

Quality inspection of bag packaging red beans (*Phaseolus vulgaris*) using fuzzy clustering algorithm

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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 approach for fast quality control of bag packaging red beans (*Phaseolus vulgaris*) using flatbed scanning. The proposed approach combines fuzzy c means with spatial transformation (FCM_ST) to reduce FCM iteration. We used the labeled 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 surprisingly 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 depend on their texture and between 10% to 15% with presence of low discoloured red beans of same commercial type.

Keywords: Packaging red beans (*Phaseolus vulgaris*), Fuzzy logic, Wavelet transform, Quality control.

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] (Hyde et al., 1973). 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], [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 own 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 neighbor pixels and spatial information of image [17].

It is in this context that we analyzed in this paper the contributions of a new approach 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 (CoreDuo 2.1 GHz, 3GB RAM, 300GB HDD) and the IRAD¹ 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 (Fig. 3.a 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 (Fig. 2.a and b) for the reception of lots of beans to be analyzed.

2.2.2 Texture analysis and feature extraction

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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 $f(x) \in L^2(R)$ with respect to the mother wavelet can be expressed as:

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

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

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

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 used to coverage time frequency plane (Fig. 1). Therefore, the dilatation parameter ' a ' and the translate parameter ' b ' is taken from the following relation:

$$\begin{cases} a = a_0^m \\ b = nb_0 a_0^m \end{cases} \quad (3)$$

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 :

$$C = \{A_1, (d_1^h, d_1^v, d_1^d)\} \quad (4)$$

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.

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:

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

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

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

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112 2.2.3 The framework of the new approach development

113 **2.2.3.1 FCM Objective Function**

114 Let I and monochromatic image of size $M \times N$, the objective function for partitioning intensity value
115 $\{h_i, i = 1, 2, \dots, n\}$ of all pixel into C cluster is given by [12]:

$$116 \quad J_f = \sum_{j=1}^c \sum_{i=1}^n [\mu_j(h_i)]^m \|h_i - v_j\|^2 \quad (6)$$

117 Where $n = M \times N$ is a number of pixel, $m > 1$ is a constant that control fuzzy degree of cluster results,
118 $\{v_j, j = 1, 2, \dots, c\}$ are the prototype of the cluster and the array $[\mu_{ij}]$ represents the partition matrix
119 satisfying:

$$\begin{cases}
0 < \mu_{ij} < 1, \forall i, j \\
\sum_{j=1}^c \mu_{ij} = 1, \forall i \\
0 < \sum_{i=1}^n \mu_{ij} < n, \forall j
\end{cases} \quad (7)$$

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

122

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

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

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

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

128 2.2.3.2 FCM Based on Spatial Transformation (FCM_ST)

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

$$s_i = T(h_i) \quad (10)$$

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

133 Operator T , which transforms h_i to s_i related to Eq. (10) must be able to reduce FCM iteration by making
 134 $(\mu_j(h_i))$, $(\forall j, i)$ rapidly changeless.

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

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

138 Where p is an integer

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

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

$$\text{For a high value of } P, \text{ while computing we have: } \begin{cases} \| [h_i]^p - v_k \| \approx [h_i]^p \\ \text{or} \\ \| [h_i]^p - v_k \| \approx v_k \end{cases} \quad (\forall i, k) \quad (13)$$

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 approach 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 , $\mathcal{E}$, 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:

$$\|v_{new} - v_{old}\| \prec \mathcal{E} \quad (14)$$

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 (Fig. 2.a 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):

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

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

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

With c the number of cluster

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

$$DA = \frac{P_i}{P_m} \times 100 \quad (17)$$

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.

