Short Note

Analyzing magnetic resonance images of Iberian pork loin to predict its sensorial characteristics

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Abstract

Iberian pork comes from genuinely bred Southwest Iberian Peninsula pigs traditionally fattened with acorns and pasture in an extensive production system. Dry-cured loins and hams constitute the main uncooked pork products with high sensorial quality and a first rate consumer acceptance, leading to high prices in the market. Several aspects related to quality in Iberian products have been examined by using chemical and sensorial procedures to provide quality. However, all these approaches are tedious and destroy the item. In addition, food science has shown little interest in MRI to explore meat products in a non-invasive way. Therefore, this paper introduce an objective and non-destructive methodology to classify Iberian loins consistently. It is based on texture analysis of MRI images displaying dry-cured pork loins. A statistical evaluation is provided for a set of 47 loins to predict three levels of different sensorial characteristics.

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1. Introduction

Iberian pigs are exclusively bred in Southwestern Spain, i.e., Iberian Peninsula; this herd traditionally feeds on acorn and pasture in an extensive production system. Its characteristic feeding system has some points in common with other Mediterranean in-bred pigs [1].

The meat from these pigs is usually targeted to the dry-cured product market. In particular, Iberian dry-cured products (loins and hams) constitute the main uncooked pork products, which have a high sensory quality and first rate consumer acceptance. These products are characterized by a high intramuscular fat content [2], as well as, a particularly intense flavor [3].

Iberian pork loins and hams have excellent sensorial characteristics, which implies a high price in the market. Thus, not only hygienic but also sensorial quality should be guaranteed. On the past years, several aspects related to Iberian pork quality have been studied: influence of crossbreeding [4], rearing system [5], and processing [6]. Currently, chemical procedures are the only means, empirically verified, to analyse physical–chemical parameters in Iberian pork [7,2,6]. In contrast, the final quality of these products has also been assessed by sensorial evaluation using trained panellists [8,3].

Nevertheless, all the above methods to determine quality are tedious and destroy the product. As a result, meat industries have shown a great interest in finding an objective, consistent, and non-destructive method to classify Iberian pork items of different qualities.

The use of image processing and pattern recognition techniques to predict meat quality is not widely spread in the literature. Early approaches were devoted to examining different characteristics of beef, bovine, and pork meat by using images taken with a CCD camera. Shiranita et al. [9], and Yoshikawa et al. [10] developed a grading system for Japanese beef marbling with the use of texture analysis. Li et al. [11] predicted cooked-beef tenderness from fresh-beef images by using colour, marbling, and texture image features. Tan et al. [12] focused on pointing out beef marbling and colour score. Basset et al. [13] applied texture image analysis to the classification of bovine meat. Duran et al. [14] classified different types of raw Iberian ham by using statistical texture analysis. Cernadas et al. [15] developed a method to recognize marbling in dry-cured Iberian ham.

In contrast, magnetic resonance imaging (MRI) is widely used in medical diagnosis and surgery for tissue composition probing within bodies [16]. Non-invasive and non-destructive capabilities are decisive advantages of MRI, which supplies a discrete three-dimensional (3D) data set consisting of two-dimensional (2D) slices of the object. MRI provides important digital information regarding muscle, bone, or other soft tissue, which combined with advances in digital image processing, has led to significant progress in the case of medical diagnosis and surgery [17]. Food science has shown little interest in MRI, which has remained essentially confined to research activities, despite many potential applications: process optimisation of animal production (animal diet, genetic type), consumer satisfaction, and so on. A few MRI applications have been published showing
muscle characterization. Bonny et al. [18], and Laurent et al. [19] characterize bovine muscle structure. Cernadas et al. [20] apply texture analysis to MR images to classify raw loins from Iberian pigs. Caro et al. [21] use active contours to recognize muscles from Iberian ham MRIs along different processing steps to quantify muscle volume decrease.

In this paper, we describe an automatic methodology to classify dry-cured Iberian pork loins based on computer vision techniques. Such procedure should allow food technology industries to evaluate and characterize Iberian pork loins, prior to marketing them, in a more economic, speedy, objective, and non-destructive way. MRI images are developed to ensure the analysis of pork products non-invasively. Then, loin cut images are analysed to determine several sensorial characteristics in the pork loin. We describe a novel methodology to predict three levels (low, medium, and high) of different sensorial characteristics in cured Iberian pork loins based on texture image analysis.

This paper is organized as follows: Section 2 describes characteristics in the data set of pork loins used in the experimental study and, as well as, the sensorial evaluation and image caption process. Section 3 presents an overview of the system. Then, while Sections 4–6 describe every step in the system, Section 7 provides the actual results obtained. Section 8 contains a discussion of these results, and Section 9 the main conclusions of the paper.

