British Journal of Applied Science & Technology
2(2): 96-111, 2012

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Color and Texture Information Processing to Improve Storage Beans

Ngatchou Alban[1,2*], Bitjoka Laurent[2], Boukar Ousman[2], and Tonye Emmanuel[3]

[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, University of Ngaoundéré, P. O. Box 455, Ngaoundéré, Cameroon.
[3]National School of Engineering, Electronics and Signal Processing Laboratory (LETS), University of Yaoundé 1, P. O. Box 8390, Yaoundé, Cameroon.

Research Article

Received 25th August 2011
Accepted 11th January 2012
Online Ready 27th March 2012

ABSTRACT

Aims: This paper attempts to improve automatic temporal change detection on a pair of beans images, acquired before and after storage under high temperature (≥ 25°C) and high relative humidity (≥ 65%), conditions that promote « Hard-To-Cook » phenomenon.
Study Design: Image processing, Hard-To-Cook beans**.**
Place and Duration of Study: Laboratory of Modelisation, Image Processing and Applications Research (MOTRIMA) Department of Electrical Engineering Energetic and Automatics, Laboratory of Biophysics and Food Biochemistry Department of Food Science and Nutrition of National School of Agro-Industrial Sciences (University of Ngaoundéré, Cameroon), Institute of Agricultural Research for Development (IRAD) between August 2009 and March 2010.
Methodology: We want to get a robust extracting seed in acquired images and a good dissimilarity parameter for temporal change detection on a pair of textured images. To reach this goal, we analyze the characterization of textural properties and space color which are more relevant to textured beans seeds. We use wavelet transform and apply fuzzy logic segmentation. We define a confidence limit for the dissimilarity parameter before analyzing its evolution during storage of beans seeds. Finally we correlate this parameter with another Hard-To-Cook indicator.

**Corresponding author: E-mail: ngatchou_alban@yahoo.fr;*

Results: After many tests, Daubechies 2(db2) wavelet family in RGB space allowed best extracting beans seeds in scene with fuzzy-c-means segmentation. The global intensity variation was a pertinent parameter for dissimilarity detection between two images. We obtained highly correlation between this parameter and cooking times beans (-0.96; -0.88; -0.72 respectively in Red, Green and Blue color space).

Conclusion: The global intensity variation in red color space allowed the determination level of browning beans seeds as indicator of their Hard-To-Cook degree.

Keywords: Texture and color image processing; wavelet transform; global intensity variation; ECA PAN 019 beans (Phaseolus vulgaris); hard-to-cook; fuzzy logic image segmentation.

1. INTRODUCTION

Storage of beans seeds in warm temperatures (≥ 25° C) and high humidity (≥ 65%), which are actual conditions of the tropics, reduced quality of the protein (Stanley and Anguila 1985) and depressed their economic value because of the increased energy requirements for cooking. The beans do not soften during cooking which is as a result of the fact that the do not absorb much water. This is referred scientifically as the Hard-To-Cook phenomenon (Kilmer et al., 1994).

The Hard-To-Cook beans, was evaluated by sensory analysis (with significant differences between taste panel) and also by the Mattson bean cooker (1946), using the cooking times as an indicator.

A potential drawback of these techniques which is the destruction of beans sample, has been reduced recently by digital image processing methods using color histogram (Bitjoka *et* al., 2010).

In fact, there is a link between the quality cooking, browning and hardness of beans (Vindiola et al., 1986; Cabrejas et al., 1997; Bitjoka et al., 2010) which basically justified the assumption used in the color histogram methods to assess Hard-To-Cook beans. The fact that both images of beans seeds (taken before and after storage) have different parameters has helped to conclude that the color histogram can detect changes during storage of beans in tropical area conditions. The color histogram uses descriptors that characterize the color distribution in an image (Manjunath et al., 2001) but is not effective in the textured image (Tonye et al., 2000).

The detection of temporal change on a pair of images has been developed in a non variation of the scene other than the location changes. This approach required a good spatial segmentation (Keith and Reddy, 1977) or spatial frequency representation (in the case of moving images). Dane and Ying Sun (1994) provide image analysis by K-means segmentation. In fact, segmentation algorithm performance is linked to the variability of the attributes and the risk of error representation in images. Olivier Desprez et al. (1997) used an operator based on principal component analysis of the spatio-frequential attributes extracted from Walsh-Hadamard analysis in sequential representation, to solve it. Among the spatial-frequency analysis, the wavelet approach which gives an excellent way to decompose a signal in different sub-bands in which it is easier to characterize image, is the best texture descriptor (Kechida et al., 2005).

