COMPUTER VISION BASED APPROACHES FOR BEAN DEFECTS DETECTION

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Abstract. In this work are proposed computer vision approaches to detect three of the main defects found in beans: broken, bored by insect (*Acanthoscelides obtectus*) and moldy. In addition, we describe a fast and robust segmentation step that is combined with the proposed approaches to compose a computer vision system (CVS) applicable to the Brazilian beans quality inspection process, to determine the type of the product. The proposed approaches constitute an important practical contribution since, although there are some papers in the literature addressing visual inspection of beans, none of them deals with defects. In the conducted experiments a low-cost equipment, composed by a table made in structural aluminum, a conveyor belt and an image acquisition chamber, was used to simulate the characteristics of an industrial environment. The CVS evaluation was performed in two modes: offline and online. In the offline mode, a database composed by 120 images of bean samples containing grains of different classes and with different defects was employed, while in the online mode the grains contained in a batch were spilled continuously in the conveyor belt of the equipment for the proposed CVS to perform the tasks of segmentation and detection of defects. In the experiments the CVS was able to process an image of 1280×720 pixels in approximately 2 s, with average hit rates of 99.61% (offline) and 97.78% (online) in segmentation, and 90.00% (offline) and 85.00% (online) in detecting defects.

Keywords: Computer Vision, Beans, Defects, Inspection, Visual Quality

1 Introduction

The visual properties of many agricultural products, including beans, are important factors in determining their market prices and assisting the consumer choice. Thus, visual inspection processes are essential to ensure the quality of these products [1-4].

Brazil is the world's largest producer and consumer of beans, followed by India, China and Mexico. Beans, together with rice, form the basis of the Brazilian people's diet. The visual inspection of Brazilian bean quality is done manually following operating procedures established by the Ministry of Agriculture, Livestock and Supply, which instruct how to frame the beans in a group, according to the botanical species (Group I comprises the specie *Phaseolus vulgaris* and Group II the specie *Vigna unguiculata*); class, according to the skin color of the grains and type, according to the quantities of defects [5].

Since manual quality inspection processes are usually subject to problems such as high operational costs and difficulty in standardizing results [6,7], the automation of such processes represents an important alternative to reduce costs and standardize results, generating a competitive differential for companies, especially in the context of agroindustry 4.0, in which is preconized the use of intelligent technologies in order to optimize decision making and improve production processes, making it possible to obtain products with greater quality, respecting the environment and sustainability [8].

In the literature of the last two decades we can find several works proposing computer vision systems (CVS) for quality inspection of grains. Specifically, for beans there are the works [6, 9-16]. Surprisingly none of them addresses defects detection, which is an indispensable task for a CVS developed to classify and typify the beans. Obviously, there are several works in the literature addressing the detection of defects in fruits and vegetables. However, the defects considered in these works are different from those that affect beans.

It is in this context that this work is inserted, with the proposition of computer vision-based approaches to detect three of the main defects found in beans: broken, bored by insect (*Acanthoscelides obtectus*) and moldy. These approaches, besides consisting in a novelty in terms of application, are feasible for embedded systems since they require low computational cost. In addition, we describe a fast and robust segmentation step that is combined with proposed approaches to compose a CVS applicable to the quality inspection process of Brazilian beans, to determine the type of the product.

2 Related Works

In the literature of last two decades we can find some works addressing automated approaches for visual quality inspection of beans. Kiliç et al. [6], for example, proposed a computer vision system (CVS) for beans classification based on color and grain size, using color histograms and a Multilayer Perceptron artificial neural network (MLP-ANN). In Venora et al. [9, 10] computer vision approaches were proposed for the identification of varieties of beans grown in Italy, based on the attributes of grain size, shape, color and texture. Laurent et al. [11] employed image processing techniques to evaluate changes in bean color during storage, in order to correlate such changes with a phenomenon called "hard-to-cook grains".

The works [6, 9-11] show the necessity and importance of computational systems for bean inspection. However, the segmentation approaches proposed in these works fail in images containing glued grains (touching grains). For this reason, in the experiments conducted, the authors manually positioned the grains, spaced from each other, to acquire the image or acquired an image for each grain, in order to facilitate the segmentation step. This is a severe limitation that hinders the practical application of the systems proposed in such works.