2. Description of data set

Forty-seven loins from the same number of iberian pigs (140–145 kg live weight) were processed for a period of 60 days according to the traditional method of maturation. Once MRI images of the loins have been developed, chemical and sensorial analyses are performed.

2.1. MRI image acquisition

MRI scans are carried out with a medical apparatus. The MRI volume data set is obtained with a field of view (FOV) of 120 × 120 mm$^2$ and slice thickness of 2 mm, i.e., a voxel resolution of 0.23 × 0.23 × 2 mm$^3$, and it is stored as gray level images of 512 × 512 pixels. Fifteen samples have been selected for each pig to obtain a MRI sequence. The total number of images is 705 (47 specimens × 15 slices from each). Fig. 1 shows slice No. 10 for some animals. In the images, fat content is associated with the whiter regions.

2.2. Chemical analysis

The fat content of dry-cured pork loin was extracted and purified with chloroform, methanol according to the method described by Bligh and Dyer [22].
2.3. Sensory analysis

Loin slices were assessed by a trained 18-member panel, who used a descriptive analysis method [23]. Consistency of panellists was validated by using a Rasch model [7]. Three different pork loins were evaluated in each session, a total of 15 sessions being carried out (3 per week). Sample orders were randomized. For each loin, two thin slices (1.0 mm) were given to the panellists. Six traits concerning sensorial texture (perception obtained by panellist when loin slice has been inserted in mouth: dryness, hardness, and juiciness), and visual appearance of dry-cured Iberian pork loin (brightness, marbling and size of marbling) were analyzed. The traits were assessed by the panellists by using a non-structured 10 cm line, ranging from less (0 cm) to more length (10 cm), and following a sensory descriptive test developed by Garcia et al. [7]. The sensory traits, their definitions, and extremes are explained in Table 1.
For each trait (sensorial or chemical), pork loins have been grouped into three classes (low, medium, and high). Table 2 shows the number of specimens for each class during each sensorial and chemical analysis.

<table>
<thead>
<tr>
<th>Sensorial characteristics</th>
<th>Categories</th>
<th>Low</th>
<th>Medium</th>
<th>High</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brightness (B)</td>
<td>8</td>
<td>15</td>
<td>24</td>
<td></td>
</tr>
<tr>
<td>Marbling (M)</td>
<td>22</td>
<td>13</td>
<td>12</td>
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<tr>
<td>Marbling size (MS)</td>
<td>15</td>
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<tr>
<td>Hardness (H)</td>
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<td>17</td>
<td></td>
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<tr>
<td>Dryness (D)</td>
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<td>13</td>
<td></td>
</tr>
<tr>
<td>Juiciness (J)</td>
<td>22</td>
<td>9</td>
<td>16</td>
<td></td>
</tr>
<tr>
<td>Fat Content (FC)</td>
<td>18</td>
<td>14</td>
<td>15</td>
<td></td>
</tr>
</tbody>
</table>

For each trait (sensorial or chemical), pork loins have been grouped into three classes (low, medium, and high). Table 2 shows the number of specimens for each class during each sensorial and chemical analysis.

3. System overview

Many pattern recognition systems can be partitioned into components such as the ones shown in Fig. 2 [24,25]. A sensor converts the input into digital data (MRI scanner). The pre-processing stage transforms the digital data into a suitable form for the next stage. A feature extractor measures object properties that are useful for classification. The feature selection stage selects a subset of features that reflect the best candidates. The classifier uses these features to assign the input object to a predetermined category. Finally, once the classifier has been designed, the system evaluation stage assesses the performance of the designed classifier. These stages can be interre-
lated and, depending on the results, one may go back to redesign earlier stages to improve the overall performance.

Stage design for the purpose of meat quality characterization using MRI images is relatively novel. In turn, as mentioned in the previous section, most published research analyse textural image features to discriminate meat categories. In the following sections, we shall describe the design of each stage in our system.

4. Region of Interest extraction

As a pre-processing stage, an algorithm is introduce to extract irregular region of interest (ROI) from the MRI images. MRI slices are segmented into two regions: sample and background. Sample contains image textural information. Background includes not only the loin outside but also the inter-muscular fat content in the image. The algorithm can be summarized as follows: a combination of median and morphological operators [26] is applied to the original image, \( f(x,y) \), to narrowly smooth out fat streak information within the loin. From the histogram of the resulting image, \( f_S(x,y) \), we calculate two thresholds, \( T_1 \) and \( T_2 \) (\( T_1 < T_2 \)), by using the Otsu’s algorithm [27,28]. A thresholded image \( f_t(x,y) \) is defined as

\[
f_t(x,y) = \begin{cases} 
1 & \text{if } T_1 \leq f_S(x,y) \leq T_2, \\
0 & \text{otherwise}.
\end{cases}
\]

