Analysis and classification of commercial ham slice images using directional fractal dimension features

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Abstract

This paper presents a novel and non-destructive approach to the appearance characterization and classification of commercial pork, turkey and chicken ham slices. Ham slice images were modelled using directional fractal (DF) dimensions and a minimum distance classifier was adopted to perform the classification task. Also, the role of different colour spaces and the resolution level of the images on DF analysis were investigated. This approach was applied to 480 wafer thin ham slices from four types of hams (120 slices per type): i.e., pork (cooked and smoked), turkey (smoked) and chicken (roasted). DF features were extracted from digitalized intensity images in greyscale, and R, G, B, L, a’, b’, H, S, and V colour components for three image resolution levels (100%, 50%, and 25%). Simulation results show that in spite of the complexity and high variability in colour and texture appearance, the modelling of ham slice images with DF dimensions allows the capture of differentiating textural features between the four commercial ham types. Independent DF features entail better discrimination than that using the average of four directions. However, DF dimensions reveal a high sensitivity to colour channel, orientation and image resolution for the fractal analysis. The classification accuracy using six DF dimension features (\(a_{90}^{90}, a_{135}^{90}, H_D, H_{45}, S_{45}, H_{90}\)) was 93.9% for training data and 82.2% for testing data.

1. Introduction

The term ‘ham’ means cuts of pork that come from the hind leg of a hog, which may be fresh, dry cured (country hams) or wet-cured (city hams) and then boiled or smoked. However, in the trade, a variety of hams made from countless meat products can be found that are cured and smoked by different methods (Feiner, 2006). Thus, hams made from the front leg of a hog or shoulder are called ‘picnic or sandwich hams’ and they are ready-to-eat when purchased. The picnic hams are more economical but contain more internal fat than the blade shoulder and are less tender in texture. Other varieties such as the ‘turkey’ and ‘chicken’ hams, which could also be considered picnic hams, are made from the thigh or breast meat of these birds. These hams are frequently cooked, smoked, and roasted in combination with a variety of curing brine solutions or dry-cure mixtures of salt and other ingredients to produce more attractive products in colour, flavour and tenderness (USDA, 2007).

Although picnic hams are considered inexpensive substitutes for regular hams, the production and commercialization of thin ham slices made particularly from pork, turkey and poultry is now going through its most significant increase as demanded by the industry and consumers for catering, delicatessen, and ingredient usage. Accordingly, quality inspection based on the identification of objective methods and quality features of these products becomes increasingly important to the pre-sliced ham product manufacturers (Becker, 2002).

In the pork industry, colour is considered one of the most important quality parameters in the identification of PSE (pale, soft, exudative) meats, since they define the price of raw carcasses and also the final quality of processed products, like pre-sliced hams (Adorni, Bianchi, & Cagnoni, 1998). In the local store, however, the main quality parameters of pre-sliced hams influencing acceptability and buying decision of consumers are not only an attractive and stable colour of the ham, but also the amount and size distribution of other appearance features such as pores (Du & Sun, 2006), marbling or fat-connective tissue (Sánchez, Albarracin, Grau, Ricofelt, & Barat, 2008), which frequently define the textural appearance of these samples. It is well known that consumers need first to be entirely satisfied with the sensory properties of the food product, before other quality dimensions become relevant (Chambers & Bowers, 1993; Giusti, Bignetti, & Cannella, 2008).

Being a non-destructive, rapid, and objective quality evaluation tool, computer vision (CV) techniques have been introduced for quality assessment and measurement of meats and their related...
products, overcoming most of the drawbacks of the traditional methods, i.e., human inspectors and instrumental measurements (Du & Sun, 2005; Zheng, 2006). However, although great achievement and impressive progress has been accomplished in this area, CV systems are not yet completely developed to manage the high variability in colour and image texture appearance of many food surfaces such as those found in hams. What is needed is the insertion of new image features with simple computer algorithms for distinguishing particularly among many natural textures having no periodic structure. Image texture is a prevalent property of most physical surfaces in the natural world. It is therefore crucial to have robust and efficient methods for processing textured images (Tuceryan, 1998, chap. 2).