The basic idea of this work is to try to use the wavelet transform family in RGB space color for good segmentation which well allows the extraction of seed beans in a scene. The choice of best fit parameters of dissimilarity to the detection of spatial change without perfect matches in the two images of beans (before and after storage) helped for the good correlation with another Hard-To-Cook indicator. This technique is applied to control the browning of textural beans stored, under the conditions prevailing in tropical area. This enters in a global aim to predict by video monitoring the degree of hardness of the beans to maintain their marketability in the post-harvest conservation in tropical condition (warm temperature and high humidity).

2. MATERIALS AND METHODS

The camera (Fujifilm FinePix F480) and a light box (Silvania 50-60Hz, 220V, 36W) were the same as those used (Figure 1) by Bitjoka et al. (2010).

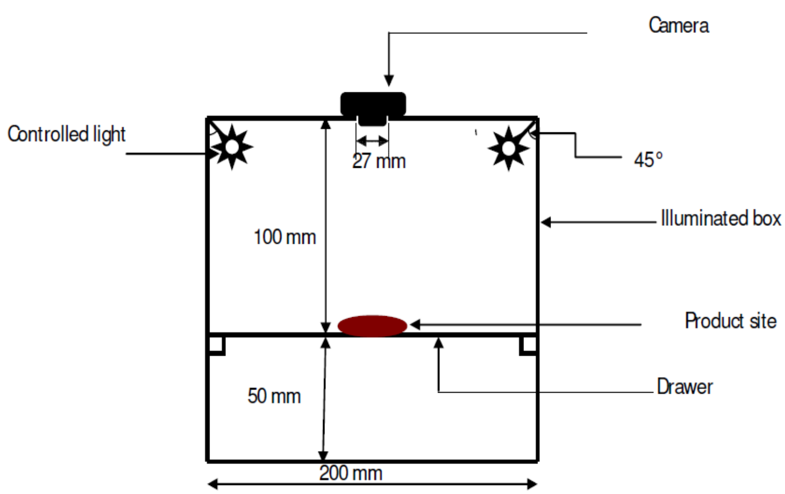

Figure 1. Set up of images capturing

Freshly harvested beans "Phaseolus vulgaris", used here, were obtained from IRAD[1]. Sub-sample of 32 dry beans were selected and grouped to four in a net. The eight packets are stored in a drying oven (temperature: 60° C, relative humidity 65-70%) to accelerate the development of hard-to-cook beans condition (Vindiola et al., 1986). Packets of beans seeds were removed carefully, one by one, after 3, 4, 5, 7, 8, 9, 12, 15 days of storage. The image of four beans seeds, storage in the same period, was captured in the two faces before and after storage and no seed was returned to the drying oven.

After the segmentation by fuzzy c-means algorithms, the dissimilarity of the two images of the beans seeds was analyzed (before and after storage) and this by ensuring the facial perfect match. Performance attributes of dissimilarity were analyzed in four beans seeds that

[1] Institute of Agricultural Research for Development

have undergone the same storage condition. The coefficient of variation was used to check the power of the attributes used to analyze the dissimilarity of the beans seeds. We can use this to check the relationship between storage time and the evolution of the texture color. Finally it was important to compare the results with existing methods for detecting hardness of the beans seeds as PC-Based Instrumentation system (Figure 2) (Bitjoka et al., 2008) to know the cooking time of each seed, indicator of the degree of softening. Figure 3 explains the general methodology of processing.