(1)

The pixels labelled 1 correspond to region of interest (ROI), whereas pixels labelled 0 correspond to the background (the pixels which satisfy the expression \( f(x,y) \geq T_2 \) correspond to inter-muscular fat areas in the loin). Multiplying the original image \( f(x,y) \) by its corresponding segmented image, \( f_t(x,y) \), yields the image \( f_O(x,y) \). Since \( f_O(x,y) \) has sometimes small spurious regions in the background and/or small holes in the region of interest, a post-processing step is applied to remove and fill in the spurious regions and holes of a constant size (in our treatment, we consider 1000 pixels). A rectangular area is also formed to enclose the ROI. An example of these steps is shown in Fig. 3 for slice No. 10 of loin 039.

Some texture features must be applied to square regions. To test the performance of these features, a square region of \( 64 \times 64 \) pixels is searched in each irregular region (see Fig. 3) and extracted. Fig. 4 shows \( 64 \times 64 \) pixel-ROIs extracted from irregular regions for some slices.

Fig. 3. Irregular region of interest (ROI) extracted from slice 10 of loin 039 by using the algorithm described in Section 4. From left to right: 1, Original image; 2, take after processing with median and morphological operators; 3, ROI before post-processing; and 4, irregular ROI where background is presented in black and the loin area is shown in gray levels.
5. Texture analysis

As mentioned above, in the area of Meat Science, several authors have proposed texture analysis approaches to characterize meat quality. Texture refers to properties that represent the surface or structure of an object. People usually describe texture as fine, coarse, grained, smooth, etc., which entails that some more precise features must be defined to make machine recognition possible. Despite the lack of a complete and formal definition of texture, a large number of approaches for texture classification has been suggested. Some researchers identify five major categories of features for texture identification: statistical, geometrical, syntactic, model-based, and signal processing [29–34]. Statistical and signal processing features are, perhaps, most widely used. A common denominator of many approaches is that the textured image is described by a feature vector of properties which represents a point in a multi-dimensional feature space. Then, the aim is to find some discrimination criterion assigning a texture to some specific class.

Some well-known first-order and second-order statistical features or wavelet packet signatures provided good performance in other texture classification problems. The texture feature vectors tested in this study are:

- **Haralick’s coefficients (HC)**. The gray level co-occurrence matrix of the image, GLCM, is based on the estimation of the second-order joint conditional probability density functions, \( P(m,n,d,\alpha) \), \( \alpha = 0^\circ, 45^\circ, 90^\circ, 135^\circ \). Each \( P(m,n,d,\alpha) \) is the probability of going from gray level \( m \) to gray level \( n \), provided that the intersample spacing is \( d \) and the direction is given by \( \alpha \). If an image has \( N_g \) gray levels, then the GLCM can be written as \( N_g \times N_g \) matrices. Each matrix is computed in a digital image by counting the number of times that each pair of gray levels occurs at separation \( d \) and in the direction \( \alpha \). We assume \( d = 1 \). The matrices are combined by averaging the GLCM for each angle to obtain some degree of rotation invariance. To deal with irregular areas, only those pairs that fell inside the irregular ROI were taken into account, and this number of pairs is also used to normalize the co-occurrence matrix. This 2-D vector may be used directly as a texture feature vector. However, it is common to use the following derived features from the matrix defined by Haralick et al. [35,30]: ENE (energy), ENT (entropy), Cor (Correlation), IDM (inverse difference moment), INE (inertia), CS (cluster shade), and CP (cluster prominence).
- **Gray level run length statistics (GLRLS).** A set of consecutive pixels in the image having the same gray level value [29,36]. The *length of the run* is the number of pixels in the run. So, a run length matrix is yielded, from which the following features are derived: SRE (short run emphasis), LRE (long run emphasis), GLNU (gray level non-uniformity), RLN (run length non-uniformity), and RP (run percentage). Length matrix was also beem normalized by the number of runs in the irregular ROI.

- **Neighboring gray level dependence statistics (NGLDS).** This method considers the relationship between an element and all its neighboring elements at one time. It is based on the calculation of the gray level spatial dependence matrix (NGLDS) of an image [36]. The usual numerical measures are: SNE (small number emphasis), LNE (large number emphasis), NNU (number non-uniformity), SM (second moment), and ENT (entropy).

- **First-order statistics.** The texture feature vector contains the following 12 measures [25]. Let $x$ be the random variable representing the gray levels in the region of interest. The fraction of pixels with gray level $x$, $P(x)$ is its histogram. Let $N_g$ be the possible number of gray levels. We define the following first-order statistics:
  
  - **Moments:** $m_i = E[x^i] = \sum_{x=0}^{N_g-1} x^i P(x)$ $i = 1, 2, 3, 4$, where $m_1$ is the mean value and $m_2$ the energy in the region.
  
