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Method for the Recovery of Images in Databases of Rice Grains from Visual Content

Noel Varela[a], Jesus Silva[b]*, Fredy Marin Gonzalez[c], Pablo Palencia[d], Hugo Hernandez Palma[e], Omar Bonerge Pineda[f]

[a, ,c] *Universidad de la Costa, Barnaquila, Colombia*
[b]*Facultad de Negocios, Universidad Peruana de Ciencias Aplicadas, Lima, Peru.*
[d]*Corporacion Universitaria Minuto de Dios (UNIMINUTO), Barranquilla, Colombia.*
[e]*Corporacion Universitaria Latinoamericnaa, CUL, Barranquilla, Colombia*
[f]*Universidad Tecnológica Centroamericana (UNITEC), San Pedro Sula, Honduras*

Abstract

This paper presents a method for detecting and identifying defects in polished rice grains from their scanned image using an expert system. The sample used is designed to contain specimens with the most common defects. Digital image processing techniques were used to identify different types of visible defects in rice grains that affect the quality of the sample. The proposed method has advantages over manual identification such as reduced analysis times, repeatability of results, eliminates subjectivity in identification, records and stores information, uses easily accessible equipment and has a relatively low cost.

Keywords: Imágenes; calidad; escáner; Arroz; Sistemas de Visión Artificial (SVA).

1. Introduction

Machine vision systems (MVS) basically consist of an image acquisition device, a PC and software to acquire

* Corresponding author. Tel.:+51-975857503.
E-mail address: jesussilvaUPC@gmail.com

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and process the image in order to obtain information from the objects in it [1].

Recent advances in hardware, image processing and pattern recognition make machine vision a very popular technique for automatic product inspection. The performance of an MVS depends on the procedure of segmentation of the stained regions of the defective grains. The use of a threshold on the grey scale [2] is a widely used segmentation technique. It has been successfully used in fruit and seed inspection for shape grading, defect detection, quality determination and variety grading [3], [4], [5], [6], [7], [8], [9]. Among all the methods based on image analysis, color processing techniques played an important role in the inspections of different fruits.

In other studies, such as [10], [11] and [12] they developed expert systems based on image processing to define the quality of rice considering its morphology and appearance. There are libraries such as OpenCV [13] that have developed algorithms for morphological and aspect analysis of objects in general. However, their application to grains requires important structural modifications as presented in [12]. Also, in [14] a classification system for rice grains of a single variety is developed using digital image processing in Windows environment, with high success rates compared to human inspection, classifying around 1400 grains per minute. In relation to the classification of varieties from parameters obtained by digital image processing (DIP), [15], [16] and [17] present different metaheuristic techniques, being the artificial neural network the one with the best performance in the classification process.

A methodology is developed to determine the descriptors of the visual characteristics of the mentioned defects. These descriptors and their ranges serve as input values to an expert system that evaluates the quality of polished rice grain samples. The system presented is of very low cost, needing for its operation elements of easy availability. Neither does it require operators with special training. It is fast and its performance is only limited by the speed of the processor used, being able to be used in old computers as well as in new models.

2. Materials and methods

All the following concepts and techniques were developed in an information system whose main objective is to analyze an image of a rice grain sample and provide a quality report [18] [19].

2.1 Digital image processing techniques.

The results of the processing sequence are presented in Figure 1. The initial image (a) is separated into the red, green and blue channels (RGB). Then with the binarization of the blue band of the RGB image using an appropriate threshold, the grains are separated from the background (b). An algorithm is then applied to identify the pixels belonging to each grain (c), and from this result the image of the outline of each grain is obtained (d).

These operations were performed in 8 seconds on a PC with an Intel® Core(TM) i3 CPU M330 @ 2.13GHz and 3GB RAM.

With the binary image, which identifies each grain, the outline image and the original image, the following attributes of each grain in the sample are obtained: signature (graphic representation of the distance to the center of gravity as a function of the angle between it and the horizontal), height, width, area, and histogram by color band.

(a) (b) (c) (d)

Fig. 1. Original image (a), (b) Binarized (c) With grains identified by levels of grey (d) from the contours of the grains

2.2 Set of test rice grains.

The set of rice grains used in this study was obtained before packaging for marketing and was designed to contain examples of all the defects mentioned in [19]. See Figure 2.

