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Quality Inspection of Bag Packaging Red Beans (*Phaseolus vulgaris*) Using Fuzzy Clustering Algorithm

Ngatchou Alban[1*], Bitjoka Laurent[2], Yemefack Martin[1] and Boukar Ousman[2]

[1]*Institute of Agricultural Research for Development (IRAD), P.O.Box 2067 or 2123 Yaoundé, Cameroon.*
[2]*Modelisation, Image Processing and Applications Research Group (MOTRIMA), Biophysics and Food Biochemistry Laboratory, National school of agro-industrial sciences, The University of Ngaoundéré, P.O.Box 455, Ngaoundéré, Cameroon.*

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Abstract

Food industry is currently focusing on fast and unsupervised quality inspection techniques. This paper deals with the development of new method for fast quality control of bag packaging red beans (*Phaseolus vulgaris*) using flatbed scanning. The proposed method combines fuzzy c means with spatial transformation (FCM_ST) to reduce FCM iteration. We used the labelled pixel, in the clustering image, for the evaluation of grain mixture in acquired image. The performance of the FCM_ST was compared to the standard FCM approach and it reveals itself very good for fast clustering and efficient detection of grain mixture. The detections accuracies of grain mixture in the bag packaging red beans (*Phaseolus vulgaris*) was 96% for acquired image with presence of other self-colour commercial beans type, 70% with presence of defected cotyledons beans, between 30% to 89% with presence of multi-coloured beans depending on their texture and between 10% to 15% with the presence of low discoloured red beans of same commercial type.

Keywords: Packaging red beans (*Phaseolus vulgaris*), fuzzy logic, wavelet transform, quality control.

*Corresponding author: ngatchou_alban@yahoo.fr;

1 Introduction

Dry legume seeds, as grains, are important foods in the diets of people throughout the world [1], and one of the most cultivated Africa staple crops, but with mixture of varieties of grain in the same field. Therefore post-harvest grain here is sometimes influenced by packaging multiple varieties without sorting, which lowers their market value and good storage management. Moreover, the sensitivity to insect attack, hardening, discolouration and taste depend on dry grain varieties [2]. Several African countries are thus facing with the problem of quality standards resulting from the packaging of harvested products with several varieties in the same bag, because all seeds do not meet the same storage characteristics [2] and the common commercial requirement that every varieties grains stocks should be renewed at regular intervals [3]. Studies have shown a correlation between the storage conditions of the common beans (*Phaseolus vulgaris*), and the culinary qualities and discolouration [4]. This was already examined in red beans by digital camera image processing [5].

However, optimal time storage grains, before direct human consumption, practiced by many farmers and distributors can render the adoption of this video camera discolouration control difficult. In order to facilitate the optimal time storage and marketing value of grains, quality factor based on limited presence of different colour seeds (other than discoloured seeds) is done by visual examination (Standard CODEX STAN 171). This visual examination is ineffective and not reassuring, because of contingencies related to human weakness (errors, tiredness, morality) which makes the bag packaging control risky.

Several studies [6,7,8,9] have used imaging for the identification, detection and classification of dry seeds based on morphological, texture and colour analysis algorithms by scrolling seed after seed.

This scrolling seed by seed is tedious and time-consuming if you must perform quality control (without necessity of sorts) of tons seeds and with the risk of stopping business ("times is money"). Therefore fast analysis and efficient control requires a new approach.

The unsupervised fast classification is still a difficult problem without unanimous solution because every texture has its owner feature extraction. Fuzzy clustering algorithm, an unsupervised classification method, has a wide application [10,11,12] especially in control engineering. FCM is very popular because it is simple, easy, convergent, unsupervised and can keep more image information [13].

The learning techniques in computer vision for food quality evaluation, presented by [14] has shown that fuzzy clustering unanimous solution for best classification accuracies in food quality inspection [15,16] is still difficult.

In fact, the FCM iterative algorithms provide a partition of the pixels into a given number of clusters which can help for food inspection. However, most of the FCM algorithms present several drawbacks such as long computing time, taking no account of the neighbour pixels and spatial information of image [17].