Consequently, suitable descriptors for the complex texture appearance of meat products, such as pre-sliced hams, could provide objective information about the characteristic uniformity or dissimilarity in texture between regions on the same ham slice and also between different production batches. Moreover, these texture descriptors could also be related to the product specifications of the manufacturer for chemical composition, physical properties, and sensory attributes (Amadasun & king, 1989; Li, Tan, Martz, & Heymann, 1999). Studies by Zheng (2006) have shown the correlation of textural properties in cooked beef joints such as hardness, chewiness, gumminess, cohesiveness, and tenderness with separated image textural features determined by co-occurrence matrix (COM), neighboring dependence matrix (NDM), run-length matrix (RLM), and first order statistics (FOS). The author showed that using partial least square regression, RML can be used to predict gumminess with the highest correlation coefficient of 0.717 while the lowest correlation was in determining cohesiveness, which was only 0.574. COM and RLM can be used to predict tenderness, but not chewiness. In contrast, NDM and FOS can predict chewiness, but not tenderness. Nonetheless, when all the features from COM, NDM, RLM, and FOS were combined together to predict the textural properties of beef, the correlation coefficient for gumminess was as high as 0.954, while for cohesiveness the correlation coefficients was 0.660.

It should be noted that the meaning of the term ‘texture’ in image processing is completely different from the usual meaning of texture in foods. Image texture can be defined as the spatial organization of intensity variations in an image at various wavelengths, such as the visible and infrared portions of the spectrum (Haralick, Shanmugam, & Dinstein, 1973). These features provide summary information derived from intensity maps of the scene which may be related to visual characteristics (texture coarseness, regularity, presence of a privileged direction, etc.), and also to characteristics with the finest textures that cannot be visually differentiated (Basset, Buquet, Abouelkaram, Delachartre, & Culioli, 2000; Mendoza & Aguilera, 2004).

Thus, there exist a variety of methods for modelling texture images. One of the characteristics among most of these methods using neighbourhood intensities is that they require the application of a template to a given image, pixel by pixel, to yield a new image (Zhang, 2006), such as those based on grey-tone spatial dependence matrices (Haralick et al., 1973). An advanced approach is to describe the texture roughness degree from an extended self-similar (ESS) model that is constructive in nature. The estimated fractal dimension of these images represents the roughness of the clutter at various scales. By following this approach, this paper presents a technique that integrates statistical texture analysis and pattern recognition methods to characterize and classify picnic ham slice images of four commercial types (cooked and smoked pork, smoked turkey and roasted chicken). In particular, the proposed technique models ham slice images using directional fractal (DF) dimensions, which are the measurement of the image roughness degree along a certain spatial direction. In addition, the role of the colour channels and image resolution level on DF analysis is investigated, and the colour components and image resolutions that are best suited for characterization and classification purposes are also suggested.

2. Materials and methods

2.1. Ham samples

Four types of commercial wafer thin hams (120 slices per type) made from pork (cooked and smoked), turkey (smoked), and chicken (roasted) were purchased from a supermarket in Dublin, Ireland. On the front of the pack, the studied products are labelled as hams ‘with no added water’. The declared percentage of meat for all ham samples is 97% (with a typical composition of protein, carbohydrates and fat for pork hams of: 20%, 1%, and 2%, respectively; and for breast meat in poultry hams of: 22%, 1%, and 1%, respectively). The remnant 3% is represented by additives such as salt, species, dextrose, condiments, stabilisers, antioxidants, and preservatives.

2.2. Image acquisition

Ham images were captured using a colour calibrated image acquisition system which consisted of the following elements:

(i) A cold light unit (Kaiser Fototechnik, Germany) with four light banks, each fitted with one daylight fluorescent lamp (41.1 cm long) of 36 W, with a colour temperature of 5400 K and a colour rendition index of 90–100 (1A). To ensure uniform illumination conditions, the four light banks were covered with light diffusers and arranged as a square, 36 cm above and at an angle of 45° with the sample.

