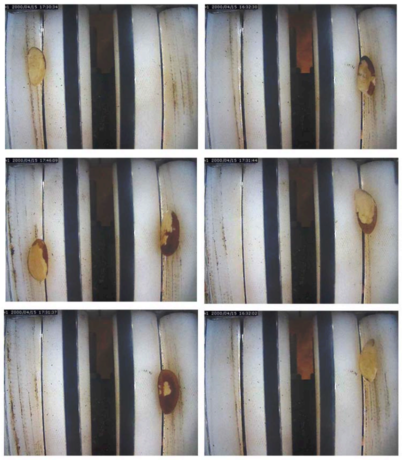

Fig. 6. Image taken by VIVOTEK - FD8161 camera, with their respective enumeration: 297, 2698, 172, 3224, 580 y 581

TABLE I
PARAMETERS FOR DETECTING DEFECTS IN CHESTNUTS

Parameters for Detecting Defects

Defects	**Space**	**Channel**	**Threshold (t_min - t_max)**	**Area (a_min - a_max)**
Eyes	YCrCb	Y	133 - 133	12 -230
Husk	Luv	v	64 - 71	50 - 130
Stained	Luv	v	94 - 99	13 - 500
Rancid	XYZ	Z	73 - 79	180 - 2000
Chipped	RGB	B	114 - 135	2 - 200
Cracked	XYZ	X	192 - 208	1 - 200

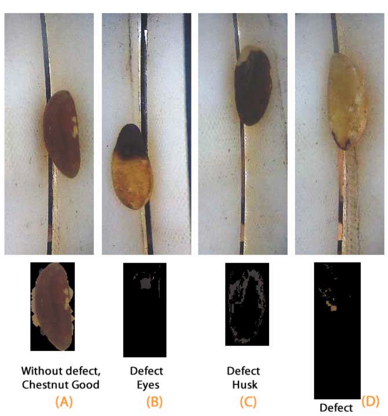

Fig. 7. Where (a) Chestnuts quality, (b) Defect Eye, (c) Defect Husk and (d) Defect Stained

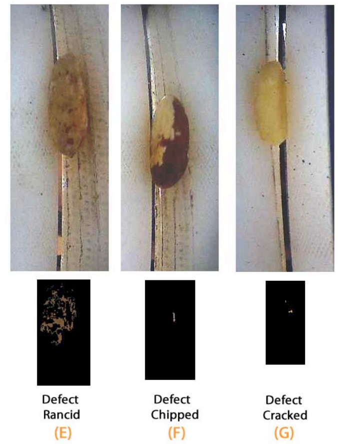

Fig. 8. Where (e) Defect Rancid, (f) Defect Chipped and (g) Defect Cracked

To perform the tests, several chestnuts groups were made based on defects (Eyes, Husk, Stained, Rancid, Chipped and Cracked). The chestnuts were manually selected without an algorithm or a machine help. So, in this paragraph are shown two statistics tables, the Table II was made considering only the software for chestnuts selection, using a pre-created database to find the parameters of the different chestnuts defects types. The Table III was made using the results obtained from the industrial machine with the software developed installed.

TABLE II
STATISTICS PERFORMED BY IMAGES OF DATABASE, TO FIND THE PARAMETERS OF THE DEFECTS (I) PRESENT IN CHESTNUTS

Types Defects in Chestnut	**Amount**			**Percentage**	
	Successes	Errors	Total	**Accuracy (%)**	**Erroneous (%)**
Eyes	225	20	245	91.84	8.16
Husk	300	33	333	90.09	9.91
Stained	282	28	310	90.97	9.03
Rancid	298	19	317	94.01	5.99
Chipped	183	15	198	92.42	7.58
Cracked	161	15	176	91.48	8.52
Total				91.80	8.20

TABLE III
STATISTICS PERFORMED BY CHESTNUTS SELECTION MACHINE

Types Defects in Chestnut	**Amount**			**Percentage**	
	Successes	Errors	Total	**Accuracy (%)**	**Erroneous (%)**
Rancid/Stained	270	2	272	99.26	0.74
Eyes	194	43	237	81.86	18.14
Husk	347	122	469	73.99	26.01
Chipped/Cracked	205	15	220	93.18	6,82
Quality	137	23	160	85.63	14.38
Total				86.78	13.22

V. CONCLUSIONS

This study showed that it is possible to automate the chestnuts selection process, using real time computer vision techniques to detect external chestnut characteristics like its oval shape, its color and its size.

After obtaining these features, two methods were used: Color spaces and multi-threshold binarization. These methods allowed to detect the defects present in the chestnut. The color spaces used were HSV, HLS, YCrCb, Lab, Luv, XYZ and RGB. Then, Luv (v), XYZ (X,Z), YCrCb (Y) and RGB (B) showed the bests results (86.78 %). An other important issue is that each color space must detect only one defect.

Finally, this work can be applied to real exportation work environment, in order to improve the efficiency and effectiveness in the chestnuts selection process of the people or companies interested.

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