It is in this context that we analyzed in this paper the contributions of a new method developed here by taking spatial transformation to reduce FCM iteration and accelerating the automatic classification of pixels in acquired image during quality control by machine vision. We used the result of the new approach for inspecting the presence of another commercial grain type in the bag packaging of the red beans by analysis in a single frame of a large number of grains acquired in the same image.

2 Materials and Methods

2.1 Equipment and Grain Samples

We used the flatbed scanning system Canoscan LiDE70, a laptop (Core Duo 2.1 GHz, 3GB RAM, 300GB HDD) and the IRAD[1] beans samples: MEX 142, LUNDAMBA, MAC 33, K26-35CFM, TY33, ECAPAN 021, MAC 55, RED BEANS (with Defected cotyledon, Broken pulses, Discolouration). MATLAB for image processing were involved.

2.2 Methods

2.2.1 Imaging system and processing

The background colour was blue (Figs. 3a and b), because there are no common blue bean seeds in nature and also it has been shown that blue background favoured the image segmentation procedure [9]. Red beans seeds that meet the standards were aligned at both ends on a well straight line. The different colour seeds for detection are inserted in a wide corridor (Figs. 2a and b) for the reception of lots of beans to be analyzed.

2.2.2 Texture analysis and feature extraction

2.2.2.1 Wavelet transform analysis

Wavelet transform is the best trade-off to represent both time and frequency content (Fig. 1) of a signal [18,19]. It is one of the main reasons for the use of it for beans surface texture analysis [20]. The continuous wavelet transform of a one-dimensional function $f(x) \;\varepsilon\; L^2(R)$ with respect to the mother wavelet can be expressed as:

$$W_f(a,b) = \langle f, \psi_{a,b} \rangle = \int_{-\infty}^{+\infty} f(x)\psi_{a,b}(x)d(x) \tag{1}$$

The wavelet base functions $\psi_{a,b}(x)$ are dilations and translations of the mother wavelet $\psi(x)$.

$$\psi_{a,b}(x) = \frac{1}{\sqrt{a}}\psi\left(\frac{x-b}{a}\right) \tag{2}$$

[1]*Institute of Agricultural Research for Development*

Where $a, b \in R$: parameter $'a'$ is the dilatation or scaling factor and parameter $'b'$ is called translation factor.

When digital images are to be viewed at multiple resolutions, the discrete wavelet transform is the mathematical tool of choice. Exponential discretization of the scaling function and the wavelet function is commonly use to coverage time frequency plane (Fig. 1). Therefore, the dilatation parameter $'a'$ and the translate parameter $'b'$ is taken from the following relation:

$$\begin{cases} a = a_0^m \\ b = nb_0 a_0^m \end{cases} \tag{3}$$

with $a_0, b_0 \in Z$

In fact, wavelet uses filter bank [21], [22] to decompose at first level the input image into four sub-bands contained in c:

$$c = \{A_1, (d_1^h, d_1^v, d_1^d)\} \tag{4}$$

With A_1 approximation in lower resolution and d_1^h, d_1^v, d_1^d the contained detail sub-band respectively in horizontal, vertical and diagonal orientations.