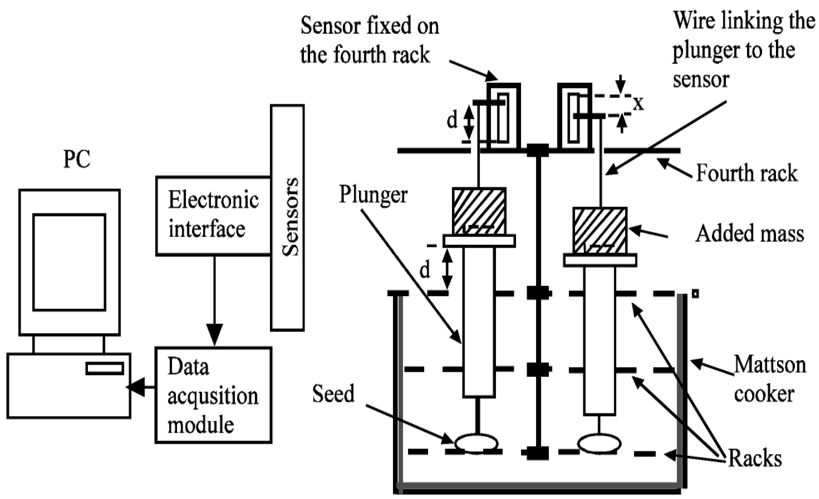

Figure 2. Schematic block diagram of PC-based bean cooker system

2.1 Texture and Color Characterization

2.1.1 Texture analysis

Textural feature, acquisition model of images and times computing algorithm determined choice of texture analysis methods. When digital images are to be viewed or processed at multiple resolutions, the wavelet is the mathematical tool of choice. The various wavelet transforms are related by the fact that their expansion functions are “smaller waves” (hence the name wavelets) of varying frequency and limited duration (Truchel et al., 1998).

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

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

where a, b $\in$ R. Parameter ‘a’ is the dilation or scaling factor, and parameter ‘b’ is called translation factor.

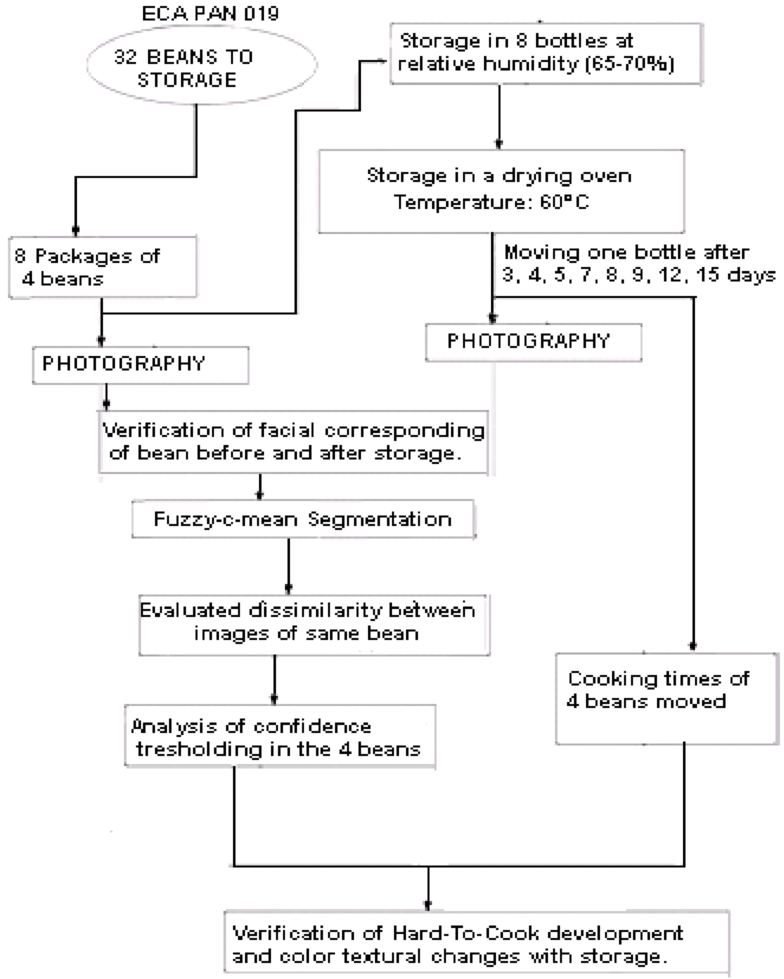

Figure 3. General methodology of processing

In digital image, wavelet can be characterized by transform kernel pair expressed as:

- $\psi^{H}(x, y) = \psi(x)\varphi(y)$
- $\psi^{V}(x, y) = \varphi(x)\psi(y)$
- $\psi^{D}(x, y) = \psi(x)\psi(y)$

Where $\psi^{H}(x, y)$, $\psi^{V}(x, y)$ and $\psi^{D}(x, y)$ are called horizontal, vertical and diagonal wavelets respectively, and one scaling function.

- $\varphi(x, y) = \varphi(x)\varphi(y)$

Scaling and wavelets functions respectively $\varphi(x)$ and $\psi(x)$ can be expressed as linear combinations of double-resolution copies of themselves via the filter coefficients (h_{φ}, h_{ψ}).