  - **Central moments:** $\mu_i = \sum_{x=0}^{N_g-1} (x - m_1)^i P(x)$ $i = 1, 2, \ldots$ The most frequently used central moments are $\mu_2$, $\mu_3$, and $\mu_4$, which are known as the variance, third and fourth statistical moments respectively.
  
  - **Absolute moments:** $\bar{\mu}_i = E[|x - E[x]|]^i$ $i = 1, 2, \ldots$ We also consider the first four moments.
  
  - **Entropy:** Entropy is a measure of histogram uniformity, which is defined by $H = -\sum_{x=0}^{N_g-1} P(x) \log P(x)$. The closer to the uniform distribution ($P(x) = \text{constant}$), the higher $H$.

- **Features from wavelet packets.** Wavelet packets represent a generalization of orthonormal and compactly supported wavelets [37]. For 2-D images, a basic function can be expressed as the tensor product of two 1-D basis functions in the horizontal and vertical directions, which correspond to 2-D filter coefficients that represent low-pass and high-pass filtering effects in the $x$ and $y$ direction, respectively [38]. Daubechies wavelet of filter length 4, 6, 12 and/or 20 ($D_4$, $D_6$, $D_{12}$, and $D_{20}$) are commonly used to extract texture information for several applications [39]. The standard decomposition proposed by Mallat [38,39] with filter length of $D = 20$ was used. The most frequent statistics employed are the energy and entropy of each packet. We also compute other texture measures such as mean ($m_1$), variance ($\mu_2$), 3rd ($\mu_3$), and 4th ($\mu_4$) central moments for wavelet packet coefficient matrix in each channel. Wavelet packets must be applied to square regions.

Features resulting from first-order statistics provide information related to the gray level distribution of the image. Second-order statistics features exploit the spatial dependencies that characterize the texture of an image region (features from cooccurrence matrices, gray level run lengths, or neighboring gray level dependence matrices). Another way of extracting texture-related spatial dependencies is by
applying local linear transformations to an image. The first-order statistics of the transformed image encodes texture properties.

Let $f(m,n)$ be the original image and may a neighborhood of size $L \times L$ be centered at pixel location $(m,n)$, and $x_{mn}$ be the array of original images with $L^2$ points within that area. The local feature extractor is defined as $y_{mn} = A x_{mn}$, where $A$ is the convolution mask, and $y_{mn}$ is the respective filter output sample. Laws \[40,30,29\] suggests the mask to be constructed from the following three basic vectors: $[1,2,1]^T, [1,0,1]^T,$ and $[1,-2,-1]^T$ for $L = 3$. The first vector corresponds to a local averaging operator, the second one to an edge detection operator, and the third to a spot detector. The respective nine masks, $A_i \ i = 1, \ldots, 9$, are formed by their cross-products

$$A_1 = \begin{pmatrix} 1 & 2 & 1 \\ 2 & 4 & 2 \\ 1 & 2 & 1 \end{pmatrix}, \quad A_2 = \begin{pmatrix} -1 & 0 & 1 \\ -2 & 0 & 2 \\ -1 & 0 & 1 \end{pmatrix}, \quad A_3 = \begin{pmatrix} -1 & 2 & -1 \\ -2 & 4 & -2 \\ -1 & 2 & -1 \end{pmatrix},$$

$$A_4 = \begin{pmatrix} -1 & -2 & -1 \\ 0 & 0 & 0 \\ 1 & 2 & 1 \end{pmatrix}, \quad A_5 = \begin{pmatrix} 1 & 0 & -1 \\ 0 & 0 & 0 \\ -1 & 0 & 1 \end{pmatrix}, \quad A_6 = \begin{pmatrix} 1 & -2 & 1 \\ 0 & 0 & 0 \\ -1 & 2 & -1 \end{pmatrix},$$

$$A_7 = \begin{pmatrix} -1 & -2 & -1 \\ 2 & 4 & 2 \\ -1 & -2 & -1 \end{pmatrix}, \quad A_8 = \begin{pmatrix} 1 & 0 & -1 \\ -2 & 0 & 2 \\ 1 & 0 & -1 \end{pmatrix}, \quad A_9 = \begin{pmatrix} -2 & 4 & -2 \\ -2 & 4 & -2 \\ 1 & -2 & 1 \end{pmatrix}.$$ 

(2)

Each element of the array $y_{mn}$ is the result of filtering the local image neighborhood centered at $(m,n)$ with each of the masks. By moving the mask around at the various $(m,n)$ positions that satisfy $f(x,y) \neq 0$, nine different images are obtained, each encoding different aspects of the texture of the original image. We compute for each image the following first-order statistics: mean $(m_1)$, variance $(\mu_2)$, 3rd $(\mu_3)$ and 4th $(\mu_4)$ central moments, energy $(m_2)$, and entropy (Ent.). The six features per filtered image, when multiplied by nine masks equal 54 features, which we use for texture classification.