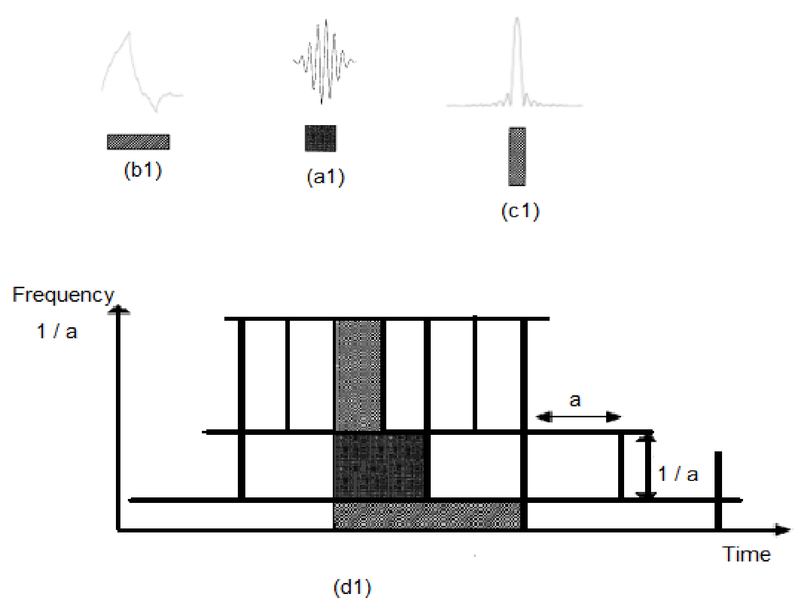

Fig. 1. Multiresolution analysis: (a1) Basis function, (b1) Scaling function, (c1) Wavelet function, (d1) Coverage of time frequency plane

The significant image information, at first level, is obtained in approximation coefficient A_1 and can be further decomposed at next levels using the same filter bank. After decomposition of the discrete image of J levels, we end up with $3J+1$ channel.

2.2.2.2 Feature extraction

Four types of texture features, given by Eq. (5), were extracted in this study. Each pixel of the approximate image A_J in level *J,* is assigned an analysis window $R = A_J[m,n]$ to measure in around pixel (x,y), the texture characterization:

$$\begin{cases} E_J = \dfrac{1}{m \times n} \displaystyle\sum_{(x,y)\in R} A_J^2(x,y) \\ M_J = \dfrac{1}{m \times n} \displaystyle\sum_{(x,y)\in R} \left\| A_J(x,y) \right\| \\ e_J = \dfrac{1}{m \times n} \displaystyle\sum_{(x,y)\in R} A_J(x,y) \log_2(A_J(x,y)) \\ H_J = \dfrac{1}{m \times n} \displaystyle\sum_{(x,y)\in R} \dfrac{A_J(x,y)}{1+|x-y|} \end{cases} \tag{5}$$

With E_J, M_J, e_J and H_J respectively energy, mean, entropy and homogeneity (Table 1).

The local energy and mean was applied in standard FCM and all the feature was used in the new FCM approach.

2.2.3 The framework of the new approach development

2.2.3.1 FCM objective function

Let I and monochromatic image of size *M*x*N*, the objective function for partitioning intensity value $\{h_i, i = 1, 2, ... n\}$ of all pixel into c cluster is given by [12]:

$$J_f = \sum_{j=1}^{c} \sum_{i=1}^{n} [\mu_j(h_i)]^m \left\| h_i - v_j \right\|^2 \tag{6}$$

Where $n = MxN$ is a number of pixel, $m \succ 1$ is a constant that control fuzzy degree of cluster results, $\{v_j, j = 1, 2, ... c\}$ are the prototype of the cluster and the array $[\mu_{ij}]$ represents the partition matrix satisfying:

$$\begin{cases} 0 \prec \mu_{ij} \prec 1, \forall i, j \\ \sum_{j=1}^{c} \mu_{ij} = 1, \forall i \\ 0 \prec \sum_{i=1}^{n} \mu_{ij} \prec n, \forall j \end{cases} \tag{7}$$

The minimum value of J_f, is given by [23]:

$$\mu_j(h_i) = \frac{1}{1 + \sum_{k=1}^{c} \left(\left\| \frac{h_i - v_j}{h_i - v_k} \right\| \right)^{\frac{2}{m-1}}_{k \neq j}} \quad j = 1,2,\ldots\ldots c \ ; \ i = 1,2,\ldots\ldots n \tag{8}$$

$$v_j = \frac{\sum_{i=1}^{n} [\mu_j(h_i)]^m h_i}{\sum_{i=1}^{n} [\mu_j(h_i)]^m}, \qquad j = 1,2,\ldots\ldots c \tag{9}$$

Segmentation by FCM, consisted of compute out ($\mu_j(h_i)$), $(\forall j, i)$) from Eq. (8), and changed cluster centre according to computed results and Eq. (9), repeated until ($\mu_j(h_i)$), $(\forall j, i)$) is changeless [23].