- $\varphi(x) = \sum h_{\varphi}(n)\sqrt{2}\varphi(2x - n)$
- $\psi(x) = \sum h_{\psi}(n)\sqrt{2}\varphi(2x - n)$

In fact, wavelet used filter bank to decompose the input image into four lower scale components. The Aj+1 coefficients (figure 4) are created, for the first iteration of the input image (Aj), via two lowpass (Lo_D-based) filter and are thus called approximation coefficient. The detail coefficients created are Horizontal (Hj+1) via lowpass (Lo_D-based) and highpass (Hi_D-based) filter, vertical (Vj+1) via highpass (Hi_D-based) and lowpass (Lo_D-based) filter, and diagonal (Dj+1) via two highpass (Hi_D-based) filters.

2.1.2 Color characterization

Color is one perceptual result of light in the visible range 400-700 (nm) incident upon the retina (Younès et al., 2007). It is perhaps the most expressive (Manjunath et al., 2001) of all the visual features in terms of family representation (figure 5). Color image processing also included convenient or appropriated color space choice. Lab is a perceptually uniform space used a single component to represent luminance information (L) and two components (a, b) to color-difference. HSV (Hue, Saturation, Value) perceptually space is based on cylindrical coordinates of color. RGB (Red, Green, Blue) primary space, is composed of three monochrome intensity images.

These color space participation in texture analysis is more used in classification and segmentation images.

2.2 Fuzzy-c-Means Segmentation

The objective of segmentation is to partition an image into regions. Segmentation was accomplished via texture feature extraction method and classification by fuzzy logic.

2.2.1 Texture attributes extraction

After decomposing the input image in lower resolution by wavelet transform in J level, the number of subband N=1+3J were used to rearrange the output of the filter bank into the N-component vector c.

$$c = \left\{a_J, \left(d_k^1, d_k^2, d_k^3\right),\ k = 1......J\right\}$$

With a_J approximation in lower resolution and d_k the subbands containing detail in different orientations. Texture characterized by considering local energy frequency or medium energy respectively E_J and M_J, measured around a pixel (x,y) was evaluated as follow:

$$E_J = \frac{1}{R}\sum_{(x,y)\in R} c^2(x,y)$$

$$M_J = \frac{1}{R}\sum_{(x,y)\in R} \left|c(x,y)\right|$$

The vector of local energy X or medium energy Y can be obtained according to:

X=($E_1, E_2, ... E_{3J+1}$) ;
Y=($M_1, M_2, ... M_{3J+1}$) ;

2.2.2 Classification by fuzzy-c-means

This approach is based on partitioning an image into regions that are similar according to a set of texture attributes criteria (energy or medium energy).

Fuzzy-c-means (FCM) algorithm measure distance between vector energy X and the prototypes clusters V:

$$D_{jk} = \left\|X_k - V_j\right\|^2$$

The standard FCM objective function for partitioning

$\{X_k\}_{k=1}^{N}$ into c clusters is given by (Mohamed et al., 2002):

$$J = \sum_{i=1}^{c}\sum_{k=1}^{N} \mu_{ik}^{P} \left\|X_k - V_i\right\|^2$$

Where $\{V_i\}_{i=1}^{c}$ are the prototypes clusters and the array $[\mu_{ik}]$ represents a partition matrix $\in U$ namely $U = \left\{ \mu_{ik} \in [0,1] \middle| \sum_{i=1}^{c} \mu_{ik} = 1, \forall\ k\ and\ 0 \prec \sum_{k=1}^{N} \mu_{ik} \prec N\ \forall\ i \right\}$

The parameter P is a weighting exponent on each fuzzy membership and determines the amount of fuzziness of the resulting classification. The FCM objective function must be minimized.

2.2.3 Fuzzy-c-means algorithm segmentation

Decompose the input image in lower resolution (with db2 wavelet).

Select the approximation image a_J and padding it.

Measure local energy X for a_J in each RGB plan with pixel-wise analysis.

Use the fuzzy parameters coefficient (m=2), number of classes c=3 and stop criteria ε (ε =0.0001).

Put counter at zero.

Take hazardous vector V with C centers.

Measure distance between X and the center of classes V.

$$D_{jk} = \left\| X_k - V_j \right\|^2$$

Construct and partition matrix U with size (C x n) by the following expression:

$$\mu_{ik} = \frac{1}{\sum_{j=1}^{c} \left(D_{jk} / D_{ik} \right)^{\frac{2}{m-1}}}$$

Measure the new center of V:

$$V_i = \frac{\sum_{i=1}^{n} (\mu_{ik})^m x_i}{\sum_{i=1}^{n} (\mu_{ik})^m}$$

Update the partition using matrix U and counter.

Evaluate the distance h between the last center and the update :

$$h = \left\| V^{t-1} - V^{t} \right\|^2$$

Repeat steps 3-10, while *h*>ε.