6. Feature selection and classification

Once the textural features have been computed, a next issue is the assignment of each query case to a pre-established class. The minimum distance classifier is the simplest found in the literature [24]. Let $M$ be the number of classes, $L$ be the number of pork loins, and $J$ be the number of loin slices. Let also $x_{lj}^n = [x_{lj1}, x_{lj2}, \ldots, x_{ljm}]$ be the feature vector of $n$ elements that uniquely identify slice $j$ in loin $l$. The metric used to measure the similarity between a query case and the mean class prototypes is the Mahalanobis distance to each class $i$, $D_i$, defined as:

$$D_i = (x_{lj}^n - m_i)^T \Sigma^{-1} (x_{lj}^n - m_i) \quad i = 1, \ldots, M,$$  

(3)
where $\Sigma$ is the covariance matrix in the training set and $m_i$ is the mean class prototype for each class $i$. The prototype class is calculated by taking the mean vector in the training set. We assume the same covariance matrix for all classes. The training set is performed by using $L - 1$ loins and the test is conducted with the excluded one (the leave-one-loin-out approach). If classification is done correctly, a hit is counted. This is repeated $L$ times, each excluding a different loin. The class of the excluded one is derived by applying the following two strategies:

1. **Voting system.** Each slice is classified, and the resulting classes receive some votes. When all the slices in a loin have been classified, the loin is listed under the class with the highest number of votes.

2. **Sum of similarities.** For each pork loin slice, the Mahalanobis distance to each prototype class is calculated. The final distance of the loin to each class prototype is computed as the sum of distances for all slices. The loin is classified within the class with a minimum distance.

Some of the texture features may have meaningless classification capabilities or do not improve the overall system performance due to the correlation existing among them. In order to improve the classification ratio and efficiency of the system, an important issue is the selection of optimal features. An exhaustive search of $k$ features from available $n$, yields a high number of combinations of characteristic sets for a low number of features. Thus, in practice, other suboptimal searching algorithms are suggested [25], which are divided into three categories: scalar, vector, and global feature selection.

Scalar feature selection is based on the measure of the classification effectiveness of individual features. We compute a discrimination criterion $C(p)$ for each feature $p = 1, 2, \ldots, n$. Features are then ranked in the order of descending $C(p)$ values. The $k$ features corresponding to the $k$ highest values of $C(p)$ are selected to form the feature vector. We adopt two criteria $C(p)$: The Fisher discriminant rate (FDR), and minimum individual sensitivity (MIS). The FDR for each feature $p$ is defined as $FDR(p) = \sum_{i \neq j} (\mu_{ip} - \mu_{jp})^2 / (\sigma_{ip}^2 + \sigma_{jp}^2)$. The MIS method computes the percentages for correct pork loin classification in each feature $p$. Scalar approaches have the advantage of computational simplicity. However, such approaches do not take into account existing correlations between features.

Feature vector selection approaches measure the capabilities of feature vector (or subsets of the set of available features). We use the sequential forward selection (SFS) and floating search method (FSM) [41], which can be described as follows: consider a set of $n$ features. The idea is to search for the best subset of $k$ for $k = 1, 2, \ldots, l \leq n$ so that a cost criterion $C$ can be optimized (for us, $C$ is the sensitivity of the system when using Mahalanobis distance).

For the SFS method, the criterion value $C$ for each of the original $n$ features is computed. Then, the feature with the highest value, i.e., $x_m$, is selected, and all possible 2-D vectors that contain it are formed. The criterion value for each is again computed and the best selected. The procedure continues until the number of features equals $k$. The main drawback of this method is that once a feature has been selected, there is no way to discard it at a later stage.
FSM offers the possibility of discarding previously selected features. Let \( X_k = x_1, x_2, \ldots, x_k \) be the set of the best combination of the features \( k \), and \( Y_{n-k} \) the set of the remaining \( n-k \) features. We also keep all the lower dimension best subset \( X_2, X_3, \ldots, X_{k-1} \) features, respectively. The algorithm can be summarized according to the following steps:

1. **Inclusion.** The best subset of \( k + 1 \) elements, \( X_{k+1} = X_k, x_{k+1} \) is formed. The feature \( x_{k+1} \) is chosen from \( Y_{n-k} \). It is the one that, combined with \( X_k \), results in the best value of \( C \).

