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A Nondestructive Method Based on an Artificial Vision for Beef Meat Quality Assesement

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Abstract: The performance of artificial vision as a nondestructive technology has been evaluated in monitoring beef meat quality at a storage temperature of 4°C for more than two weeks. A reference method based on bacteriological measurement is performed in parallel with the artificial vision system to analyse the meat samples. Artificial vision data were collected from color image of meat samples in parallel with data from microbiological analysis for the enumeration of the population dynamics of total viable counts (TVC). Two color models are used to define fresh beef color in this study: the RGB (Red, Green and Blue) and HSI (Hue, Satutation and Intensity) model. Fuzzy ARTMAP artificial neural network based on a classification technique is used to investigate the performance of the artificial vision system in the quality classification of beef meat. The Fuzzy ARTMAP models built classified beef meat samples based on the total microbial population into “unspoiled” (microbial counts $< 6 \log_{10}$ cfu/g) and “spoiled” (microbial counts $\geq 6 \log_{10}$ cfu/g). Good classification rates are obtained (95.24 %). Finally training and testing an artificial system will be considered as a useful alternative tool for beef meat quality assesement.

Keywords:Bacterial measurement; Artificial vision; Image analysis; Features extraction; Fuzzy ARTMAP classification model.

I. INTRODUCTION

Beef meat is a staple food in many parts of the world including Morocco. So, the quality assurance and Food Safety is highly important. Hence determine meat quality parameter has always being very essential throughout all processes of the food industry because consumers are always demanding high quality of meat and meat products [1, 2]. Meat quality includes many attributes, such as odour, color, texture, pH, tenderness and freshness, etc [3-5]. The last feature (freshness) is regarded as the most important parameter in assessing meat’s quality and safety.

A number of methods have being used to assess meat freshness. Traditionally, three key techniques were used: sensory, chemical methods including TVB-N and microbial population evaluation [6-8]. Currently, the conventional plating method remains the most widely used to estimate the number of viable microorganisms in food samples [9]. The last method involves preparing appropriate dilutions of the sample and incubating the plates at 30 °C for 48 h or 72 h [3, 10].These methods are not only destructive, time-consuming and inefficient, but also not competent with modern industrial processing and production technologies.

The artificial vision system can offer a solution to all of the above problems [11-17]. Hence this technology has the capacity to deliver the required objectives of consistent, speedy and affordable quality judgements without losing the important benefits of non-destructive grading while avoiding gross misclassifications.

An artificial vision system is an attempt to replicate the human eye to brain assessment process [18], where the human eye is replaced by a digital camera and the human brain is replaced by a learning algorithm.The camera can record objective and consistent image data without substantial confounding noise. Then the learning algorithm links the image data to the appropriate quality class or level [19]. The aim of this work was (i) to extract the most important feature from the images of beef samples and (ii) to build classification models for differentiation between spoiled and unspoiled samples.

II. MATERIALS AND METHODS

A. *Meat samples*

Beef meat used in the experiments has been bought from the local market of the city of Meknes (Morocco). Test samples were chopped into 112 pieces of 4 × 4 × 2 cm (length × width × thickness) on a sterile surface of the laboratory and the weight of each sample was about 50 ± 0.5g. The samples were placed in plastic boxes and kept under cold storage at 4 ± 1°C before being analysed. Samples were analysed each day of cold storage for up to two weeks. In every sampling day (i.e. from day 2 to day 15, a total of 14 sampling days) two replicate samples which were withdrawn from the refrigerator to undergo microbiological analysis and six replicate samples that were employed for the electronic system. In total 8 samples were analysed each sampling day.

B. *Microbiological population enumeration*

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A 25g sample of beef meat was taken aseptically and placed in a sterile stomacher bag containing 225 ml of 0.1 % (wt/vol) peptone water (PW, Oxoid Ltd., Hampshire. England). The sample and the PW were stomached for 2 minutes. Decimal dilutions were prepared using the same diluent. Those dilutions were subsequently plated on the surface of a Plate Count Agar (PCA, Oxoid Ltd.). The plates were incubated at 30 °C for 2 days. The total viable counts (TVC) were obtained by enumerating the colonies present, and calculated as $\log_{10}$ colony forming units (cfu)/g of the sample.

C. Artificial vision set-up and methodology

Image acquisition is the first step in artificial vision, and data quality is the main concern during acquisition. Thus, consistent sample preparation, noise reduction, consistent illumination and mitigation of specular reflection are essential [19]. The artificial vision set-up (Fig.1) developped in this application includes a lighting chamber, a lighting source, a digital camera and a personal computer.

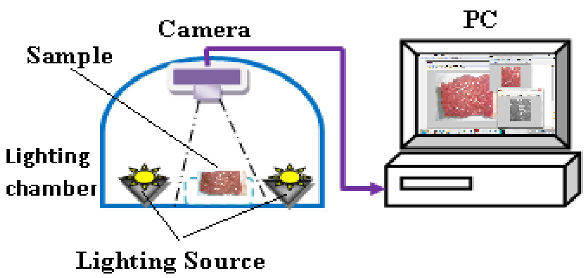

Fig. 1. Artificial vision set-up for beef meat quality evaluation using color information obtained from a digital image.