If result is not good, change vector X to medium energy Y at step 3 and repeat steps 3 to 12.
Else decompose the approximation image in lower resolution and repeat steps 2 to 12.

Take the RGB plan which give best result.

Apply inverse wavelet transform.

After segmentation, label image (figure 6).

2.3 Dissimilarity Measure

Dissimilarity measure is done in two images of same beans obtained at time t_0 and t_1 respectively before and after storage (figure 7).

We used the following parameters.

- Spectral energy for approximation image B (after segmentation).
  S = |B|²

- Global energy of image.

$$E = \sum_{i=1}^{N} \sum_{j=1}^{M} S(i, j)$$

Various techniques have been proposed to measure dissimilarity between two textural images B(M,N,t0) and B(M,N,t1) and the most efficient one is global intensity variation which can be evaluated by EQMI (Olivier Desprez and Eric Petit, 1997):

$$EQMI = \sqrt{\frac{1}{N \times M} \sum_{i=1}^{N} \sum_{j=1}^{M} \left[B(i, j; t_0) - B(i, j; t_1)\right]^2}$$

3. RESULTS AND DISCUSSION

3.1 Influence of Color Space and Texture Characterization

In addition to being efficient for the camera (CCD matrix) and the light box used (under unstable lighting condition), wavelet transform provides powerful insight into an image's spatial and frequency characteristics (Gonza et al., 2005). The interest to analyze the images with wavelet transform is the fact that it processes as human vision to preserve both locally and entirely the information (Havlicek et al., 1992) and essential information contained in the image lies in the evolution of their spatial and frequency characteristics. The significant image information is obtained in approximation coefficient. We realized more wavelet family test and Daubechies 2 gives best result (figure 4). The color system which is suited for describing colors in terms that are practical for human interpretation is the RGB space (figure 5).

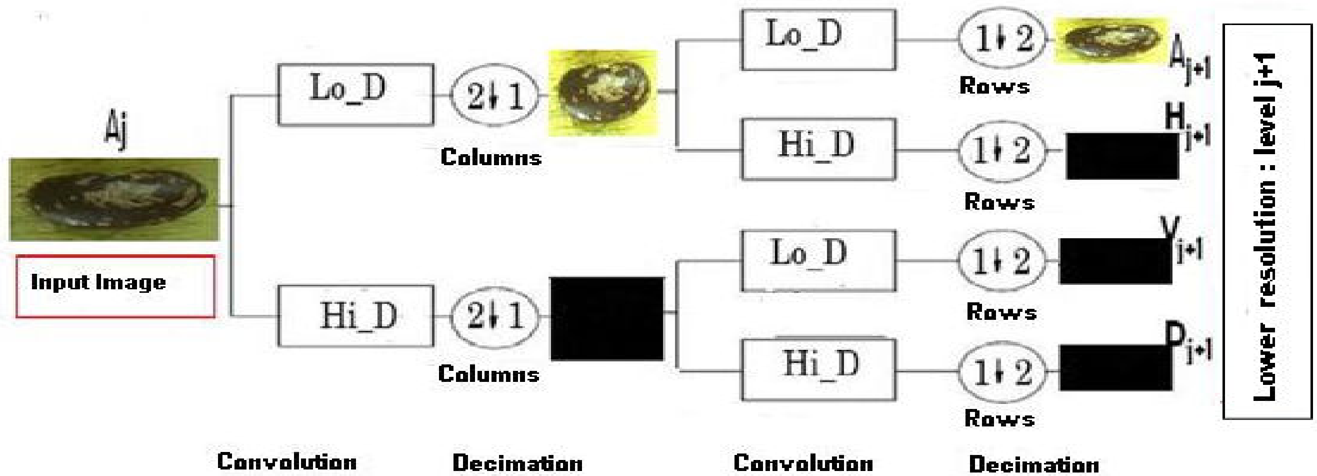

Figure 4. Wavelet transform (by Daubechies 2 wavelet)

