Could Machine Vision Replace Chemical Procedure to Evaluate Fat Content in Iberian Pig Meat? An Experimental Study

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Abstract

The Iberian pig is an autochthonous animal bred from the southwestern area of Spain. Its dry-cured ham is one of the most appreciated meat products of our country.

It has been proved that juiciness and acceptance of meat is mainly influenced by its fat content, either in calf, pig and lamb meat. Chemical procedure is currently the only proved way to determine meat intramuscular fat (IMF) level. Nevertheless, this is a tedious and expensive technique. For the food industries, a cheaper, faster and non-destroying technique to determine fat content before ham selection for maturation process, would be very worthy.

We investigate the feasibility of an alternative methodology to determine IMF content of Iberian pig meat using computer vision techniques. The evaluation of the proposed methods is carried out over a dataset of 100 slices of muscles from pig thighs. Correlation values with respect to chemical analysis are provided and discussed.

1. Introduction

The Iberian pig is fattened extensively with acorns and pasture (feeding system called "montanera") until the animal reaches a live weight at slaughter of about 160 kilograms. Its meat is mainly used to produce dry-cured meat products, in particular, cured hams. The meat characteristics from Iberian pigs (high intramuscular fat content, fatty acid composition, antioxidative status, etc.), together with the prolonged ripening process, occasion a dry-cured ham with quite special flavor, that makes it one of the most valuable meat products in Spain.

Different authors have proved that juiciness and acceptance of the meat is mainly influenced by its fat content, either in calf [1], pig [2] or lamb [3] meat.

Currently, chemical analysis is the only proved way to determine the intramuscular fat (IMF) level in Iberian pig ham [4], [5]. But, this technique is expensive and tedious. Davies et al. [6] propose the NIRS technique, which uses near infrared radiation to evaluate fat content. Nevertheless, current methods do not permit us determine fat content without destroying the samples.

We investigate the feasibility of an alternative technique to determine IMF level using computer vision techniques. Until now, related work in the literature to evaluate IMF level from images has been performed by a group of food technology researchers of our University [7]. This is done as follows: Iberian raw meat of thigh muscles is cut in slices which are digitized by a camera. Then, digital images are divided into two regions of interest (fat and background) using a semiautomatic image analysis system in which fat regions are drawn on the image by an expert in food technology. Then, IMF level is calculated by the computer. The quite encouraging results obtained are shown in section 4. Although this technique is fast, no-contaminant and cheap, such manual drawing can be tedious and susceptible to interobserved or intraobserved variability. So, fully automatic image analysis would be desirable.

For the automatic segmentation of intensity images, thresholding techniques are the simplest and most widely used methods described in the literature [8]. They are based on the postulate that all pixels whose gray value lies within a certain range belong to one class (said for example fat). That range or thresholds are automatically determined from the image characteristics. Nevertheless, such methods neglect all the spatial information of the image and do not cope well with noisy images, as we have proved in a previous preliminary work [9].

In this paper, an hybrid thresholding method is proposed to achieve automatic segmentation of ham images in two classes (fat and background) in order to evaluate their IMF degree. Contextual information of the images is incorporated to our method by pre-processing the original images with a rule-based spatial algorithm at different scales and then applying general thresholding techniques to the resultant images. More intuitive pre-processing techniques like median filters and morphological operators are also tested. Correlation curves comparing the results obtained by chemical procedure and semiautomatic image analysis are provided and discussed.

2. Data description

The database used in our experiment consists of 100 images taken from raw muscle slices of Iberian pig thighs. There are 34 *biceps*, 32 *quadriceps* and 34 *semi-membranous* muscles. The slices are digitized at 0.2 mm spatial resolution and 8 bits depth. Since the outline of meat slices is imperfect, an expert in food technology manually draws their contours in order to reduce extern effect. Intramuscular fat content of the slices was previously analyzed by chemical procedure.

3. Methods

Thresholding is one of the simplest and most widely used image segmentation techniques. The goal of thresholding is to segment an image into regions of interest or classes (in our case, fat and background).