(ii) A colour digital camera (CDC), model Powershot A75 (Canon, USA) located vertically over the background at a distance of 25 cm. The angle between the camera lens and the lighting source axis was approximately 45°, since the diffuse reflections responsible for the colour occurs mainly at this angle from the incident light (Francis & Clydesdale, 1975). Also, considering that ambient illumination is critical for reproducible imaging (Shahin & Symons, 2001), sample illuminators and the CDC were placed inside a wooden box whose internal walls were painted black to avoid the external light and reflections. A standard grey card with 18% reflectance (Neutral Test Card, Kodak, USA) was used as a white reference to set the white balance of the CDC and to standardize the illumination level. A mean L* value of 48 in the image histogram of the grey card ensured the 18% reflectance of the acquisition system. As standard capture conditions, images of one size of the ham slices were acquired on a matte black background using the following camera settings: manual exposure mode with lens aperture value at f = 4.5, speed at 1/100 (zoom and flash functions were off), resolution of 1024 × 768 pixels, and storage in JPEG format using the CDC mode ‘high resolution’ and ‘superfine quality’. All the samples were captured with the same setting conditions.

(iii) An image processing software package. All the algorithms for image pre-processing and segmentation, colour transformations, fractal analysis, and classification were written in MATLAB v7.0 (MathWorks, Inc., USA).

2.3. Image processing

For analysis, the background was removed from the pre-processed greyscale image using a threshold value of 80 combined with an edge detection technique based on Gaussian lowpass filter
with mask size [3 3] and sigma 0.5, which permits pre-smoothing of the image. This segmented image is binary, where ‘0’ (black) and ‘1’ (white) means background and object respectively. Therefore from this binary image, the localization of the pixels into the ham region permitted the extraction of the true colour image of the ham slice from the original RGB image.

Since the RGB signals generated by a CDC are device-dependent and not identical to the RGB intensities of the CIE (Commission Internationale de l’Eclairage) system, the sRGB standard for the spectral sensitivities of practical recording devices adopted by the International Telecommunication Union (Rec. ITU-R BT. 709-5, 2002) was implemented to define approximately the mapping between RGB signals from the CDC and a device-independent system such as CIE XYZ (Mendoza, 2005; Mendoza, Dejmek, & Aguilera, 2006; Stokes, Anderson, Chandrasekar, & Motta, 1996). The sRGB standard defines a virtual display based on a typical cathode ray tube (CRT) colour gamut including phosphor characteristics, a white point and the maximum luminance of the display, and a single linear transform that are applied to all three primaries (R, G, and B) obtained from a capture device (IEC 61966-2-1, 1999). Thus, after segmentation of the image, the original colour data (RGB primaries) were converted to linear sRGB and CIE XYZ and then to CIELAB (L’ a’, b’), and from ‘as is’ recorded in sRGB to greyscale intensities (Grey) and HSV colour space using the Image Toolbox functions rgb2gray (i.e., from sRGB to HSV) and rgb2gray (i.e., from sRGB to greyscale) of MATLAB v7.0, respectively. The intensity images from each colour scale (Grey, R, G, B, L’, a’, b’, H, S, and V) were stored for further analysis. The colour calibration procedure allowed well-defined and reproducible colour images as well as an objective comparison among the extracted DF dimensions using different colour components.

2.4. Fractal model

In this work, an observed greyscale image \( Y = \{ y(s) \} \) is assumed to be a stationary Gaussian process or random field defined on an \( M \times M \) lattice \( \Omega \), where \( y(s) \) denotes the grey level of a pixel at location \( s = (i, j) \), \( i, j = 0, 1, \ldots, M - 1 \). Given an image \( Y \), its fractal dimension \( D \) approximately satisfies the following (Kaplan, 1999; Kube & Pentland, 1988; Mandelbrot, 1982):

\[
v(d) = c \cdot d^{(a-2)} = c \cdot d^a
\]

where \( a \) is termed the fractal index, \( c \) is a constant, \( d \) is the separation distance in pixels and \( v(d) \) is the variogram of the image. The image variogram \( v(d) \) represents the variance or dispersion of the difference between two random variables (that is, all possible pairs of intensity pixel values in the image) and can be estimated by

\[
v(d) = \frac{1}{N(d)} \sum_{N(d)} |y(s + d) - y(s)|^2
\]

where \( N(d) \) denotes the cardinality of the set of pairs of observations whose spatial locations are separated by a particular distance \( d \). Given different distances \( d_i, i = 1, 2, \ldots, K \) (with \( K \) being typically a small integer), a set of \( v(d_i) \) can be obtained using Eq. (2).