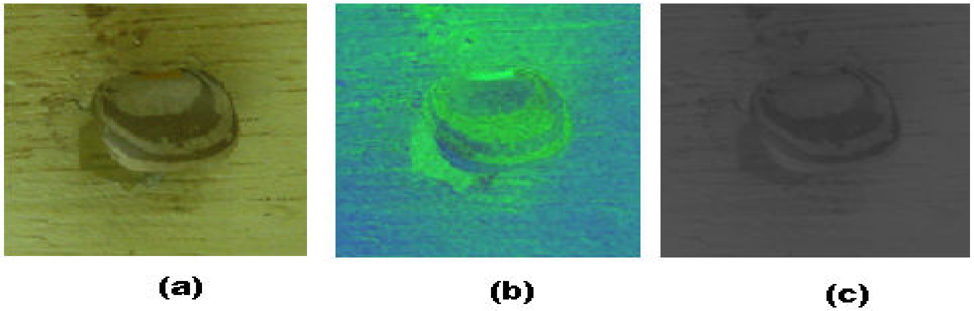

Figure 5. Color space representation: (a) RGB, (b) HSV, (c) Lab

3.2 Implementation of The Texture Feature Extraction Method

If wavelet transform has the ability to decompose the image into two bands (high and low frequencies), Daubechies 2 wavelet which has the advantage of a cost savings calculation (Mohamed et al., 2002) has proven to be effective in the fuzzy-c-means segmentation and optimized the automation of the analysis of hard-to-cook bean texture (figure 6).

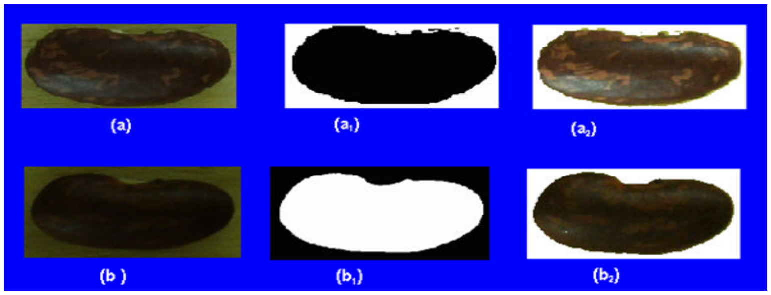

Figure 6. (a,b) original image, (a_1) and (b_1) best segmented image respectively in Red and Blue plane, (a_2,b_2) labeling

3.3 Analysis of Confidence Limit

The analysis of the confidence limit helps us to understand the errors that can be justified by the difference in the results from one operation to another. We have evaluated the parameters of global intensity variation designed as EQMI in table 1 chosen for the dissimilarity detection of change in texture. The confidence limit, for each color texture analysis was calculated (table 1). The variance of the parameters of dissimilarity was determined to see if there is dispersion in the evolution of the textural color (table 1). It should be noted that the confidence limit, between 75% and 90% can be explained by quality of the image acquisition device and defects related to some seeds segmentation (figure 7). The analysis of the confidence limit is important to illustrate the performance of results.

We integrate the approach in the study of seeds of the same sample which suffered the same phenomenon hard-to-cook, during the same period, and filmed in the same conditions. This allowed us to verify the effectiveness of the image acquisition and its ability to produce the same results for a reproduction of the same phenomenon. The study led to the selection of indices to predict the behavior of the textural color during storage of beans. It was difficult to take the average of the four selected beans (figure 7). We set therefore a confidence limit of 85% at 90% (a margin of error of 10% at 15%) to estimate an average parameter of dissimilarity. The choice of the parameter value for each bean in the period of analysis (figure 8) thus took into account the requirement of this confidence limit.

3.4 Effects of Storage on the Color-Texture Features of Beans Seeds

Effects of storage on the color component are showed in table 2 and figure 9.The variation of EQMI in RGB space is clearly verified, but its decrease in red color is more proven. Therefore EQMI can detect the overall intensity color change of beans seeds during storage.

Table 1. Scattering analysis of Global intensity changes

Sample	ECA PAN 019								
Period	Four beans (I, J, K, L) in same times storage in dry oven (nine days)								
EQMI ($*10^3$)	Beans	I0-I9	J0-J9	K0-K9	L0-L9	Medium	Standard deviation	Coefficient of Variation	Confidence limit
	Red	10.03	11.87	11.93	11.23	**11.26**	**0.76**	**0.06**	**90%**
	Green	9.52	9.97	11.13	9.77	**10.09**	**0.62**	**0.06**	**90%**
	Blue	10.15	10.33	12.54	9.45	**10.61**	**1.15**	**0.11**	**90%**

Period	Three beans (M,O,P) in same times storage in dry oven (twelve days)							
EQMI ($*10^3$)	Beans	M0-M12	O0-O12	P0-P12	Medium	Standard deviation	Coefficient of Variation	Confidence limit
	Red	10.77	11.62	10.85	**10.96**	**0.40**	**0.03**	**75%**
	Green	10.96	11.49	10.54	**10.88**	**0.40**	**0.03**	**85%**
	Blue	11.64	12.16	12.47	**11.96**	**0.40**	**0.03**	**70%**