In a previous work [9], we have tested the behavior of seven well-known standard thresholding techniques to evaluate fat content in commercial slices of dry-cured Iberian ham. Otsu [10], Pun [11], Tsai [12] and multi-level Otsu [13] revealed rather low correlation with chemical analysis; but Kapur [14], Johansen & Bille [15] and Kittler [16] methods showed extremely poor correlation.

In this paper, spatial image information is added to standard thresholding techniques in order to improve our previous work. For the sake of notation, let the original image f be defined on the discrete set as $F = \{x, y / x \in [0,N], y \in [0,M]\}$ where NxM is the image size and $f(x,y)$ is the gray-level at position (x,y). We denote by $S = \{(x,y) / x \in [0,N], y \in [0,M], f(x,y) \neq 0\}$, $S \subset F$, the subset of pixels representing the ham slice (sample image). Then, IMF percentage is obtained dividing the number of fat pixels by the number of pixels in the sample image.

In the following, we describe some general thresholding techniques and the proposed hybrid methods, which combine spatial and statistical information in the original image.

3.1. Thresholding techniques

All the addressed methods automatically determine a threshold from the gray level histogram of the original image by minimization, maximization or preservation of a criterion function.

Hence, Otsu and multi-level Otsu methods minimize the weighted sum of group variances: let σ_w^2, σ_B^2 and σ_T^2 be the within-class, between-class and total variance, respectively. An optimal threshold t can be determined by maximizing one of the following criterion functions with respect to t:

$$\lambda = \frac{\sigma_B^2}{\sigma_w^2} \qquad \eta = \frac{\sigma_B^2}{\sigma_T^2} \qquad \kappa = \frac{\sigma_T^2}{\sigma_w^2}$$

Kapur, Johannsen and Bille, Pun and Kittler methods are based on the minimization of functions which depend on *a priori* and *a posteriori* image entropy. Tsai method is based on moment's preservation criteria before and after image segmentation. The i^{th} moment m_i is calculated as:

$$m_i = (1/n) \sum_j n_j (z_j)^i = \sum_j p_j (z_j)^i$$

where n is the total number of pixels in the image, n_j is the number of the pixels with grey value z_j and $p_j = n_j / n$ is the probability of occurence of grey level z_j.

From all methods, except multi-level Otsu, a single threshold T is determined. It only allows us to classify pixels into two classes. Nevertheless, visual appearance of original images, from the viewpoint of optical density, seems to indicate that pixels could be macroscopically classified into three classes (lean, fat and intermediate). From this fact, multi-level Otsu method is applied to obtain two thresholds T_1 and T_2 ($T_2 > T_1$) and pixels higher than T_2 are classified as fat.

3.2. Proposed technique

In spite of the above considerations, spurious noise in the images may be erroneously classified as fat. So, contextual or spatial image information is incorporated to our method by pre-processing the original image with a rule-based algorithm before applying uniform thresholding techniques to S, the sample image.

Our pre-processing technique consists of moving a kernel across the original images, pixel by pixel, to generate an output image which will be segmented by the addressed thresholding techniques. In our work, three different approaches are used: a proposed rule-based algorithm and two widely used preprocessing techniques, i.e. median filters [8], which attenuate spurious noise in the original image, and opening morphological operators [17], for the purpose of removing up features smaller than the kernel size, which we believe could be associated with noise or artifacts.

Our rule-based algorithm works as follows: let μ_s be the mean gray value on S, and μ_{xy} the average gray value of pixels in the image which fall into the kernel. The input image value at each position (x,y) remains unchanged when $\mu_{xy} > \mu_s$ and is labeled as background (0 gray level) otherwise in the pre-processed image. The effects of applying this pre-processing are twofold. Firstly, spurious noise in S is partially removed and, secondly, pixels that clearly belong to lean are rejected in the subsequent processing.

For all methods, scale information is added by processing sample images with different kernel sizes (in our study, we consider two different kernel sizes: 3x3 and 7x7 pixels).

4. Results

The evaluation of the proposed methods is carried out on our dataset of images. Tables 1, 2 and 3 show the Pearson correlation coefficient of IMF content obtained by the addressed automatic methods with respect to chemical analysis for *biceps*, *quadriceps* and *semi-membranous* muscles.

For the purpose of comparison, correlation between chemical analysis and the semiautomatic image analysis system is shown in table 4 [7].