Thus, the relationship between \( a \) and \( v(d) \) can also be represented using the linear regression model below, by applying log function to both sides of Eq. (1):

\[
\log \{ v(d) \} = \log(c) + a \cdot \log(d)
\]

By applying the least square (LS) fitting algorithm to Eq. (3), the estimates of fractal index \( \hat{a} \) can be computed. Then, the fractal dimension of \( Y \) can be estimated such that

\[
\hat{D} = 3 - 0.5\hat{a}
\]

2.5. Experimental design and analysis

In the above model (Eq. (3)), the variogram of the image and hence the fractal dimension is estimated at a fixed image resolution level without specifying any spatial direction along which the set of pairs of observations is constructed. This means that the image is assumed to be isotropic. Since the proposed fractal texture parameters of ham slices could not be expected to have isotropic patterns, in this work, for a given pixel location \( s \) of a given image, four variograms that are respectively computed along the directions 0°, 45°, 90°, and 135° (namely horizontal, first diagonal, vertical, and second diagonal) were analysed.

Then, after some initial screening of the appearance quality of the wafer thin ham slices, the DF features were used to model the texture of these ham images. In the first experiment, DF values were computed from different colour channels (grey, R, G, B, L’, a’, b’, H, S, and V) to analyse their suitability to characterize and identify ham types. In the second experiment, the effect of the resolution level on the robustness of DF estimators for the characterization and classification of ham slice images was evaluated. For this, from the original RGB images (0.2041 mm/pixel) mathematical images were generated with diminished resolution levels to 50% (0.4082 mm/pixel) and to 25% (0.8164 mm/pixel), so that the new images were scaled to \( M \times N \times 120 \) for each ham type (i.e., 120 images per type where \( M \times N \) have values of 1024 × 768, 512 × 384, and 256 × 192 pixels, respectively). This means that the images were shrunk by skipping in each row and column one pixel for getting images with 50% resolution level and two pixels for images with 25% resolution level.

Finally, using the best fractal dimension features for ham type’s characterization, the effects of resolution were studied in two ways. First, the DF_{DF0}, DF_{DF5}: DF_{DF0}: and DF_{DF135} features from each colour component were used independently in the classification process, and second, the DF features from each colour component were averaged and their values were used for classification.

3. Results and discussion

3.1. Surface appearance of ham slices

Fig. 1 shows representative ham slice images used in this study. Different colour and texture patterns can be appreciated among them. In general, cooked and smoked pork hams look similar, with inhomogeneous colour surfaces and an irregular distribution of fat-connective tissue which appears elongated and showing some orientation. By contrast, the smoked turkey and roasted chicken hams appear more homogeneous in colour and without any apparent presence of fat-connective tissue regions. However, in the smoked turkey and roasted chicken hams the presence of pores and holes and particularly unevenness and small fissures on the surface were more persistent and pronounced; turkey and chicken ham samples are thinner, and therefore, more susceptible to structural damage caused by handling during slicing and packing. Visually, the cooked and smoked pork samples showed seemingly coarser textures than those seen in smoked turkey and roasted chicken hams, but their textures do not contain any detectable quasiperiodic structure.
Instead, they exhibit random but persistent patterns that result in a cloudlike texture appearance. These visual textures are generally formed by the interaction of light with a rough surface (McGunnigle & Chantler, 1999).

Because the final colour and texture perception of hams depends on the formulation, microstructure imparted to the ham during fabrication (i.e., due to curing, roasting, cooking, smoking and cooling processes), and storage conditions among others, these appearance features are expected to be specific for each ham type. Nowadays, the labelling of processed and packed foods regarding chemical composition and treatment during fabrication is mandatory everywhere. In the UK for example, ham producers have to declare the percentage of meat and ingredients in the packaged ham. They also have to label water as an ingredient if it constitutes more than five percent of the cold meat product. However, consumer complaints are still received, demanding ham companies to spell out exactly the added water and ingredients on the packages. Recently, some well-known ham manufacturers have been blasted out exactly the added water and ingredients on the packages. Re-complaints are still received, demanding ham companies to spell out the percentage of meat and ingredients in the packaged ham. Among these commercial hams, wafer thin hams were found to be for selling more water and additives and less meat than expected.