FCM algorithm is high computing time related to the use of all data while clustering.

2.2.3.2 FCM Based on Spatial Transformation (FCM_ST)

Because they depend only on intensity values $\{h_i, i = 1,2,\ldots\ldots n\}$, spatial transformation is given in simplified form as:

$$s_i = T(h_i) \tag{10}$$

Where T is an operator defined in a single intensity value h_i and s_i is the output processed image.

Operator T , which transforms h_i to s_i related to Eq. (10) must be able to reduce FCM iteration by making ($\mu_j(h_i)$), $(\forall j,i)$) rapidly changeless.

We proposed here a new and efficient spatial transformation approach define by the following mathematical model:

$$s_i = T(h_i) = \sum_{\alpha=1}^{p} [h_i]^{\alpha} \tag{11}$$

Where p is an integer

Substituting h_i into Eq. (8) by the mathematical model from Eq. (11) we obtain:

$$\mu_j(h_i) = \frac{1}{1+\sum_{k=1}^{c}\left(\frac{\left\|\sum_{\alpha=1}^{p-1}[h_i]^{\alpha}+([h_i]^{p}-v_j)\right\|}{\left\|\sum_{\alpha=1}^{p-1}[h_i]^{\alpha}+([h_i]^{p}-v_k)\right\|}\right)^{\frac{2}{m-1}}_{k\neq j}} \quad j=1,2,\ldots\ldots c\ ;\ i=1,2,\ldots\ldots n \tag{12}$$

For a high value of P, while computing we have:

$$\begin{cases} \left\|[h_i]^{p}-v_k\right\| \approx [h_i]^{p} \\ or & (\forall i,k) \\ \left\|[h_i]^{p}-v_k\right\| \approx v_k \end{cases} \tag{13}$$

Using (13) in Eq. (12) we see that, depending on the value of P, iteration number is reduce and ($\mu_j(h_i)$), $(\forall j,i)$) is rapidly constant.

2.2.4 Applying the new method in the grain mixture control

2.2.4.1 Clustering and segmentation algorithm

The FCM_ST algorithm for segmenting the acquired grain image into different clusters can be summarized in the following steps:

Step 1) Fixe value of parameter m, c , ε and select initial class prototypes $\{v_j\}_{j=1}^{c}$
Step 2) Apply spatial transformation using Eq. (11)
Step 3) Apply discrete wavelet transform
Step 4) Apply feature characterization using Eq. (5)
Step 5) Update the partition matrix using Eq. (8)

Step 6) The new prototypes of the clusters are obtained using Eq. (9)
Step 7) Repeat Steps 3)–6) till termination and good clustering. The termination criterion is as follows:

$$\left\| v_{new} - v_{old} \right\| \prec \varepsilon \tag{14}$$

Step 8) Label each cluster obtained

2.2.4.2 Grain mixture control

After clustering the acquired image, the partition matrix is labelled. The number of cluster must be chosen as we can label the image background, label grains references (red beans) and the grains inspection image.

Then, the number of each pixel with same intensity labelling value can be found. The red beans, placed at both ends of two straight lines (Figs. 2a and b) used as a reference, can be evaluated using intensity labelling value and approximate surface of one bean. In this way the other seeds that must parade can be detected by their pixel intensity labelling value. The decision of the presence or not of other seeds varieties is taken by using Eq. (15):

$$Al_i = \frac{Total \quad of \quad pixel \quad with \quad labelling \quad value \quad (i)}{Total \quad pixel \quad of \quad one \quad grain} \tag{15}$$

The percentage of grains of cluster (i) in the acquired red beans image is given by Eq. (16):

$$P_i = \frac{Al_i}{\sum_{i=1}^{c-1} Al_i} \times 100 \tag{16}$$

With c the number of cluster

The detections accuracies (Fig. 4) is given by:

$$DA = \frac{P_i}{P_m} \times 100 \tag{17}$$

Where P_i is the percentage of the presence of other grains (result of machine vision inspection) given by Eq. (16) and P_m the percentage of other beans result of visual examination.