Pearson correlation value varies between –1 and 1, where a higher absolute value indicates a better estimation of chemical IMF content of the muscles.

By analyzing the correlation obtained for each muscle, it can be seen that the combined method consisting of rule-based algorithm and generalized Otsu method provides the best scores for *biceps* and *quadriceps* muscles, and there is no significant difference between the two kernel sizes used. Correlation values for *semi-membranous* muscle are extremely poor for all automatic segmentation methods tested.

Pre-processing technique	*kernel size*	*Otsu method*	*Pun method*	*Tsai method*	*Multi-level Otsu method*
-	-	0,10	0,04	0,14	0,23
Morphological opening operator	3	-0,02	-0,03	0,12	0,21
	7	0,00	0,06	0,04	0,10
Median filter	3	0,03	-0,01	0,13	0,27
	7	-0,03	0,00	0,10	0,22
Rule-based algorithm	3	0,29	0,00	0,23	0,35
	7	0,32	-0,02	0,25	0,32

Table 1. Pearson correlation for the fully automatic studied methods to evaluate IMF content in *biceps* muscle.

Pre-processing technique	*kernel size*	*Otsu method*	*Pun method*	*Tsai method*	*Multi-level Otsu method*
-	-	0,25	0,30	0,09	0,05
Morphological Opening operator	3	-0,27	-0,10	-0,09	0,02
	7	-0,25	-0,11	-0,11	-0,06
Median Filter	3	-0,21	-0,24	-0,09	0,07
	7	-0,23	-0,09	-0,07	0,03
Rule-based Algorithm	3	0,22	-0,16	0,34	0,44
	7	0,14	-0,23	0,27	0,36

Table 2. Pearson correlation for the fully automatic studied methods to evaluate IMF content in *quadriceps* muscle.

Pre-processing technique	*Kernel size*	*Otsu method*	*Pun method*	*Tsai method*	*Multi-level Otsu method*
-	-	0,12	0,23	0,04	0,00
Morphological Opening operator	3	-0,09	-0,22	-0,07	-0,09
	7	-0,13	-0,11	-0,06	-0,15
Median Filter	3	-0,09	-0,08	-0,06	-0,02
	7	-0,09	-0,08	-0,03	-0,06
Rule-based Algorithm	3	-0,01	-0,10	0,09	0,08
	7	0,03	-0,01	0,11	0,11

Table 3. Pearson correlation for the fully automatic studied methods to evaluate IMF content in *semi-membranous* muscle.

Biceps	*Quadriceps*	*Semi-membranous*
0.61	0.5	0.44

Table 4. Correlation coefficients for the semiautomatic image analysis procedure for all muscles (p<0,01).

Correlation values often improve when images are pre-processed with the rule-based algorithm for all standard thresholding techniques. Nevertheless, median and opening operators produce results almost opposite to the ones we expected and they do not normally increase correlation values of the studied standard thresholding techniques.

5. Discussion

This research has provided us with some significant results. Firstly, the correlation depends on the muscle in hand. Secondly, pre-processing images sometimes improves correlation. Finally, correlation values obtained for the fully automatic methods are only slightly lower than semiautomatic image analysis.

A detailed analysis of the results shown in the above section is not so easy. We believed that the performance of the tested algorithms would be similar due to the fact that a visual appearance of all muscles is comparable. But, in fact, the reverse is true and specific methods for each muscle may improve performance.

Original images are very noisy. Water content in the meat generates noise in the image during the acquisition process. An intuitive reasoning leads to think that pre-processing techniques, which attenuate spurious noise or remove small features, should improve global performance. In this experiment, only the rule-based algorithm normally improves performance, especially in *biceps* and *quadriceps* muscles.

From the viewpoint of the standard thresholding techniques studied, the performance comparison is very difficult due to the fact that the effect of some algorithms varies significantly when combined with pre-processing techniques.

Correlation values are still low to replace chemical evaluation of IMF content of Iberian pig meat. They are also lower than semi-automatic image analysis. For *quadriceps* muscle, we found one fully automatic technique that provides comparable results to semi-automatic method without human supervision. We believe that these results are quite encouraging, but further improvement is needed in order to apply these methods to food industry.

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