2. **Test and exclusion.** The previously selected lower dimension subsets are revised to examine whether the inclusion of the new element improves criterion \( C \). If it does, the new element replaces one of the previously selected features, and the backward search is performed until \( C(X_{k+1}, x_r) \leq C(X_k), x_r \in X_{k+1} \). If it does not, step inclusion is restarted.

The algorithm starts by running the inclusion step twice to form \( X_2 \). The algorithm ends when the \( k \) features have been selected.

Global feature selection or transformation can be performed by a principal component analysis (PCA) [24]. The principal components of a set of observation vectors \( x_i \) are the characteristic vectors of the covariance matrix \( \Sigma_i \) constructed from the data set. The characteristic values describe the variances associated with the principal components. The dimensionality of the data set can be reduced by ignoring the principal components with low (or zero) characteristic values. Observation vectors can be approached from the PCA model by using \( x_i \approx P b_i + m \), where \( x_i \) is the \( i \)th observation vector, \( m \) is the mean observation over a class population, \( P \) the matrix of the most significant principal components, and \( b_i \) a vector of lower dimensionality than \( x_i \). The weights of the principal components \( b_i \) for an observation can be obtained by \( b_i = P^{-1}(x_i - m) \). The PCA is applied to produce a population of parametric vectors \( b_i \) with a reduced dimension.

### 7. Experimental results

We test the performance of our system to predict different sensorial characteristics by using data sets described in Section 2. Table 3 shows the complete results for all combinations of texture feature generators (Section 5) and feature selectors (Section 6) for predicting marbling size sensorial characteristic. Such a prediction is enable by managing irregular ROIs and the voting method in the classification step. For MIS, FDR, SFS, and FSM feature selection methods, a best subset of \( k \) features is obtained. For computational simplicity, we assume \( k = \max\{n, 16\} \), where \( n \) is the number of originally available features. When \( n \) is greater than 16, we only search subset of \( 1, 2, \ldots, 16 \) features. The results provided by the summing method are very similar in all cases (system effectiveness only less than 5 points in relation to the voting method). Results are consequently not shown and what follows, corresponds to only results obtained by implementing the voting method.
The feature selector named floating search method (FSM) clearly provides higher sensitivities for all sets of texture features. This fact is true for the rest of the sensorial characteristics. Thus, Table 4 shows the results obtained for all the sensorial characteristics by using the FSM feature selector.

Table 5 presents the same results as Table 4 when square ROIs, extracted from irregular regions, are applied. We also include the performance provided by filtering texture features that compute signatures such as energy, entropy, mean, variance, 3rd, and 4th central moments for a standard wavelet decomposition in three levels using Daubechies basis $D_{20}$. In general, FSOS, LLT, and FSOS + LLT feature extractors provide the highest percentage of correct pork loin classification (system sensitivity). Sensitivities range from 68% for marbling characteristic to 83% for fat content. As can be observed on comparing Tables 4 and 5, the use of irregular ROIs leads to similar or higher sensitivities for all sensorial characteristics except for the classification of marbling (in this case, sensitivity increases from 62% when applying irregular ROIs to 72% when square ROIs).

Table 3
Percentages for correct pork loin classification obtained for marbling size (MS) sensorial characteristic, when the voting criterion is applied to various combinations of texture feature vectors (columns) and feature selectors (rows).

<table>
<thead>
<tr>
<th>Features</th>
<th>$N$</th>
<th>Feature selectors</th>
</tr>
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<tbody>
<tr>
<td></td>
<td></td>
<td>PCA MIS FDR SFS FSM</td>
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<td>GLRLS</td>
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<td>All above (FSOS)</td>
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</tr>
<tr>
<td>FSOS + LLT</td>
<td>83</td>
<td>45 55 60 66 68</td>
</tr>
</tbody>
</table>

The results are calculated by operating with irregular ROIs. $N$, number of features; FSOS, first- and second-order statistics.

The feature selector named floating search method (FSM) clearly provides higher sensitivities for all sets of texture features. This fact is true for the rest of the sensorial characteristics. Thus, Table 4 shows the results obtained for all the sensorial characteristics by using the FSM feature selector.

Table 5 presents the same results as Table 4 when square ROIs, extracted from irregular regions, are applied. We also include the performance provided by filtering texture features that compute signatures such as energy, entropy, mean, variance, 3rd, and 4th central moments for a standard wavelet decomposition in three levels using Daubechies basis $D_{20}$. In general, FSOS, LLT, and FSOS + LLT feature extractors provide the highest percentage of correct pork loin classification (system sensitivity). Sensitivities range from 68% for marbling characteristic to 83% for fat content. As can be observed on comparing Tables 4 and 5, the use of irregular ROIs leads to similar or higher sensitivities for all sensorial characteristics except for the classification of marbling (in this case, sensitivity increases from 62% when applying irregular ROIs to 72% when square ROIs).