The images were acquired using a digital camera in the illumination chamber and displayed it in a personal computer. Image acquisition was facilitated by the Matlab Image Acquisition Toolbox and the images were formatted in JPEG and placed into computer's memory. The camera is placed vertically at a distance of 12 cm from the sample; and illumination was achieved with 2 Philips, fluorescent lights. The illuminating tubes and the camera were placed in a lighting chamber.

D. Features extraction

Color is visually one of the most important parameters in defining the quality of any food, and its evaluation has always being crucial and a theme of concern in the food industry as well as in food research and development [20, 21]. In this context, the sensory properties of food such as its appearance and surface color, which are the first parameters visually evaluated, consequently have a relationship with the food quality [22, 23]. Currently, new tools are being used to measure changes in color characteristics of food. The artificial vision technique is being projected as an alternative to sensory evaluation [24-27]. Color features provide information about the color intensity of beef meat region. Red, Green, Blue (RGB) and Hue, Saturation, Intensity (HSI) models are the commonly used color coordinate systems [5]. Therefore, color features of each meat sample were extracted in RGB and HSI color spaces.

The HSI color model, that hue is a color attribute that describes a pure color (pur yellow, orange, or red), where as saturation gives a measure of the degree to which a pure color is diluted by white light. The HSI color model owes its usefulness to two principal facts. First, the intensity component, I, is decoupled from the color information in image. Second, the hue and saturation components are intimately related to the way in which human beings perceive color. These features make the HSI model an ideal tool for developing image processing algorithms based on the same of color sensing properties of the human visual system.

The conversion formulates to go from RGB to HIS is:

$$H = \cos^{-1}\left(\frac{\frac{1}{2}[(R-G)+(R-B)]}{\left[(R-G)^2+(R-B)(G-B)\right]^{\frac{1}{2}}} \right),$$

$$S = 1 - \frac{[\min(R,G,B)]}{I},$$

$$I = \frac{(R+G+B)}{3}.$$

Color features provid information about the color intensity of beef meat region. In our approach, 2 features (mean and variance δ) per color channel were extracted, i.e., 2×6 features for 6 color channels: Red, Green and Blue (from RGB color space); Hue, Saturation and Intensity (from HSI color space). First we get a part of the window containing beef meat with a size of 100×100 pixels (Fig. 2).

The features $(\bar{R}, \bar{G}, \bar{B}, \delta_R, \delta_G, \delta_B, \bar{H}, \bar{S}, \bar{I}, \delta_H, \delta_S, \delta_I)$ were extracted from each beef sample image. The 12 features variables can reflect the color change of beef meat during experiment.

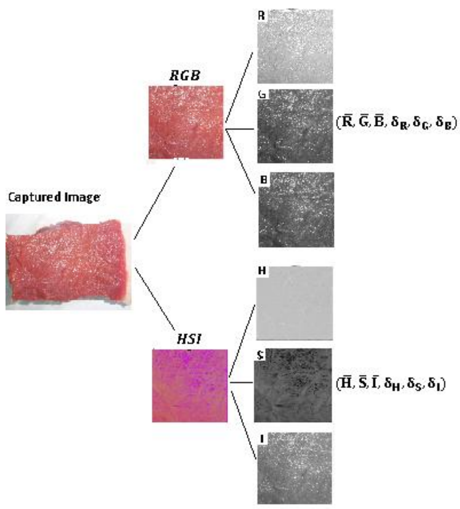

Fig. 2. Features extraction mechanism.

The artificial vision system dataset size is 84 (14 sampling days × 6 replicates) ×12 (12 features).

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III. DATA ANALYSIS

Data processing and pattern recognition are decisive factors in order to obtain a versatile instrument able to reliably recognize a wide variety of images. A dataset was elaborated corresponding to an artificial vision system. This data were used to attempt a fuzzy ARTMAP-based classification of the samples in spoiled/unspoiled beef meat samples. Interested readers are addressed to [28, 29] for a good introduction to the fuzzy ARTMAP neural network. In order to perform Fuzzy ARTMAP to discriminate unspoiled and spoiled beef samples, it was decided that a quality criterion corresponding to a 10^6 cfu/g for TVC should be applied to distinguish unspoiled and spoiled samples in this study, because this is the general microbiological safety guideline applied for food quality [30-32]. For classification models, samples were assigned with a dummy variable (Y), being 1 for 'unspoiled' or 2 for 'spoiled' according to their bacterial count. Hence after grouping the samples to their corresponding subclasses, Fuzzy ARTMAP models were developed to classify the samples based on their color attributes (extracted from their ordinary color images). In this study, a leave-one-out cross-validation approach was used for the Fuzzy ARTMAP model. Leave-one-out method is recommended when a few samples are used to build the calibration models [33, 34]. The leave-one-out cross-validation routine works by omitting one observation once a time (validation data), recalculating the classification function using the remaining data (training data), and then predicting the omitted observation. This routine is repeated until each observation in the dataset is used once as validation data. MATLAB 6.5 software is used for pre-processing and data analysis.