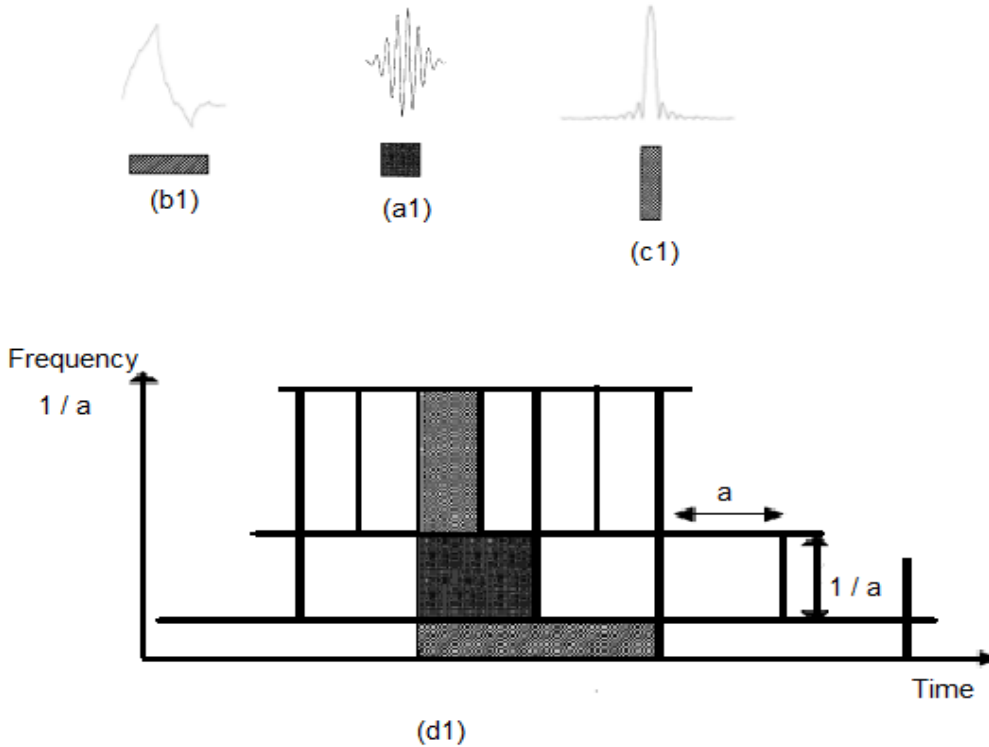


Fig. 1. Multiresolution analysis: (a1) Basis function, (b1) Scaling function, (c1) Wavelet function, (d1) Coverage of time frequency plane

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.

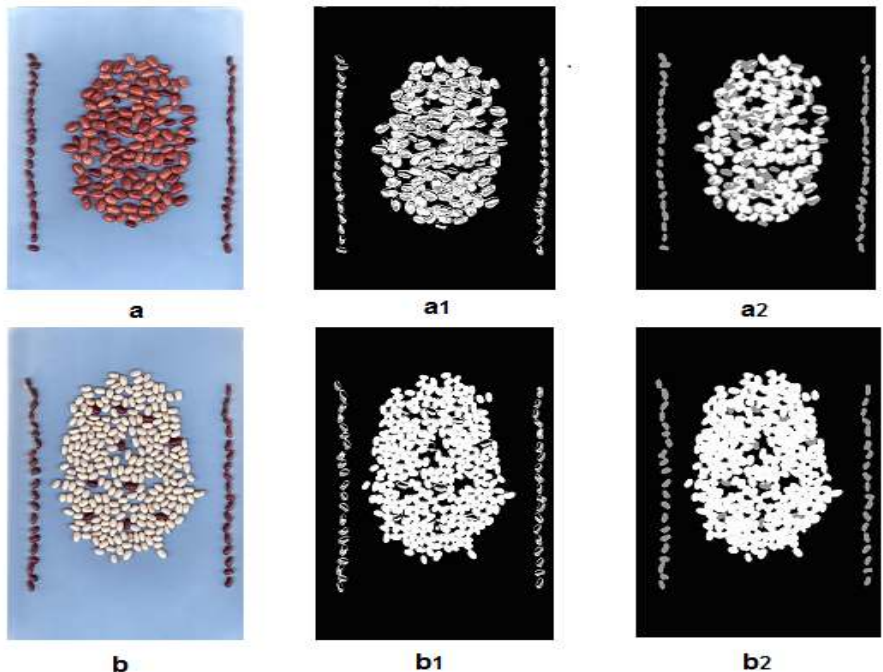


Fig. 2. FCM segmentation: (a) original image of multi-coloured beans, (b) self- coloured beans, (a1) and (b1) FCM with energy feature, (a2) and (b2) FCM with new approach

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 Fig. 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.

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.