The last row shows the two larger distances between each combination of hams (denoting maximum separability) by considering the complete table. Thus, out of a total of 6 pair combinations, 5 times DF features extracted from a’ colour scale generated the largest distance between pairs, followed by H and S scales with 4 and 3 occurrences, respectively. However, it should be noted that the largest distances were always found in the H and a’ colour channel (Table 1, values denoted with a ‘*’ symbol), being the combinations with larger separability of those for cooked and smoked pork hams against roasted chicken hams (17.72 and 17.51, respectively). The most difficult ham combination to separate was between cooked and smoked pork, where all the distances using different colour spaces were smaller than 2.32. Preliminary colour measurements on the surface of these four ham types revealed no statistical differences (p \geq 0.05) between the average colour values in L’ a’ b’ channels for cooked and smoked pork hams, as well as between smoked turkey and roasted chicken hams; but significant differences were found among these two groups (data not shown).

Additionally, it is important to note in Table 1 that the DF features from greyscale, RGB, and b’ colour components as well as the lightness components L’ and V were not found to be the best for any pair. Particularly, the Mahalanobis distances for greyscale images, which are frequently the input images in many fractal analyses, were at least 2.2 times smaller than those observed for the colour channels showing the largest distance for each combination (i.e., smoked turkey vs. roasted chicken, 4.649/2.158 \approx 2.2). It could also be noted that the same Mahalanobis distance values were registered for R and V channels. This is due to fact that the predominant colour in the ham images is represented by the red channel as observed in Fig. 1, and V values are a measurement of the image lightness calculated in MATLAB as the highest intensity value between the RGB components.

However, it will be extremely useful for classification purposes to know in detail the best DF features associated with each colour channel, that is, the colour channels and orientations with the highest discriminant power. Table 2 presents the Mahalanobis distance results for the best colour channels using independent DF estimations. Similarly, the last row shows that for a given colour channel, how many of these distance computations were maximum in the entire table. Clearly, the results reveal that the colour DF dimensions with the strongest discriminant power for the analysed ham samples are a’_90 (6 times from 6 combinations) and H_45 and S_0 (3 times from 6 combinations).

Table 3 (second column) shows the average DF dimension results for each set of hams measured by the best features at the highest resolution level (100%, 0.204 mm/pixel). The average fractal dimensions are different among types of hams and also among colour channels. Also the variation (standard deviations) of the average DF dimensions for each type of ham gives an idea of the sensitivity of the method, as well as the sensitivity of these selected colour scales and directions to describe variations in surface texture. These characteristics reflect the fact that colour DF features are good at capturing information embedded in the spatial structure of the underlying image texture. More specifically, the a’_90, H_45 and S_0 DF dimensions are robust descriptors for discriminating among different types of hams.

As mentioned before, the ham images in Fig. 1 appear rougher for cooked and smoked pork hams than for smoked turkey and roasted chicken hams, and therefore, it can be expected to find DF values higher for the first two types of hams as they are shown by the 5 colour channel (Table 3). However, the DF dimensions computed from H and a’ colour channels showed similar tendencies with a reduced variability (standard deviations), but their average DF values were higher for smoked turkey and roasted...
chicken hams. This could be explained since the RGB, \(L^*a^*b^*\) and HSV colour systems do not scale the information in the same way, and each one can reflect variations in colour not found by the others. The intensity images from \(H\) and \(a^*\) colour scales were sensitive enough to reflect intensity variations due to the presence of small pores and holes on the ham surface, which are more frequently found in smoked turkey and roasted chicken hams, and which are not easily appreciated at first sight due to their homogeneous colour appearance. This means that it is not simply the magnitude of the intensity or brightness variation that describes the roughness of the surface, but its spatial organization (Russ, 1994). In addition, it is known that when the edges of the structures in the image (such as in small particles or grit size structures) are rougher the fractal dimension increases (Bonetto, Forlerer, & Ladaga, 2002). The pores and holes as well as the slight colour variations on the surface in smoked turkey and roasted chicken hams are in fact smaller structural clusters than in cooked and smoked pork hams, and therefore, their edges are expected to be more irregular.