The works proposed in the literature in the last five years have been concerned to solve the problem of touching grains. The work of Araújo, Pessota and Kim [12], for example, presents a CVS to classify the most consumed Brazilian beans that includes a robust routine of segmentation capable of solving the problem of touching grains. It employs the k-NN algorithm for removal the background of the image and the normalized cross-correlation granulometry technique, using elliptical kernels, to segment the grains, even though they are touching each other. Despite the high hit rates obtained in segmentation and classification tasks (99.88% and 99.99%), the computational time spent to segment an image (16 s for an image of 800×600 pixels), prevents the practical application of the system proposed in [12].

Since then, the works found in the literature addressing the visual inspection of beans such [13-16], focused on the development of approaches that keep the high segmentation and classification rates obtained in [12], but requiring less computational time.

Although many advances have been achieved in terms of segmentation and classification of beans, there are no works in the literature addressing the detection of defects, which constitute an important part of the visual quality inspection of the product.

3 Proposed Approaches

Consider as input a color image denoted by a function $I: \mathcal{D} \rightarrow \mathbb{K}$, which maps a rectangular grid $\mathcal{D} \subseteq \mathbb{Z}^2$ into a set of color intensities $\mathbb{K} = \{0, 1, \ldots, 2^{nBits} - 1\}^{nBands}$, where $nBits$ is the number of bits to represent a pixel intensity and $nBands$ the number of bands of employed color system. Consider also that each pixel of I is represented by $\wp = (\wp_x, \wp_y)$ whose values $\wp_x$ and $\wp_y$ denote the horizontal and vertical coordinates of $\wp$. First, I is segmented and, after that, the approaches for detecting defects are applied.

3.1 Segmentation

The first operation is to convert the input RGB image (I_{RGB}) to the CIELab color system generating I_{Lab}. Each pixel $\wp$ from I_{Lab} is then mapped for two class of gray in I_{gray}, in which typical bean colors are represented by the darker tone (black) and the typical background colors are represented by the lighter tone (white). For this, differently from the proposal of Araújo, Pessota and Kim [12] in which a training is done for each image using the k-NN algorithm, we employ a look-up table (LUT) to compute this mapping more efficiently. Once the LUT is created it is possible to describe the mapping process to remove the background of the image, as defined by Equation 1.

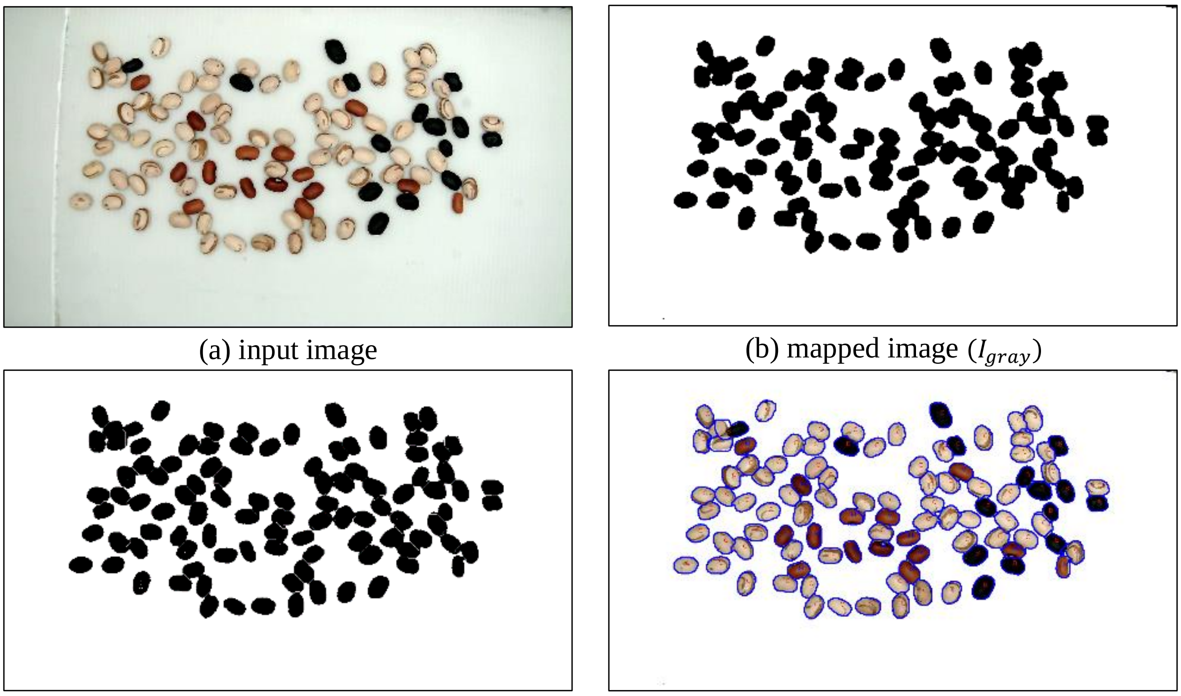
$$\forall \wp \in D, I_{gray}(\wp) = LUT\big(I_{Lab}(\wp)\big) \tag{1}$$