Table 4
Percentages for correct pork loin classification obtained when the voting criterion is applied to various feature vectors (columns) and sensorial characteristics (rows) by using floating searched method.

<table>
<thead>
<tr>
<th>Features</th>
<th>$N$</th>
<th>Sensorial characteristics</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>B M MS D H J FC</td>
</tr>
<tr>
<td>FOS</td>
<td>12</td>
<td>51 57 62 62 64 51</td>
</tr>
<tr>
<td>CCS</td>
<td>7</td>
<td>49 55 57 57 55 64</td>
</tr>
<tr>
<td>NGLDS</td>
<td>5</td>
<td>49 62 57 53 55 64</td>
</tr>
<tr>
<td>GLRLS</td>
<td>5</td>
<td>40 57 49 47 55 53</td>
</tr>
<tr>
<td>All above (FSOS)</td>
<td>29</td>
<td>53 62 64 64 77 55</td>
</tr>
<tr>
<td>LLT</td>
<td>54</td>
<td>68 62 72 68 72 83</td>
</tr>
<tr>
<td>FSOS + LLT</td>
<td>83</td>
<td>64 60 68 70 68 75</td>
</tr>
</tbody>
</table>

The results are calculated with irregular ROIs. $N$, number of features; B, brightness; M, marbling; MS, marbling size; D, dryness; H, hardness; J, juiciness; and FC, fat content.
The best subset of texture features to predict all sensorial characteristics is summarized in Table 6. LLT texture feature extractor is superior to the other ones for almost all the sensorial characteristics except for juiciness and marbling.

8. Discussion

Our objective in this research has been the design of an automatic, non-destroying, and objective computer system capable of solving the lack of systematic and:

<table>
<thead>
<tr>
<th>Features</th>
<th>Sensorial characteristics</th>
<th>N</th>
<th>k</th>
<th>%</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td>Brightness (B)</td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>FOS</td>
<td>LLT</td>
<td>54</td>
<td>10</td>
<td>68</td>
</tr>
<tr>
<td>CCS</td>
<td>FSOS + LLT</td>
<td>83</td>
<td>72</td>
<td></td>
</tr>
<tr>
<td>NGLDS</td>
<td>LLT</td>
<td>54</td>
<td>11</td>
<td>70</td>
</tr>
<tr>
<td>GLRLS</td>
<td></td>
<td>54</td>
<td>8</td>
<td></td>
</tr>
<tr>
<td>All above (FSOS)</td>
<td></td>
<td>29</td>
<td>57</td>
<td>68</td>
</tr>
<tr>
<td>LLT</td>
<td></td>
<td>54</td>
<td>6</td>
<td>70</td>
</tr>
<tr>
<td>FSOS + LLT</td>
<td></td>
<td>83</td>
<td>62</td>
<td></td>
</tr>
<tr>
<td>Wavelets(D_20)</td>
<td></td>
<td>72</td>
<td>62</td>
<td>72</td>
</tr>
</tbody>
</table>

The results are calculated with $64 \times 64$ ROIs extracted from irregular ROIs. $N$, number of features; B, brightness; M, marbling; MS, marbling size, D, dryness; H, hardness, J, juiciness; and FC, fat content.

Table 6

Best subset of texture features for all sensorial characteristics

<table>
<thead>
<tr>
<th>Sensorial characteristics</th>
<th>Texture extractor</th>
<th>N</th>
<th>k</th>
<th>%</th>
<th>Texture features</th>
</tr>
</thead>
<tbody>
<tr>
<td>Brightness (B)</td>
<td>LLT</td>
<td>54</td>
<td>10</td>
<td>68</td>
<td>$A_A(Ent), A_A(m_2), A_A(m_1, Ent), A_A(m_3, Ent), A_A(m_1, m_4, Ent), A_A(m_4)$</td>
</tr>
<tr>
<td>Marbling (M)</td>
<td>FSOS + LLT</td>
<td>83</td>
<td>72</td>
<td></td>
<td>$A_A(m_1), A_A(m_3), A_A(m_4), A_A(m_2)$</td>
</tr>
<tr>
<td>Marbling Size (MS)</td>
<td>LLT</td>
<td>54</td>
<td>11</td>
<td>70</td>
<td>$A_A(m_2), A_A(m_3), A_A(m_2), A_A(m_3), A_A(m_1)$</td>
</tr>
<tr>
<td>Dryness (D)</td>
<td>LLT</td>
<td>54</td>
<td>8</td>
<td>72</td>
<td>$A_A(m_3), A_A(m_2), A_A(m_3), A_A(m_2)$</td>
</tr>
<tr>
<td>Hardness (H)</td>
<td>LLT</td>
<td>54</td>
<td>6</td>
<td>70</td>
<td>$A_A(m_1), A_A(m_3), A_A(m_3), A_A(m_1)$</td>
</tr>
<tr>
<td>Juiciness (J)</td>
<td>FSOS</td>
<td>29</td>
<td>4</td>
<td>77</td>
<td>IDM, SNE, ENE, $m_4$</td>
</tr>
<tr>
<td>Fat Content (FC)</td>
<td>LLT</td>
<td>54</td>
<td>12</td>
<td>83</td>
<td>$A_A(m_2), A_A(m_3), A_A(m_2, m_3), A_A(Ent), A_A(m_2)$</td>
</tr>
</tbody>
</table>