A set of rice grains was formed containing 74 normal specimens, 30 broken, 22 white-bellied, 4 gypsum, 6 stained or colored, 30 reddish and 5 chopped. Figure 2 shows the image.

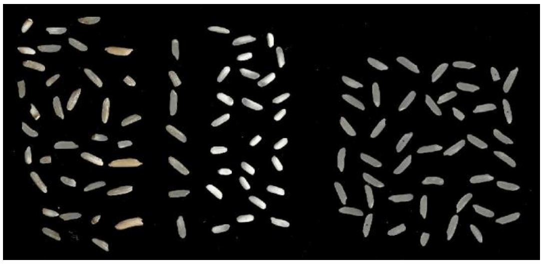

Fig. 2. Picture of the sample grain set

2.3 Detection and identification of defects in rice grains

2.3.1 Determination of the average attributes of normal grains.

In order to characterize the grains, it is necessary to obtain average attributes from the normal grains present in the sample [5]. An operator selects at least 20 normal and whole grains at random from the image of the sample in different regions of the sample.

2.3.2 Rule to classify the grains according to their size.

To characterize the grain according to size, its length L is compared to the average L_0. If the grain has a length L such that $L \geq 0.75\ L_0$, it is complete, otherwise it is broken [19].

2.3.3 Rule for sorting grains by aspect.

For the aspect classification, the mean value and the standard deviation of the intensity level of the blue band for each grain is compared with the average reference attributes for that band [4].

2.3.4 Defective Grains: Stain Analysis.

For the grains classified as defective by the above rule, a procedure is used to act on the entire image and aims to calculate the areas of reddish spots and dark spots [4].

2.3.5 Determination of thresholds.

It is necessary in the defective grains to determine the intensity thresholds that separate the stained pixels from the normal ones. Experimentally, a threshold for the blue band (U_b=100) was determined to establish that the pixel belongs to a spot, and a threshold for the red band (U_r=100) to establish whether the pixel belongs to a dark or a red spot [5][7].

2.3.6 The process of spot analysis.

It applies only to rice grains that were classified as defective. For each pixel of these grains its intensity level in the Blue band I_b is compared with U_b.

If the intensity of the i-th pixel $Ib_i \leq U_b$ then it is stained.

Compliance with this rule classifies the pixel as spotted without specifying the type of spot.

For identifying the type of stain, its intensity level in the Red band is compared with U_r.

If the intensity of the i-th pixel $Ir_i \leq U_r$ then it is dark, otherwise it is reddish [2]. Figure 3 shows examples of the application of this rule.

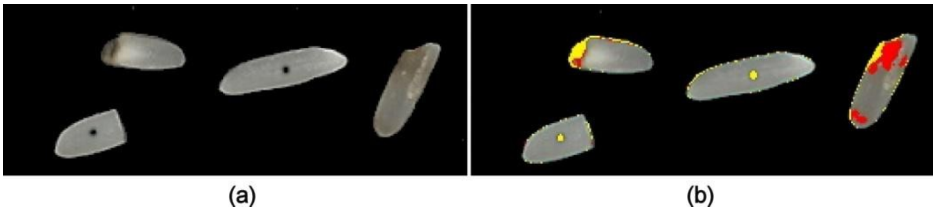

Fig. 3. Original Image (a). (b) With the reddish areas highlighted in red and the dark areas in yellow.

In this way, each spotted pixel of the defective grains is classified as a reddish or dark pixel. The reddish and dark areas are then determined by counting these pixels and consequently each bean previously classified as defective acquires two new attributes: with dark area and with red area. Figure 3 highlights the reddish areas with red color and the dark areas with yellow color.

2.3.7 Red grains or grains with reddish striations.

It is classified as red grains or grains with reddish striations, according to [5]. applying the rule:

If the reddish area > 0.5 mm^2 the grain is red or with reddish streaks. The value 0.5 mm^2 is an empirically obtained threshold. Figure 4 shows defective grains that are colored and/or have red streaks.