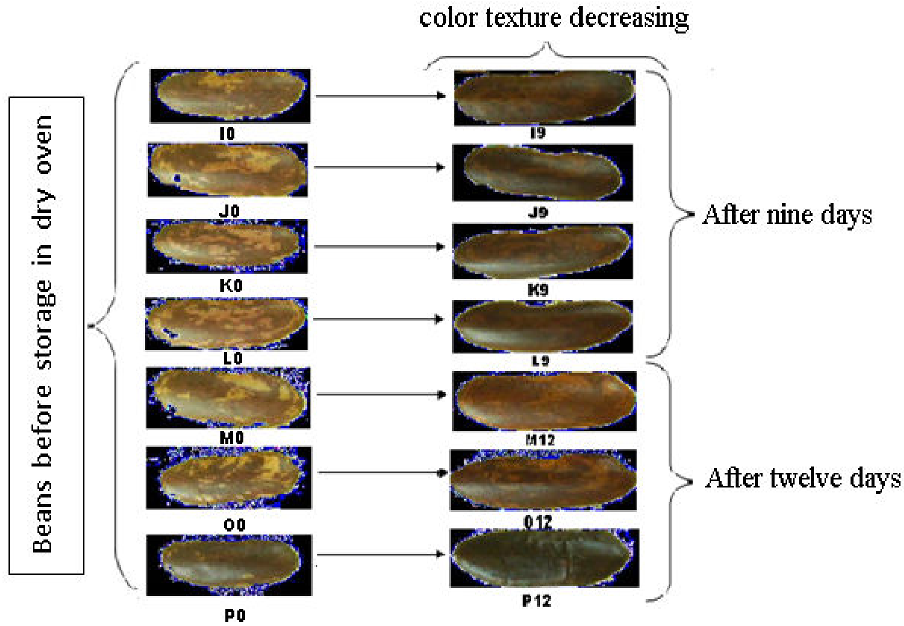

Figure 7. ECA PAN 019: Before and after 9 and 12 days storage in hard- to- cook conditions

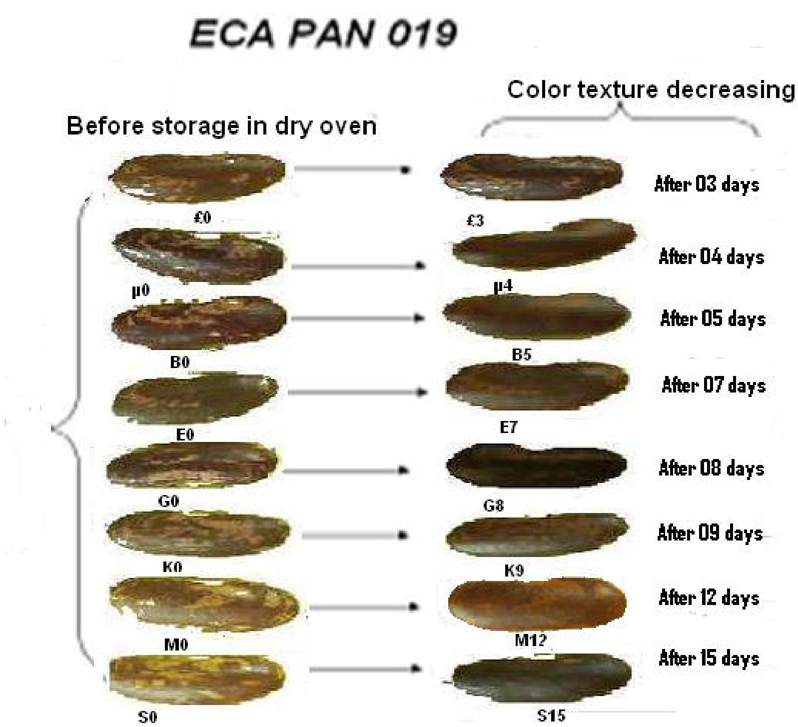

Figure 8. ECA PAN 019: Color texture decreasing during different period of storage in dry oven