Similar results were found by Bonetto and Ladaga (1998) and by Bonetto et al. (2002) using SEM images to study the interaction mechanisms between two types of bacteria and two types of plas-

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**Fig. 2.** Scatter-plot of the logarithm of representative sample variograms against log(d) estimated in their four directions using different colour components for the ham images shown in Fig. 1 (superimposed over the fitted lines appear the DF dimensions for each type of ham).
Table 1
Mahalanobis distance between different combinations of commercial types of ham slices using the average of four DF features (0°, 45°, 90°, and 135°) extracted from each colour channel.

<table>
<thead>
<tr>
<th>Type 1</th>
<th>Type 2</th>
<th>Mahalanobis distance using the average of four directions (0°, 45°, 90°, and 135°) for each colour component</th>
</tr>
</thead>
<tbody>
<tr>
<td></td>
<td></td>
<td>Grey</td>
</tr>
<tr>
<td>Cooked pork</td>
<td>Smoked pork</td>
<td>0.916</td>
</tr>
<tr>
<td>Cooked pork</td>
<td>Smoked turkey</td>
<td>1.276</td>
</tr>
<tr>
<td>Cooked pork</td>
<td>Roasted chicken</td>
<td>0.115</td>
</tr>
<tr>
<td>Smoked pork</td>
<td>Smoked turkey</td>
<td>0.030</td>
</tr>
<tr>
<td>Smoked pork</td>
<td>Roasted chicken</td>
<td>1.681</td>
</tr>
<tr>
<td>Smoked turkey</td>
<td>Roasted chicken</td>
<td>2.158</td>
</tr>
<tr>
<td># Best for two larger distances</td>
<td></td>
<td>0</td>
</tr>
</tbody>
</table>

Values in bold represent the largest distances for each combination of hams.
Values denoted with a plus symbol (+) represent the largest distance for each combination of hams.

Table 2
Mahalanobis distance results for the best colour channels using independent DF features.

<table>
<thead>
<tr>
<th>a Type 1</th>
<th>Type 2</th>
<th>a0, a24, a0, a15s</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooked pork</td>
<td>Smoked pork</td>
<td>1.937, 2.095, 2.584, 1.989</td>
</tr>
<tr>
<td>Cooked pork</td>
<td>Smoked turkey</td>
<td>0.050, 0.099, 0.163, 0.057</td>
</tr>
<tr>
<td>Cooked pork</td>
<td>Roasted chicken</td>
<td>5.099, 5.521, 6.605, 5.175</td>
</tr>
<tr>
<td>Smoked pork</td>
<td>Smoked turkey</td>
<td>2.611, 3.105, 4.046, 2.720</td>
</tr>
<tr>
<td>Smoked turkey</td>
<td>Roasted chicken</td>
<td>4.136, 4.142, 4.692, 4.146</td>
</tr>
<tr>
<td># Best</td>
<td></td>
<td>0, 0, 6, 0</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>H Type 1</th>
<th>Type 2</th>
<th>H0, H45, H90, H135</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooked pork</td>
<td>Smoked pork</td>
<td>0.162, 0.018, 0.010, 0.058</td>
</tr>
<tr>
<td>Cooked pork</td>
<td>Smoked turkey</td>
<td>7.541, 6.450, 6.281, 5.681</td>
</tr>
<tr>
<td>Cooked pork</td>
<td>Roasted chicken</td>
<td>12.498, 17.951, 15.637, 16.899</td>
</tr>
<tr>
<td>Smoked pork</td>
<td>Smoked turkey</td>
<td>5.496, 7.158, 6.786, 6.882</td>
</tr>
<tr>
<td>Smoked pork</td>
<td>Roasted chicken</td>
<td>9.818, 19.120, 16.428, 18.717</td>
</tr>
<tr>
<td>Smoked turkey</td>
<td>Roasted chicken</td>
<td>0.623, 2.881, 2.097, 2.903</td>
</tr>
<tr>
<td># Best</td>
<td></td>
<td>2, 3, 0, 1</td>
</tr>
</tbody>
</table>