For the refinement of the mapping process the morphological opening operator is applied to remove small connected components, considered as noise. The next step consists in the application of the watershed transform (WT)), using distance transform (Euclidean distance), to segment the grains in I_{gray}. As WT is very susceptible to the problem of super-segmentation [17], we use some information such as average grain size and distance between the centers of two grains to join two or more fragments erroneously divided by WT.

Finally, the cross-correlation granulometry (CCG) technique described in [12] is applied in regions of I_{gray} where WT was not able to segment correctly the grains. It is identified from connected components considered too large. However, instead of the 162 templates originally used in [12], we employed a set of 72 elliptical templates ($\mathcal{T}p$) defined from 4 scales and 18 rotation angles at each scale. The CCG operation can be mathematically formulated as:

$$\forall\, \wp \in \mathcal{D}, \big[CCG\big(CC(I_{gray}), \mathcal{T}p\big)\big](\wp) = \arg\max_{\mathcal{T}}\big\{\big[NCC\big(CC(I_{gray}, \mathcal{T})\big)\big](\wp) : \mathcal{T} \in \mathcal{T}p\big\} \tag{2}$$

where $CC(I_{gray})$ is a connected component extracted from I_{gray}, NCC is the normalized cross-correlation operation and $\mathcal{T}$ is a template belonging to the set of templates $\mathcal{T}p$. The working of segmentation process is shown in Figure 1.



(a) input image

(b) mapped image (I_{gray})

(c) Result of segmentation by WT

(d) Final result of segmentation step

Figure 1. Working of segmentation process

It should be noted that the fact of applying CCG only in some regions of the image leads to a large reduction in segmentation processing time.

3.2 Detection of Bean Defects

Broken Beans: As known, the shape of a whole bean grain is very close of an ellipse. Thus, the detection of a broken bean can be done using some algorithm that extracts the signature of the image of a grain and compares it with the signature extracted from the image of an ellipse or from a whole grain, considered as standard.

The verification of the broken grain signature, described by equations 3 to 5, is conducted using the seven invariant moments of Hu [18]. Basically, we compute the difference between signatures ($diff\_sign$) of a standard grain and the grain under analysis. If this difference is greater than a threshold t_diff_sign (in our experiments $diff\_sign$ = 0.4) then the grain is considered as broken. The choice of this scheme was motivated by the speed and precision of the algorithm and the facility of its implementation. In addition, it was considered that the moments of Hu are invariant to scale and rotation, essential for the purpose explored in this work.

$$diff\_sign(A,B) = \sum_{i=1}^{7} \left| \frac{1}{m_i^A} - \frac{1}{m_i^B} \right| \tag{3}$$

$$m_i^A = -sign(h_i^A).\, log\ h_i^A \tag{4}$$

$$m_i^B = -sign(h_i^B).\, log\ h_i^B \tag{5}$$

where h_i^A, h_i^B are h_i^A, h_i^B are, respectively, the seven invariant Hu moments calculated from the analyzed object A (connected component extracted from the segmented image) and the object B representing a standard grain. After each grain in the segmented image is analyzed, those identified as broken ($t\_diff\_sign > 0.4$) are labeled, as shown in Figure 2. It is worth mentioning that this threshold value was obtained experimentally.