3 Results and Discussion

3.1 Results

The new approach has used the discrete wavelet to reduce noise. Discrete wavelet decomposition with Biorthogonal 3.3 gives best result in level 2 (J=2). We used feature extraction in a square region R with 3 by 3 window, throughout this work. The mathematical model of the new approach, presented by Eq. (11), has given best result (low computing time and best segmentation) for FCM clustering than the classical model.

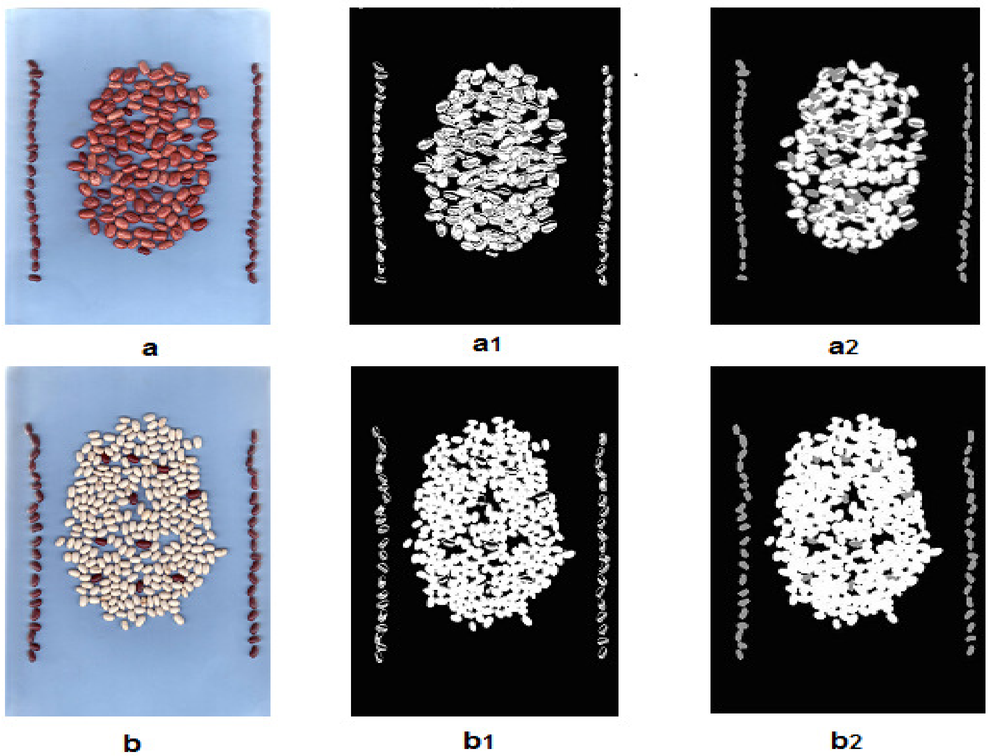

Fig. 2. FCM segmentation: (a) original image of multi-coloured beans, (b) self- coloured beans, (a1) and (b1) FCM with energy feature, (a2) and (b2) FCM with new approach

The RGB space was the best space as described by [20], for clustering algorithm of acquired beans image. The parameters were set; m=2, the number of cluster c=3 (for the acquired image background, the reference red beans and the inspecting grains).

The grain mixture inspection results are given in (Figs. 3a.3, 3b.3, 3c.3, 3d.3 and 3.e3) respectively for self-coloured beans, defected cotyledon, desired red beans, broken beans and MAC 55. The detections accuracies (Eq. (17)) results is given in (Fig. 4).