IV. RESULTS AND DISCUSSION

Bacteriological results of beef meat samples analysed are presented in Fig. 3. This figure shows the evolution of $\log_{10}$ cfu/g developed in the beef meat as a function of the days of cold storage. It can be observed that the microbial count in beef samples increases with the increasing aging time, depending on the storage conditions. Despite the important precautions we take into account when retrieving and preparing samples, we note that after the slaughtering, the samples are contaminated by bacteria. Indeed, in the first storage days, the total viable counts (TVC) values are near 3 $\log_{10}$ cfu/g. The preliminary results obtained by the bacteria total viable counts (TVC) show that the shelf-life of beef meats stored at 4 °C under these conditions are the seven day (unspoiled). After these days, the beef meat becomes unsuitable for consumption (spoiled).

In the fig. 4, we show the evoltution of the color change in cold storage day. We can see clairely the visual color change from red one to dark one. This color variation corresponding to the evolution of the number microbacterial colony formed in the beef samples. With our technical procedure, we show that the snapshot (a) and (b) was taken in days 2 and 6 whose have the neighbourhood red color and steel visually consumed.

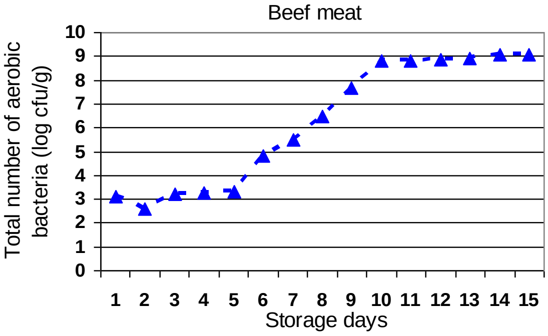

Fig. 3. Changes in the count of aerobic bacteria

This resulte coincides with the microbiological method which indicates the beef meat is unsploied. In the same way, we show that the snapshot (c) and (d) was taken in days 8 and 10 whose color decrease from blue to dark and indicate that the beef meat is sploied.

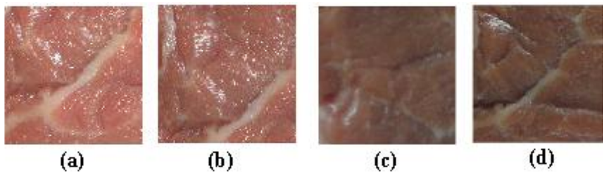

Figure 4: Evolutionary color change illutration at : (a) day 2, (b) day 6, (c) day 8, and (d) day 10.

Therefor, we will applied the Artificial Neural Network model. The fuzzy ARTMAP classification model based on the bacteriological analysis as a reference method was envisaged. Fuzzy ARTMAP was applied to test the ability of the artificial vision set-up for separating unspoiled and spoiled beef meat. Fuzzy ARTMAP classifier model was built using the training and validation dataset. Before training, the dataset must be normalised because the fuzzy ARTMAP network needs that input data which lie in the range [0,1]. The number of outputs for network was set to 2 because a 1-of-2 code was used for the two classes (1: unspoiled and 2: spoiled beef meat). The code 1 or 2 for each meat sample in the training dataset was based on the referencial method.

The performance of the fuzzy ARTMAP model was evaluated using a leave-one-out cross-validation method. The process was as follows: given n measurements (n = 84 measurements within each training matrix), the model was trained 84 times using 83 vectors. The vector left out was then used for testing the model. Performance in training was estimated as the averaged performance over the 84 tests. A very good success rate in classification was obtained in the beef meat spoilage classification by the artificial vision system, 95.24 %.

Four mistakes occurred : two measurements belonging to an unspoiled sample (having undergone 7 days of storage) was misclassified as being spoiled (8 days of storage were predicted) and two spoiled measurements (having undergone 8 days of storage) were misclassified as being unspoiled (7 days of storage were predicted). It is important to stress that these misclassified samples are close to the threshold of acceptability.

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V. CONCLUSION

We have reported here a rapid and non-destructive method in beef meat quality assesement based on an artificial vision technology. In the first, a bacterial analysis was used as a complementary method to develop a simple and rapid electronic system for the spoilage classification of beef meat. The artificial vision technique, unlike the bacteriological method, has the advantage of being fast and nondestructive. The artificial vision was used to classify beef meats according to unspoiled or spoiled. A very good success rate in the classification of spoiled or unspoiled beef meats 95.24 % was obtained when fuzzy ARTMAP classifier model was employed. According to these results, the artificial vision system can become an alternative non destructive tool, can significantly improve the efficiency of quality control of beef meat.

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