Figure 2**.** Example of result of the detection of broken grains

It is valid to mention that the signature could be extracted using other robust techniques such as Curvature Scale Space (CSS). However, in the tests performed in this work CSS spent approximately 0.73 s to analyze an image of 1280×720 pixels while the algorithm employed spent 0.01 s to perform the same task.

Beans Bored by Insect (*Acanthoscelides obtectus*): The Hough transform for circle detection (HTC) was used to detect the holes caused by the insect. The employed algorithm is implemented in the OpenCV image processing library[1]. Firstly, a median blur filter is applied to I_{gray} with a kernel of 3×3 pixels aiming to increase the successful of the HTC, that is applied in the sequence. To avoid problems of noise in the detection of the holes, maximum and minimum radii are stipulated and adopted as parameters of the HTC. These values are easy to obtain since the holes have homogeneous sizes, as can be seen in Figure 3a.

(a) bored beans (b) detected bored beans

Figure 3. Detection of bored beans

[1] https://opencv.org/

The holes caused by *Acanthoscelides obtectus* detected by HTC algorithm are marked on the output image with a red circle, as showed in Figure 3b.

Moldy Beans: For the detection of moldy grains, a convolutional neural network (CNN) was employed. It was trained using a dataset composed by 5920 sub images (central regions of the grains with 30×30 pixels, as showed in Figure 4) extracted from healthy and defective grains. This dataset was divided into two parts, being 4000 sub images for training and the remaining 1920 for validation of the training.

(a) mouldy grains

(b) helthy grains

Figure 4. Examples of images used for CNN training/validation

The CNN employed in this task was implemented in Phyton, using the Keras library[2], and its parameterization was adjusted in order to receive images of 30×30 pixels in the input layer. It comprises two convolutional layers formed by 16 maps of 3×3 intercalated with two pooling layers with dimension of 2×2, and two fully connected layers, with 64 and 1 neurons.

Finally, the following parameters were used for training of described CNN: 8000 steps per epoch and a total of 20 epochs, totaling 160000 iterations.

4 Experimental Results

The experiments were conducted, considering the modes offline and online as ex-plained in sections 4.1 and 4.2, on an PC Intel Core i7-7500U Quad Core with 2.7 GHZ processors, 16 GB Memory. In addition, preliminary experiments considering only segmentation (in online mode) were carry out on a Raspberry Pi 3. The algo-rithms, except the CNN employed to detect the moldy beans, were developed in C/C++ language using OpenCV library.

4.1 Offline Mode

In this mode, a database composed by 120 images of bean samples was employed. From these images, 100 were used to evaluate the segmentation step, since if it fails, the detection of defects will be affected. The remaining 20 images were used to evaluate the approaches for detection of defects.

Segmentation: Table 1 presents the hit rates obtained in the evaluation of the segmentation step. Each of 100 images contains 100 grains of three different classes as showed in figures 1a and 3a.

As can be seen in Table 1, in the experiments with the segmentation approach, a hit rate very close to that presented in Araújo, Pessota and Kim [12] was obtained (99.61% versus 99.88%) but spending much less processing time (0.8 s versus 16 s).

[2] https://keras.io/

Table 1. Results of segmentation in offline mode

Number of grains in the 100 images	Number of grains detected correctly (True Positives – TP)	False Negative (FN)	False Positive (FP)	Hit rate (%)
10,000	9,961	14	25	99.61

Detection of Defects: The results presented in Table 2 show that the approaches for detection of broken and bored beans were not able to detect all the defective grains contained in the images. In the case of the bored beans, some grains have dark brown streaks mixed with its predominant skin color (see Figure 2a), making it difficult to detect the hole caused by *Acanthoscelides obtectus*. In some cases, even for the human eye is a difficult task. On the other hand, the moldy detection approach did not make detection errors, demonstrating the effectiveness of the built CNN.