The highest percentage of the correct pork loin classification is obtained by using irregular ROIs except for the marbling and juiciness sensorial characteristics. $N$, number of available features; $k$, number of selected features; and %, percentages in correct pork loin classification.

The best subset of texture features to predict all sensorial characteristics is summarized in Table 6. LLT texture feature extractor is superior to the other ones for almost all the sensorial characteristics except for juiciness and marbling.

8. Discussion

Our objective in this research has been the design of an automatic, non-destroying, and objective computer system capable of solving the lack of systematic and
objective methodologies to control the quality of iberian pork products in food industries. Our paper constitutes the first scientific study to prove the feasibility of computer vision scopes and MRIs to predict pre-established sensorial profiles of cured Iberian loins in a non-invasive way.

Our findings lead us to some interesting and partial conclusions statements. First, even if the FSM feature selection algorithm is superior to others tested, it suffers from the so-called *sub-optimal* points, i.e., the search method may fall into circles, which occurs when there is a sequence of features added during the inclusion step, and excluded in the same order in the backward searching of the excluding step (as searching algorithm repeatedly moves forward and backward along the same branches of the searching tree). For instance, in Tables 4 and 5, cases can be examined where the sensitivity of a combined set of texture vectors (LLT + FSOS) is lower than the LLT vector. This fact leads to the assumption that better results may be achieved when other texture feature vectors are used for selection with the FSM method. As an example, in the brightness sensorial characteristic, sensitivity increases to 74% when the LLT texture feature vector is redefined as follows (LLT); calculating only $m_1$, $m_2$, $m_3$, and $m_4$ for the nine $A_i$ masks results in a set of 36 features.

Second, irregular ROIs seem to contain more meaningful texture information than squared ones. In Tables 4 and 5, the use of irregular ROIs shows the highest sensitivities for all sensorial characteristics except for marbling. The highest improvement is achieved for the chemical characteristic (fat content), increasing the percentage of correctness from 53% to 83%.

Third, the methodology described proves to be robust. MRI images are inherently noisy. We pre-process original images to attenuate noise in them before calculating texture features. In particular, we process images with median filters having a mask size of 3 and 5 pixels. System performance does not change significantly for all cases ($P_p = P \pm 4$, where $P_p$ and $P$ respectively equal the percentage of correct pork loin classification with and without noise attenuation).

Finally, the methodology described can be applied in situ and is automatic, objective, and non-destructive for the meat items. Although in this paper, we have relied on costly state-of-art medical MRI instruments, a lower cost solution is feasible, hence working as a more suitable proposal for the meat producing industry. In contrast, the number of pork loins tested is relatively low due to the fact that sensorial and chemical analyses are tedious and expensive. Thus, pork loin sensorial characteristics may be influenced by factors such as the amount of acorn and pasture per year (directly influenced by climatological conditions), and so on. Then, further research will be needed to test whether the results obtained can be extrapolated. We are planning to study possible dependencies among sensorial characteristics to establish different sensorial profiles for consumers. In this paper, we have demostated the potential of computer vision and MRI to consistently evaluate cured pork loin quality. We conclude that our finding are encouraging and suggestive for systematic application in food industries to select pork products with certain sensorial traits for specific consumers.
9. Summary and conclusion

A novel methodology for non-invasive and objective prediction sensorial traits in cured Iberian pork loins has been described. Applicable in situ, our approach is based on texture classification for MRI images of pork loins. System sensitivity obtained is 83% for fat content in our data set and never lower than 70% for the other characteristics. The highest scores for almost all sensorial characteristics were achieved by using the following method for each stage of the system: pre-processing of MRI slices to extract irregular ROIs; Texture feature extractor LLT (calculating first-order statistics of filtered original ROIs); and choice of texture feature subsets by running the FSM approach (floating searching method).

In future work, we plan to focus on the dependence among sensorial characteristics in order to construct sensorial profiles for pork loins in the market.

Acknowledgments

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References