<table>
<thead>
<tr>
<th>S Type 1</th>
<th>Type 2</th>
<th>S0, S45, S90, S135</th>
</tr>
</thead>
<tbody>
<tr>
<td>Cooked pork</td>
<td>Smoked pork</td>
<td>1.041, 1.125, 1.998, 0.908</td>
</tr>
<tr>
<td>Cooked pork</td>
<td>Smoked turkey</td>
<td>5.272, 1.310, 3.063, 1.111</td>
</tr>
<tr>
<td>Cooked pork</td>
<td>Roasted chicken</td>
<td>0.997, 0.189, 0.001, 0.213</td>
</tr>
<tr>
<td>Smoked pork</td>
<td>Smoked turkey</td>
<td>1.629, 0.007, 0.113, 0.010</td>
</tr>
<tr>
<td>Smoked pork</td>
<td>Roasted chicken</td>
<td>0.001, 2.238, 1.895, 2.002</td>
</tr>
<tr>
<td>Smoked turkey</td>
<td>Roasted chicken</td>
<td>1.684, 2.496, 2.934, 2.298</td>
</tr>
<tr>
<td># Best</td>
<td></td>
<td>3, 1, 2, 0</td>
</tr>
</tbody>
</table>

Values in bold represent the largest distances for each combination of hams.

3.3. Dependency of DF features on the resolution

Spatial resolution is the ability to resolve close-distance and high contrast features in the image. Two objects will not be separable in an image if the spatial resolution of the image is larger than the distance between them. Therefore increasing the resolution will have a significant advantage since scattering tends to reduce both contrast and signal-to-noise ratio, while causing blurring. The average fractal dimensions for the analysed ham types at each image resolution (100%, 50%, and 25%) are summarised in Table 3. Considering the large number of dimensional fractal features obtained by the analysis, the data shown here are only for the independent DF features with the largest Mahalanobis distance as determined in Table 2. The average fractal dimensions and standard deviations for all colour scales show an increase when decreasing resolution (Table 3). However, it has been proved for deterministic fractals by Baveye, Boast, Ogawa, PARLANGE, and STENNHUIS (1998) that the fractal dimension increases with increasing resolution (smaller-pixel size). Moreover, it could be expected that images with higher resolutions might reflect finer details of the scene, and consequently, increase the estimated ranges of surface roughness. It is assumed that this unexpected observation is related to the proposed fractal algorithm, the complexity of the ham images, and the larger range of the analysed resolutions. Using lower resolution levels, a reduced number of pixels pairs exist to build representative image variograms and therefore to compute accurate fractal dimensions. An increased variability could also be expected. On the other hand, this finding shows that we are not dealing with a strong fractal structure (self-similarity over many ranges of scale), but instead with a natural system showing fractal properties in a limited scale range. Although a natural texture may exhibit similar roughness over a large range of scales, it is improper in reality to assume the roughness to be constant for arbitrary large or small scales.
Therefore, adequate image resolution for capturing pre-sliced hams can provide well-defined images to facilitate not only the visualization of the finest details of the sample, but also the accuracy of the extracted fractal parameters. However, the selection of the resolution for DF analysis may depend on the problem under investigation and the particular application such as that for quality control in real-time. Currently, high speed machine vision systems for quality inspection are developed for an image resolution of 640 × 480 pixels. In real-time visual inspection tasks, image resolution and length of the feature vector plays a major role, irrespective of the classification principle used. As a result, the highest possible image resolution combined with a compact set of powerful features can be a successful combination in the classification process.

3.4. Classification results

For the purpose of justification, a supervised pattern recognition method was applied to simulate the ham type identification process using linear discriminant analysis as the selection criterion. Hence, in the classification experiments, the ham images were divided into the training set and the test set. The training set was used to build the discriminant model and the test set was employed to verify the trained discriminant model. In a first attempt the classification test was performed using only the best discriminant features, as determined by the Mahalanobis distance analysis, the classification test was performed using only the best discriminant features. In a second approach, the DF features were averaged and the images at different resolution levels. In the second approach, the DF features from each colour component were evaluated independently in the classification process, but considering only DF features with correlation coefficients lower than 0.7. In the second approach, the same DF features were averaged and used for classification.