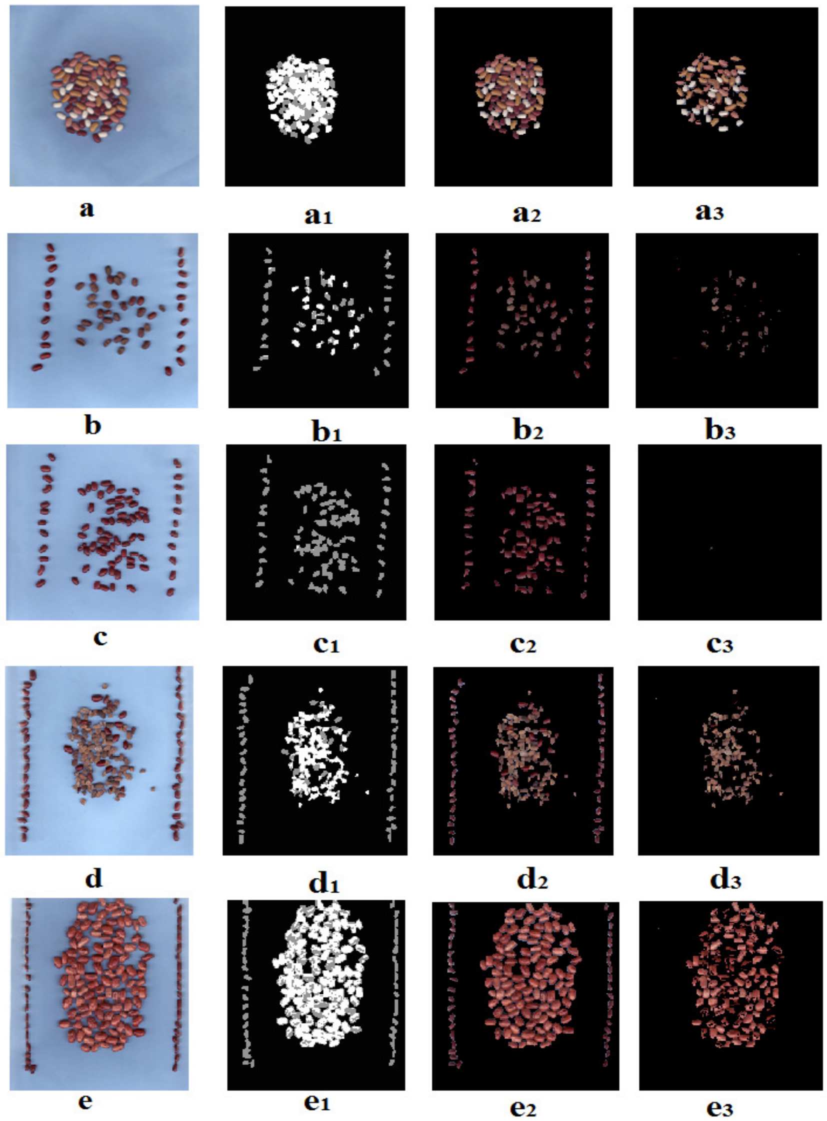

Fig. 3. Grain mixture control: (a,b,c,d,e) original image respectively of self-coloured beans, defected cotyledon, desired red beans, broken pulses and MAC 55; (a1, b1, c1, d1, e1) segmented image; (a2, b2, c2, d2, e2) after labialization; (a3, b3, c3, d3, e3) detected mixture grain