Table 2. Global intensity changes after 3, 4, 5, 7, 8, 9, 12 and 15 storage days

Sample		ECA PAN 019							
Period		**03 days**	**04 days**	**05 days**	**07 days**	**08 days**	**09 days**	**12 days**	**15 days**
EQMI	**Beans**	**£0-£3**	**µ0-µ4**	**B0-B5**	**E0-E7**	**G0-G8**	**K0-K9**	**M0-M12**	**S0-S15**
(*10^3)	Red	18,88	14,41	13,97	10,7145	**10,14**	**10,88**	**7,104**	**6,54**
	Green	18,87	14,59	11,83	9,40	**9,76**	**10,71**	**6,11**	**6,22**
	Blue	19,18	15,69	7,25	6,28	**6,99**	**7,19**	**3,57**	**3,80**

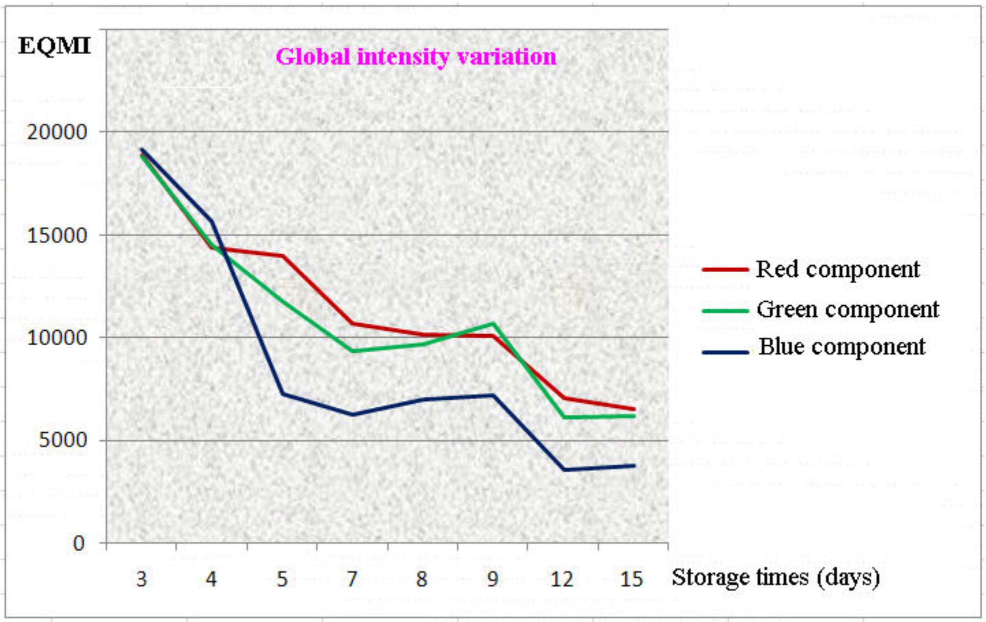

Figure 9. Detection of textural changes

There is a link between hard-to-cook beans development and cooking times (Hentges et al., 1990; Bitjoka et al., 2008). Cooking times, for each storage (in dry oven) beans seeds, used for global intensity variation in image processing, are evaluated by PC-Based instrumentation system (figure 9) proposed by Bitjoka et al. (2008). The beans seeds were introduced in Mattson cooker with water and when it becomes sufficiently tender by boiling water, the plunger penetrates the seed and drops through the hole in the saddle. A PC based system allows to follow up the beans cooking times. Cooking times have been used just to evaluate their correlation with global intensity variation. Among the features dissimilarity obtained in different color plan (Red, Green and Blue), the global intensity variation in red plan is highly correlated negatively (r = -0.96, table 3) to cooking times of beans (table 3).

Table 3. Correlation of color component with cooking times

Color component	**Red**	**Green**	**Blue**
Correlation coefficient	-0.96	-0.88	-0.72

4. CONCLUSION

Texture characterization by wavelet shows promises for detecting hard-to-cook beans development. The Daubechies 2 wavelet test gave best result. Fuzzy-c-means segmentation with Daubechies 2 is adapted for color textural Ecapan 019 (the studied sample beans). In this work, the integration of dissimilarity parameters for change detection in beans storage has been investigated. The global intensity variation with low scattering is used for robust change detection.

Hence, the proposed technique is more accurate and robust for hard-to-cook evaluation by digital image processing in color textural beans. The decrease of the global intensity of the red space color might indicate its browning and join the Vindiola hypothesis. Its high correlation with cooking times of beans seeds can help to predict their Hard-To-Cook degree.

ACKNOWLEDGMENTS

Authors thank Professor Carl Mbofung, Head of the Laboratory of Biophysics and Food Biochemistry at the National School of Agro-Industrial Sciences (The University of Ngaoundéré, Cameroon), for his help on beans hard-to-cook phenomenon.

COMPETING INTERESTS

Authors have declared that no competing interests exist.

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