Table 2. Results obtained by the approaches to detect defective grains in offline mode

Number of grains containing each defect	**Broken beans**		**Bored beans**		**Moldy beans**	
	Grains detected	Hit rate (%)	Grains detected	Hit rate (%)	Grains detected	Hit rate (%)
50	40	80.00	45	90.00	50	100.00

The computational time consumed by defects detection task was approximately 1.2 s. Eighty-three percent of this time (1 s) was consumed by CNN in detecting of moldy beans.

4.2 Online Mode

In the online mode the grains contained in a batch of 1000 grains were spilled continuously in the conveyor belt of the equipment for the proposed CVS to perform the segmentation and detection of defects. In addition, some preliminary experiments considering the segmentation task were conducted with a Raspberry Pi 3, in order to investigate the feasibility of using the proposed approaches in an embedded platform.

Segmentation: Table 3 presents the hit rates and standard deviations (σ) obtained in 3 experiments with 3 replicates in each of them. As can be seen, these results were lower than those obtained with the database of images (offline). This occurs mainly due to loss of image quality since the grains are in movement and also due to the existence of small ranges in the samples of grains between two consecutive acquisitions which are not analyzed. Although the equipment has been adjusted to acquire the images avoiding this last problem, there is still the possibility of some grains are not processed.

Table 3**.** Results of segmentation in online mode

Experiment	Number of grains detected			Average	σ	Hit rate
1 (PC)	977	998	979	984.70	9.46	98.47%
2 (PC)	985	969	999	984.33	12.26	98.43%
3 (Raspberry)	961	965	967	964.33	2.49	96.43%

As one can see in table 3, the results obtained in the experiments with Raspberry were inferior to the results obtained with the use of a PC. This was due to the decrease in the number of calls of the CCG algorithm, to enable the execution of the segmentation task on the Raspberry platform with a suitable time (4.8 s, in average).

Finally, the low standard deviations in all experiments indicate good stability of the segmentation approach.

Detection of Defects: Table 4 presents the hit rates obtained by approaches to detect defects in online mode. In these experiments the results are also lower than the results obtained in offline mode. In the case of broken grains, some of them were glued to whole grains or even to other broken grains, generating segmentation errors and, consequently, failure in the detection of this defect. Regarding to defect of bored beans (holes), again the fact that the beans are in movement leads to the small loss in the image quality that is enough to cause errors in the detection of the holes.

Table 4**.** Results obtained by the approaches to detect defective grains in online mode

Number of grains containing each defect	Broken beans		Bored beans		Moldy beans	
	Grains detected	Hit rate (%)	Grains detected	Hit rate (%)	Grains detected	Hit rate (%)
50	41	82.00	44	88.00	–	–

Unfortunately, as the approach to detect moldy beans was developed on a computing platform different than that one used for the development of other approaches, it was not incorporated into CVS and therefore was not evaluated in online mode experiments.

5 Conclusions

Regarding the segmentation, the approach described in this work presented an excellent result in all aspects, since it obtained an average hit rate of 98.24% (99.61% in offline mode and 97.78% in online mode, including the experiments on a Raspberry), requiring only 0.80 s to segment an image on a PC and 4.8 s on a Raspberry. The results obtained in the detection of defects showed that the approaches developed are good alternatives, since they presented average hit rates of 81% for broken beans, 89% for bored beans and 100% for moldy beans (considering only offline experiments for this last defect). Although the approaches for defect detection have shown reasonable performance and low computational cost, about 0.2 s for detection of broken and bored beans and about 1.0 s for the detection of moldy beans, there is still room for optimization of the processing time of the latter approach. These low processing times, without using multithread or other advanced hardware and software resources, make these approaches feasible to be executed by an embedded system, since they can be optimized. This optimization is a challenge that will be addressed in our futures works.

Acknowledgements

The authors would like to thank FAPESP – São Paulo Research Foundation (Proc. 2017/05188-9) and UNINOVE by financial support.