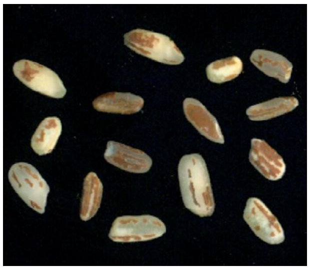

Fig. 4. Defective red or striated grains.

2.3.8 Stained grains.

It is classified as stained grains, according to [4]. applying the rule:

If the dark area > 0.5 mm^2 the grain is stained or colored. The value 0.5 is an empirically obtained threshold.

2.3.9 Chopped grains.

A dark spot with an area of < 0.5 mm^2 y and an approximately circular shape is classified as a possible chopped grain according to [5].

2.3.10 Identification of stains.

This process consists of giving each grain stain an identifier that will later allow analysis of shape and size. An auxiliary binary array is used for this purpose, where the pixels belonging to dark spots are represented with a value of 1 (one) and all the rest of the image with a value of 0 (zero) [14].

To identify each stain, a complete path of the auxiliary binary matrix is made and when a pixel with value 1(one) is detected, a spill algorithm is triggered to give the same identifier to all pixels with value 1 (one) that are part of the identified blemish, this process is illustrated in Figure 5 where the identifier of each blemish is represented with a color.

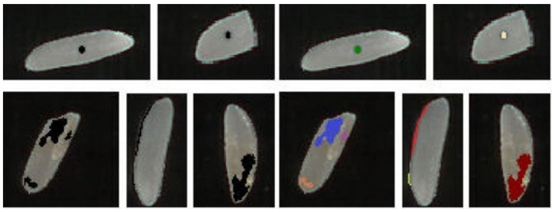

Fig. 5. Visual representation of the identification of each dark spot.

3. Results

The system allows loading the image for analysis, defining configuration parameters, obtaining average parameters from 20 normal grains, performing the analysis and generating a report of the sample and of each grain.

Table 1 shows the results obtained from the evaluation of the sample by hand and by POI, clearly coinciding. The sample report summarizes the analyses made on a rice sample according to the defect classification criteria of [3]; and classifies the analyzed sample according to the defects found in quality 00000, quality 0000, 2nd quality or non-commercial (see Figure 6).

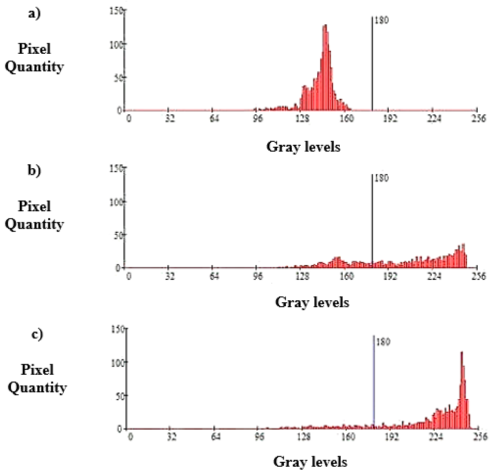

Fig. 6. Histogram of the grey levels of each normal grain (a), (b) white belly, (c) gypsum-so. The threshold is in blue.

Table 1. Final results of the quality analysis

Classification		**Manual Evaluation**	**PDI Evaluation**	**Percentages (%)**
	Normal	74	74	58,14
	Reddish	30	30	22,36
According to aspect	Dark spots	6	6	7,74
	Chopped	5	5	4,92
	Gypsums	4	4	2,36
	White belly	22	22	16,02
According to Size	Complete	90	90	76,36
	Chopped	**30**	**30**	30,14

4. Conclusions

In this study, a methodology was developed for identifying the grains that are defective in a sample of rice grains using digital image processing techniques. It determines the descriptors of the following visual defects in the rice grains: red or streaked with red, gypsum, white belly, stained, broken and chopped. These descriptors serve as input to an expert system that evaluates the quality of polished rice grain samples according to the standards set out in [8]

The results obtained with the test sample in the classification of the specimens with respect to the evaluations made manually by an expert do not present differences.

As restrictions or limitations of the model it can be concluded that it is very dependent on empirical values, so, to increase the robustness of the model, it is fundamental to expand the universe of specimens used to obtain the empirical values or to establish artificial intelligence techniques that guarantee continuous learning and permanently adjust these empirical values.

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