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

201 The flatbed scanning system is low cost and has been widely applied in the development of image libraries [24],
202 [25], [26].
203 The choice of scanner is done on an experimental basis in order to facilitate the image quality acquisition to
204 optimize a better evaluation of the new approach developed here.
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209 **3.2.1.2 The choice of Fuzzy clustering for grain mixture control**

210 In a control system for compliance Codex Alimentarius physical characteristics of the beans, the unsupervised
211 application, efficiency, robustness evaluation and low processing time is a very critical parameter since the
212 quantities of seeds contained in the package can reach many tons in weight.
213 The FCM is an unsupervised method which can use cluster to access food quality evaluation [15], [27].
214 The proposed analysis procedure allows the acquisition and unsupervised evaluation in a single frame from a
215 large number of seeds in the control of compliance with their physical parameters.
216 More than 1000 seeds can be physically analyzed in each digital image, and the method allows an optimal
217 analysis and performance of seeds.
218 Its high classification compared to the usual FCM is an indicator that bespeaks the power of the new approach
219 can control cheating in the said packaging bags in our markets. This will optimize the inspecting of seeds (for
220 grain mixture control) since the computing time of the inspecting seeds (in thousands) will be greatly reduced
221 (better than inspecting beans by scrolling them seed after seed), if they are simultaneously analyzed on a wide
222 conveyor belt.
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224 **3.2.1.3 The choice of wavelet analysis**

225 Wavelet analysis of the signals from many sensors has shown promising results for quality inspection of
226 agricultural and food products [28], [29], [30], [31], [32]. It allows space intervals where we want more precise low-
227 frequency information, and shorter regions where we want high-frequency information wavelet [21].