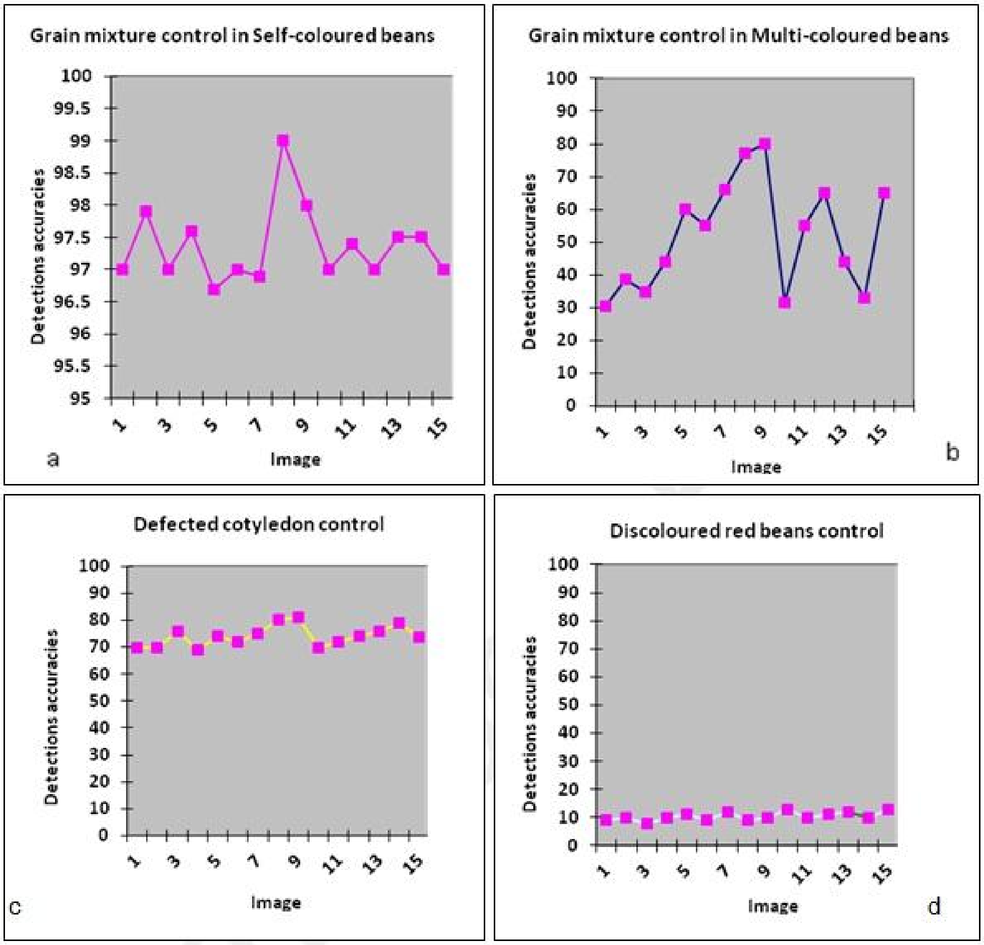

Fig. 4. Detections accuracies (a,b,c,d) for each of the 15 images results were obtained applying FCM_ST with biorthogonal 3.3 and mean feature in selected size image (521x426)

The percentage of mixture grains (Table 1) in the acquired image has used two clusters (c-1) in Eq. (16) for the label grains references and the inspecting grains, because the third cluster is the acquired image background.

Table 1. Classification and inspection red beans models

(m=2, c=3, $\varepsilon = 10^{-4}$, J^2=2, image size=2504x3468)

Grain type	Samples beans	*FCM with median*		*FCM with energy*		*FCM with spatial transformation*				
		Clustering time	P_i (%)	**Clustering time**	P_i (%)	**Clustering time**	e_J P_i (%)	H_J P_i (%)	E_J/M_J P_i (%)	**VE**[3] P_i (%)
Self-coloured	MEX 142	88s	No cluster	88s	56%	31s	61%	61,1%	61,5%	62,9%
	LUNDAMBA	84s		84s	34,4%	28s	43,7%	43,5%	44%	46,03%
	K26-35CFM	87s		87s	30,5%	31s	48,1 %	48,5%	50,5%	53%
Multi-coloured	TY33	97s	No cluster	97s	50%	28s	33%	29%	30%	89%
	ECAPAN021	84s		84s	21%	34s	19%	19,3%	21%	66%
	MAC55	88s		88s	56%	38s	53%	53 ,1%	54,5%	66%
Defect	DEFECTED Cotyledons	97s	No cluster	97s	28,1%	28s	29%	31%	31,5%	40%
	BROKEN pulses	97s		97s	51%	28s	48,5%	49%	48,4%	75%[4]
	Discoloration (Hard-to-Cook)	88s		88s	3.7%	38s	3,1%	3,4%	4,9%	41%

[2]*Level of the discrete wavelet decomposition of the input image*

[3]*Visual Examination*

[4]*The broken pulses not have same size as the normal red beans and make* P_m *evaluation difficult*

3.2 Discussion

3.2.1 The choice of materials and the method of analysis

3.2.1.1 The choice of flatbed scanning system

The flatbed scanning system is low cost and has been widely applied in the development of image libraries [24,25,26].