References

[1] A.K. Aggarwal, R. Mohan: Aspect Ratio Analysis Using Image Processing for Rice Grain Quality. *International Journal of Food Engineering*, 6(5), 1–14, 2010.
[2] L. Fernández, C. Castillero, J.M. Aguilera: An Application of Image Analysis to Dehydration of Apple Discs. *Journal of Food Engineering*, 67(1–2), 185–193, 2005.

[3] G. Stegmayer, D.H. Milone, S. Garran, L. Burdyn: Automatic Recognition of Quarantine Citrus Diseases. *Expert Systems with Applications*, 40(9), 3512–3517, 2013.
[4] H. Zareiforoush, S. Minaei, Alizadeh, M. R., A. Banakar, B. H. Samani,: Design, development and performance evaluation of an automatic control system for rice whitening machine based on computer vision and fuzzy logic. *Computers and Electronics in Agriculture*, 124, 14–22, 2016.
[5] C.C. Knabben, J.S. Costa: Manual of classification of the bean: normative instruction n. 12, March 28, 2008. *Embrapa Rice and Bean-Folder/Leaflet/Booklet* – INFOTECA-E, 2012.
[6] K. Kiliç, I.H. Boyaci, H. Köksel, I. Küsmenoglu: A classification system for beans using computer vision system and artificial neural networks. *Journal of Food Engineering.* 78, 897–904, 2007.
[7] N. K. Patil, R.M. Yadahalli, J. Pujari: Comparison between HSV and YCbCr Color Model Color-Texture based Classification of the Food Grains. *International Journal of Computer Applications*, 34 (4), 51–57, 2011.
[8] P. Parronchi: The Development Pioneers and the New Agriculture 4.0: economic development from the countryside In: XXIII *Encontro Nacional de Economia Política*, 1–18, 2017.
[9] G. Venora, O. Grillo, C. Ravalli, Cremonini, R.: Tuscany beans landraces, on-line identification from seeds inspection by image analysis and Linear Discriminant Analysis. *Agrochimica*. 51, 254–268, 2007.
[10] G. Venora, O. Grillo, C. Ravalli, R. Cremonini: Identification of Italian landraces of bean (Phaseolus vulgaris L.) using an image analysis system. *Scientia Horticulturae*. 121, 410–418, 2009.
[11] B. Laurent, B. Ousman, T. Dzudie, M.F.M. Carl, T. Emmanuel: Journal of Engineering and Technology Research. 2(9), 177–188, 2010.
[12] S.A. Araújo, J.H. Pessota, H.Y. Kim: Beans quality inspection using correlation-based granulometry. *Engineering Applications of Artificial Intelligence*. 40, 84–94, 2015.
[13] S.A. Araújo, W.A.L. Alves, P.A. Belan, K.P. Anselmo: A Computer Vision System for Automatic Classification of Most Consumed Brazilian Beans. *Lecture Notes in Computer Science* (ISVC2015), 9475, 45–53, 2015.
[14] P.A. Belan, S.A. Araújo, W.A.L. Alves: An Intelligent Vision-Based System Applied to Visual Quality Inspection of Beans. *Lecture Notes in Computer Science* (ICIAR 2016). 9730, 801–809 (2016).
[15] P.A. Belan, M.M.A. Pereira, S.A. Araújo, W.A.L. Alves: Abordagem Computacional para Classificação Automática de Grãos de Feijão em Tempo Real. In: *SeTII 2016, São Paulo, Brazil*. 1–4, 2016.
[16] P.A. Belan, R.A.G. de Macedo, M.A. Pereira, W.A.L. Alves, S.A. Araújo: A Fast and Robust Approach for Touching Grains Segmentation. *Lecture Notes in Computer Science* (ICIAR 2018). 10882, 482–489, 2018.
[17] P. Soille: Morphological Image Analysis: Principles and Applications. Springer (2003).
[18] M.K. Hu: Visual pattern recognition by moment invariants. IRE *Transactions on Information Theory*. 8(2), 179–187, 1962.