228 [33] indicated the capability of wavelet in denoising the spectral signal.
229

230 3.2.2 The framework of the new approach in the fast clustering time

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

236 Considerable work has been done in designing efficient approach for fast FCM segmentation [37], [38].
237 Pixels misclassification occurred with cluster analysis can be solved by image transformation [39] and must
238 approach consist of spatial domain analysis [38], [40], [41]. The spatial domain processing can use intensity
239 transformation [39] and the FCM with spatial analysis has been used with partition coefficients and partition
240 entropy [40], kernel induce distance measure with spatial constraints [41], gray histogram of image [42].
241 All those FCM algorithms with spatial analysis do not take direct intensity transformation as described in Eq. (11).
242 The new approach increases the distance between the intensity of image and the value of the centre of the
243 clusters (Eq. (13)). This approach which is a mathematical model to minimize FCM iteration, is a new one in the
244 useful spatial FCM analysis.
245 The new approach for the same time of computing gives higher rate classification than the FCM segmentation
246 with energy (table 1).

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248 3.2.3 Effect of the new approach in grain mixture control

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

252 The results (Fig. 4), demonstrated that FCM_ST is a promise technique for efficient and effective detection of self-
253 coloured beans ($DA \geq 0.96$). Also $P_i \approx 0$ (the presence of other grains given by Eq. (16)) when desired red
254 beans (self-coloured) is inspected (Fig. 3c.3). For beans of a similar colour but a different commercial type
255 (multi-coloured), detections accuracies depend on texture beans ($0.3 \leq DA \leq 0.89$) and for defected cotyledons
256 detections accuracies was between 70% to 80%. But it gives power information for low discoloured red beans
257 ($0.1 \leq DA \leq 0.15$).
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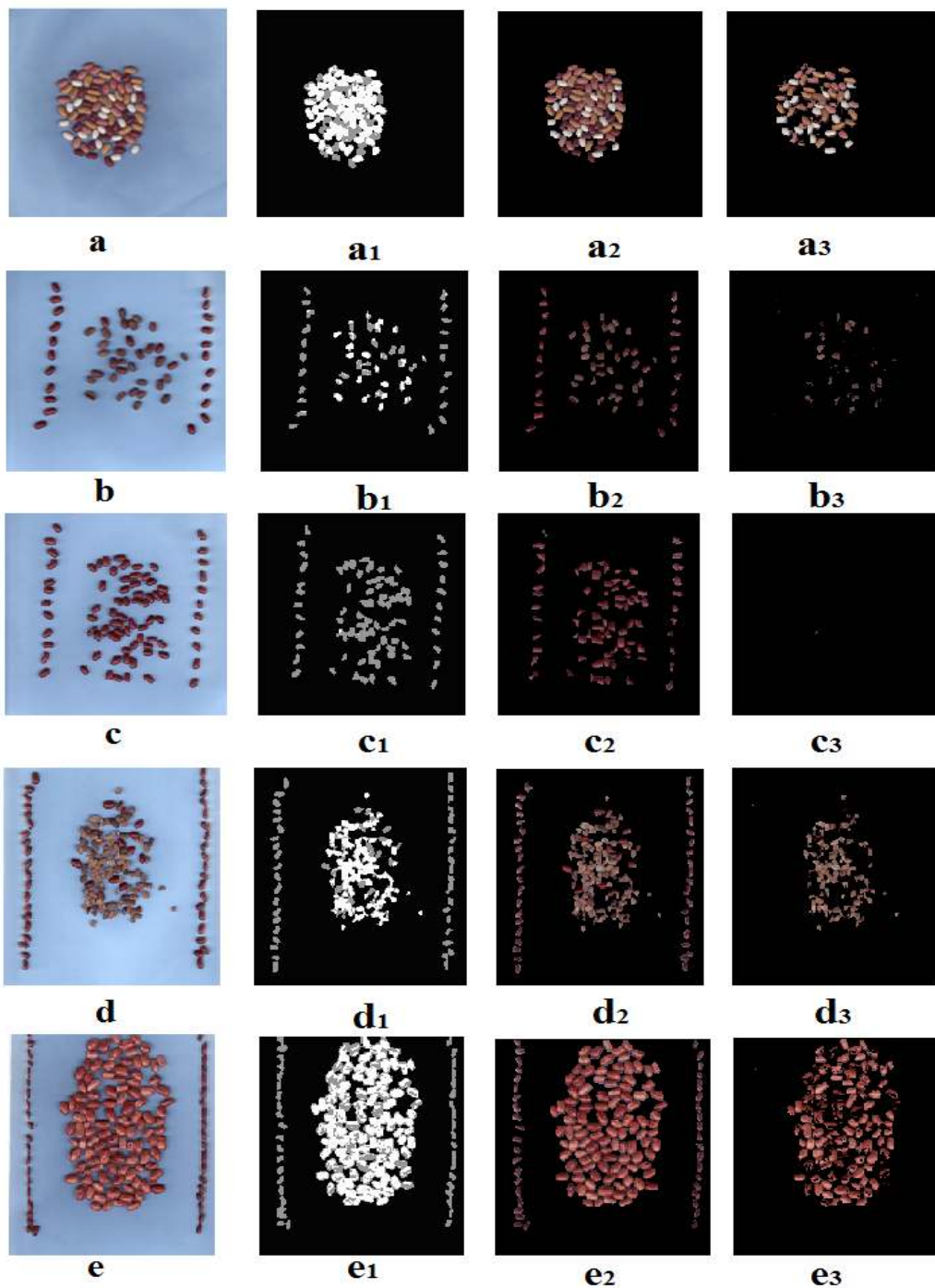