The choice of scanner is done on an experimental basis in order to facilitate the image quality acquisition to optimize a better evaluation of the new approach developed here.

3.2.1.2 The choice of Fuzzy clustering for grain mixture control

In a control system for compliance Codex Alimentarius physical characteristics of the beans, the unsupervised application, efficiency, robustness evaluation and low processing time is a very critical parameter since the quantities of seeds contained in the package can reach many tons in weight.

The FCM is an unsupervised method which can use cluster to access food quality evaluation [15], [27].

The proposed analysis procedure allows the acquisition and unsupervised evaluation in a single frame from a large number of seeds in the control of compliance with their physical parameters. More than 1000 seeds can be physically analyzed in each digital image, and the method allows an optimal analysis and performance of seeds.

Its high classification compared to the usual FCM is an indicator that bespeaks the power of the new approach can control cheating in the said packaging bags in our markets. This will optimize the inspecting of seeds (for grain mixture control) since the computing time of the inspecting seeds (in thousands) will be greatly reduced (better than inspecting beans by scrolling them seed after seed), if they are simultaneously analyzed on a wide conveyor belt.

3.2.1.3 The choice of wavelet analysis

Wavelet analysis of the signals from many sensors has shown promising results for quality inspection of agricultural and food products [28,29,30,31,32]. It allows space intervals where we want more precise low-frequency information, and shorter regions where we want high-frequency information wavelet [21,33] indicated the capability of wavelet in denoising the spectral signal.

3.2.2 The framework of the new approach in the fast clustering time

Segmentation of beans is steal a challenge related to their complexity [34]. Proposed some approach based on a self–organizing map neural network and fuzzy c–means clustering (SOM_FCM) for edible beans. The segmentation accuracies was 99.31% and the SOM_FCM approach was long computing time related to the use of neural network. In fact the neural network algorithm takes a lot of memory and may take minutes, hours, days and even longer before the network converges to the optimal point [35,36].

Considerable work has been done in designing efficient approach for fast FCM segmentation [37,38].

Pixels misclassification occurred with cluster analysis can be solved by image transformation [39] and must approach consist of spatial domain analysis [38,40,41]. The spatial domain processing can use intensity transformation [39] and the FCM with spatial analysis has been used with partition coefficients and partition entropy [40], kernel induce distance measure with spatial constraints [41], gray histogram of image [42].

All those FCM algorithms with spatial analysis do not take direct intensity transformation as described in Eq. (11). The new approach increases the distance between the intensity of image and the value of the centre of the clusters (Eq. (13)). This approach which is a mathematical model to minimize FCM iteration, is a new one in the useful spatial FCM analysis.

The new approach for the same time of computing gives higher rate classification than the FCM segmentation with energy (Table 1).

3.2.3 Effect of the new approach in grain mixture control

The percentage of grain mixture in the packaging quality control depends on the best clustering relate to Eq. (15) and Eq. (16). Every misclassified pixel reduces the quality of result and that justified the inability of the classical FCM to facilitate grain mixture control.

The results (Fig. 4), demonstrated that FCM_ST is a promise technique for efficient and effective detection of self-coloured beans ($DA \geq 0.96$). Also $Pi \approx 0$ (the presence of other grains given by Eq. (16)) when desired red beans (self-coloured) is inspected (Fig. 3c.3). For beans of a similar colour but a different commercial type (multi-coloured), detections accuracies depend on texture beans ($0.3 \leq DA \leq 0.89$) and for defected cotyledons detections accuracies was between 70% to 80%. But it gives power information for low discolourated red beans ($0.1 \leq DA \leq 0.15$).

4. Conclusion

Based on the fast classification, the proposed new method uses fuzzy c-means clustering combines with spatial transformation, for the packed red beans control. It reduces FCM iteration by using spatial transformation to increase the distance between pixels and centre of classes. Experimental results are an indicator that the new method is a promise tool for bag packaging control of red dry beans based on image inspection to improve their market values.

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Competing Interests

Authors have declared that no competing interests exist.

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