The results prove that the proposed fractal approach for appearance characterization of ham slice images ensures high classification performance and maintains robustness even with images having low resolution levels (50%, 0.4082 mm/pixel). Better prediction rates for the test set using $a_{90}$, $a_{135}$, $H_0$, $H_45$, $S_0$, $S_{90}$, and in comparison with the average set, confirmed that the inclusion of independent colour DF features gave consistent and useful information and allowed the discard of information associated with some colour channels and textural orientation of the samples that could introduce prediction errors, thus increasing the performance of the classification model. Fig. 3 shows the graphic classification performance for the four types of commercial ham slices using independent DF features at the highest resolution level. The prediction accuracy of the proposed fractal analysis using six DF dimension features is 93.9% for training data and 82.2% for testing data.

Finally, it could be important to note that it is very difficult to simulate with simple appearance features the complex human perception process. In spite of that, these DF dimensions have shown some potential for detecting different colour patterns on ham surfaces which could be useful as quality indexes. Nevertheless, more experiments are needed to completely define and confirm the success of these image analysis features for practical industrial applications. This represents the next steps of our investigation in ham slices.

4. Conclusions

In this study, a novel and non-destructive approach is proposed to analyse and characterize commercial ham slices using DF fea-

### Table 3

<table>
<thead>
<tr>
<th>Resolution level</th>
<th>$a_{90}$</th>
<th>$a_{90}$</th>
<th>$a_{135}$</th>
<th>$H_0$</th>
<th>$H_45$</th>
<th>$S_0$</th>
<th>$S_{90}$</th>
</tr>
</thead>
<tbody>
<tr>
<td>100% (0.2041 mm/pixel)</td>
<td>2.52 ± 0.029</td>
<td>2.72 ± 0.055</td>
<td>2.77 ± 0.074</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>50% (0.4082 mm/pixel)</td>
<td>2.48 ± 0.028</td>
<td>2.66 ± 0.058</td>
<td>2.69 ± 0.071</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>25% (0.8164 mm/pixel)</td>
<td>2.53 ± 0.026</td>
<td>2.74 ± 0.049</td>
<td>2.80 ± 0.078</td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
</tbody>
</table>

a–c, values with the same letters (within each resolution level and colour channel) indicate no significant differences among types of hams ($p > 0.05$).
tures extracted from different colour scales and orientations (4 directions). The input image is a segmented colour image of the ham which is processed to obtain intensity images in different colour channels (greyscale, R, G, B, L', a*, b*, H, S, and V) and with three different image resolutions of hams. Then, the fractal analysis is applied to obtain the DF texture features in order to find the average probabilistic distance of separation across four different ham types which could be used for their characterization and identification. Some of the important conclusions include:

1. The DF dimensions of ham slice images using different colour channels, determined by a straight line fit in a log–log plot, have extremely high statistical significance, with $R^2 > 0.985$.

2. The colour DF dimensions have a strong discriminant power to differentiate quality parameters from ham surface images. However, the choice of colour space and direction for the DF analysis is a crucial one.

3. Image resolution seems to have the most pronounced influence on the value of the fractal dimension and its variability, which increase markedly at lower resolution (higher-pixel size).

4. The best classification results, using half the number of images for training and the other half for testing of the classifier, were achieved using a combined set of DF colour features $(a_{090}, a_{135}, H_0, H_{45}, S_0, S_{90})$ with the correct classification rate of 93.9% for training data and 82.2% for testing data.

5. The proposed approach is easily programmed and very efficient for the roughness characterization of complex images. DF features have shown high sensitivity to reflect intensity variations due to defects (pores and holes) and fat-connective tissue (if they are present) on ham surfaces which are not easily appreciated at first sight, and therefore, their values need to be interpreted with caution. Our results indicate that DF features are promising descriptors for the appearance characterization and quality prediction of pre-sliced hams.

For future investigations, this fractal analysis technique could be applied to other ham formulations, while other colour and textural features could be used for improving the classification performance.

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References