Fig. 3. Grain mixture control: (a,b,c,d,e) original image respectively of self-coloured beans, defected cotyledon, desired red beans, broken pulses and MAC 55; (a1, b1, c1, d1, e1) segmented image; (a2, b2, c2, d2, e2) after labialization; (a3, b3, c3, d3, e3) detected mixture grain.

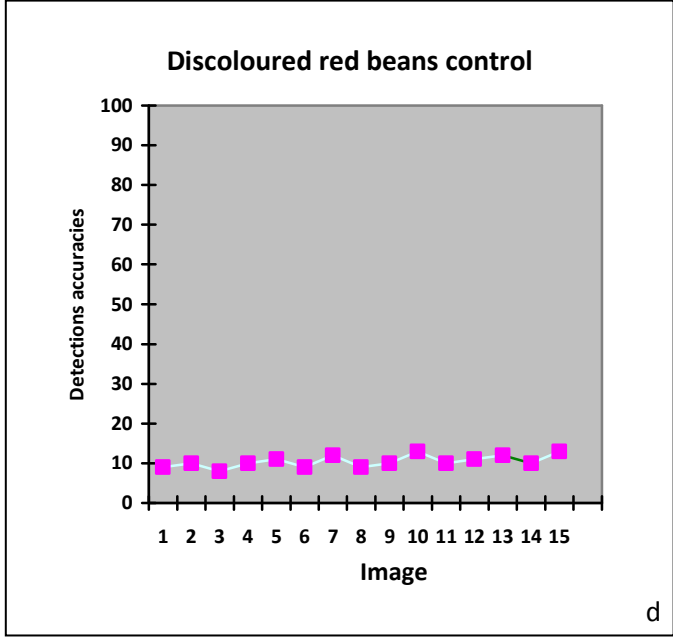
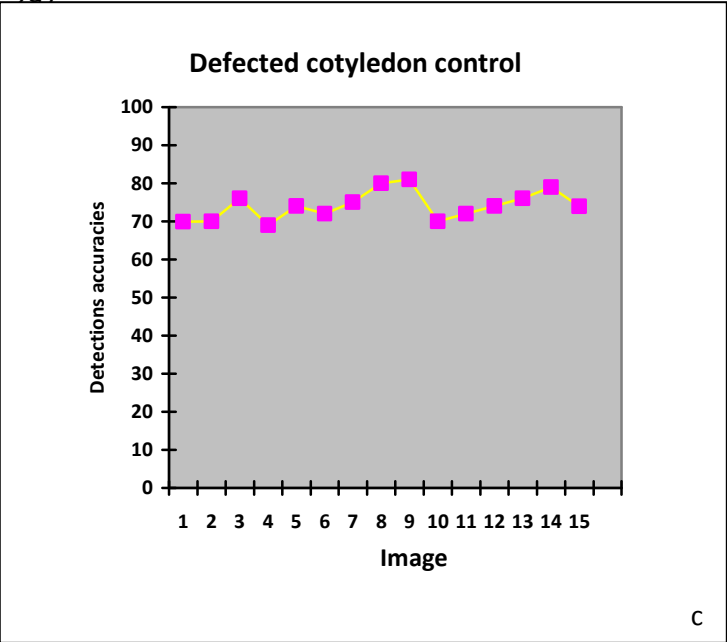
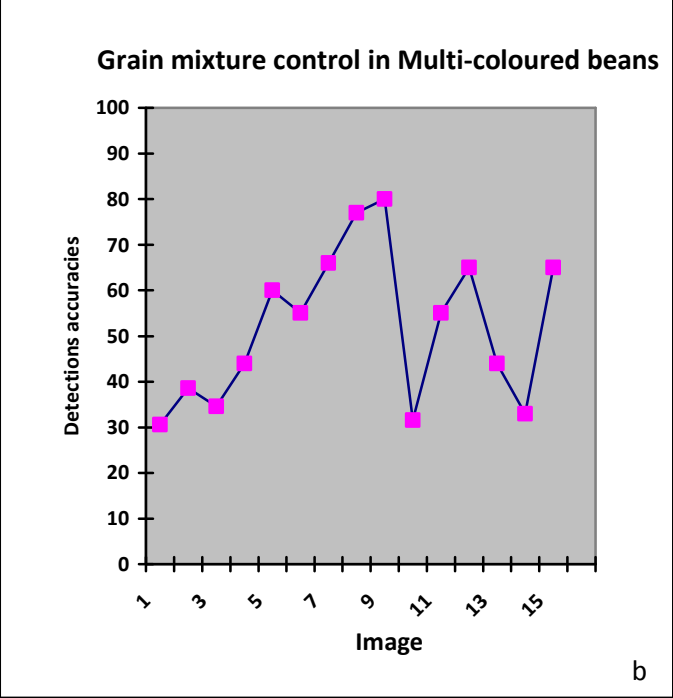
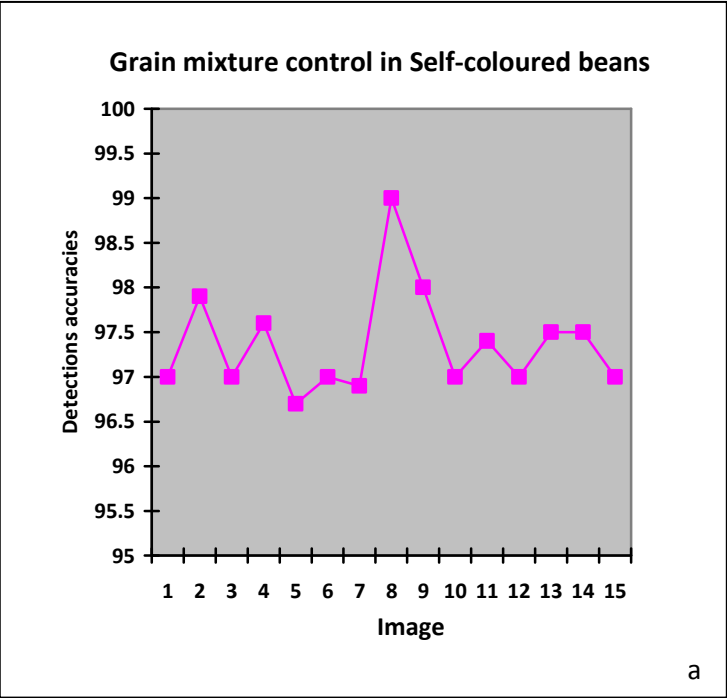


Fig. 4. Detections accuracies (a,b,c,d) for each of the 15 images results were obtained applying FCM_ST with Biorthogonal 3.3 and Mean feature in selected size image (521x426)

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%

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324 4. CONCLUSION

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

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

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