Texture appearance characterization of pre-sliced pork ham images using fractal metrics: Fourier analysis dimension and lacunarity

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A R T I C L E  I N F O

Article history:
Received 29 October 2008
Accepted 21 December 2008

Keywords:
Computer vision
Fourier analysis fractal dimension
Gliding box lacunarity
Pork ham slice
Surface characterization
Texture appearance

A B S T R A C T

An important goal for characterization of texture appearance is the quantification of spatial patterns. The objective was to investigate the potential usefulness of two fractal metrics based on fast Fourier transform and gliding box lacunarity as descriptors of visual texture in ham slices. Images were acquired from three qualities of sliced pork ham, typically consumed in Ireland (200 slices/quality). Unexpected characteristics in textural pattern were revealed; the values of fractal dimension were larger for the smoothest surface. Alternatively, the decreasing trend of the power spectrum intercept towards the smoother premium quality ham showed that it correlates well with the overall magnitude of visual roughness. The results of lacunarity suggest that it has a discriminating power among the three ham qualities and its behaviour resembles the one of an exponential decay function. Results showed that Fourier analysis dimension, power spectrum intercept and lacunarity are important fractal parameters and useful quantitative descriptors that capture information embedded in the spatial structure of the underlying image texture of hams.

1. Introduction

A fractal describes a rough or fragmented geometric shape that can be subdivided into parts, each of which is, at least approximately, a reduced-size copy of the whole. Contrary to classical geometry, fractals are not regular and may have an integer or non-integer dimension. Also, they are generally self-similar and independent of scale (Mandelbrot, 1983).

An important goal for the characterization of visual texture in biological materials, using computer vision technology, is the quantification of spatial patterns. These patterns are often complex, exhibit scale-dependent changes in structure, and are difficult to identify and describe (Plotnick, Gardner, Hargrove, Prestegaard, & Perlmutter, 1996). Consequently, the use of fractal metrics like Fourier analysis fractal dimension and lacunarity, have been increasingly applied to tackle this problem. More specifically, Fourier spectrum quantifies the periodicity of surface objects in the frequency domain in terms of frequencies and peak amplitudes, and lacunarity quantifies the degree of translational invariance of the analyzed objects, with low values of lacunarity indicating high levels of such invariance (Rodrigues, Barbosa, & Costa, 2005).

Fractal dimension is a measure of how complicated a self-similar object is. Natural objects do not show exactly the same shape, but look quite similar when they are scaled down. Self similarity is not visually obvious but there may be numerical or statistical measures that are preserved across scales. Due to their statistical scaling invariance, natural objects may exhibit statistical fractality (Klonowski, 2000). It should be noted that the meaning of the term "visual texture" is completely different from the usual meaning of texture in foods. Visual texture can be defined as the spatial organization of intensity variations in an image at various wavelengths.

Computer vision has been implemented for quality assessment in meats and meat products, overcoming most of the drawbacks of traditional methods, e.g. human inspectors and instrumental techniques (Du & Sun, 2005; Kumar & Mittal, 2009; Quevedo & Aguiler, 2009; Quevedo, Aguiler, & Pedreschi, 2009; Zheng, Sun, & Tan, 2008; Zhong, Sun, & Zheng, 2006). Ham slices in general have complex and inhomogeneous colour surfaces and their textures do not contain any detectable periodic or quasiperiodic structure (Mendoza et al., 2009). Instead, they exhibit random but persistent patterns that result in a cloudlike texture appearance. These inhomogeneities can be attributed mainly to formulation, presence of pores/defects and fat-connective tissue, and colour variations (Valous, Mendoza, Sun, & Allen, 2009). Thus, for objective characterization, image analysis techniques need to take into account the high variability in colour and texture appearance. Consequently, suitable descriptors to characterize sliced ham images...
are needed to provide objective information about uniformity or dissimilarity (Mendoza et al., 2009). One of the simplest approaches for describing visual texture is to use moments of the grey-level image histogram, i.e. mean and variance, which are considered bulk parameters. However, this analysis is somewhat limited, since information on spatial organization or periodicity is lost (Dougherty & Henebry, 2002). Second-order metrics such as fractal dimension and lacunarity are, in theory at least, able to characterize these images better, providing information about the spatial distribution of their intensity pixels (i.e. objects or elements). Numerous algorithms for estimating fractal dimension and lacunarity have been implemented for a variety of images. The Fourier power spectrum method conveniently represents the statistical nature of real images by describing them in terms of a fractional Brownian motion model (Dougherty & Henebry, 2001). Lacunarity computation using the gliding box algorithm has the advantage of the large sample size that usually leads to more consistent statistical results (Saa, Gascó, Grau, Antón, & Tarquis, 2007). Furthermore, lacunarity is suitable to describe the spatial distribution of real data sets, because translational invariance can also be a property of non-fractal sets. This is an advantage over fractal dimension, and has been commonly used as a texture descriptor of images that often exhibit limited self-similarity. Moreover, translational invariance is highly scale-dependent, so lacunarity is considered a scale-dependent measure of heterogeneity (Plotnick et al., 1996).

Several studies have applied fractal analysis to investigate food surfaces and structure (Barletta & Barbosa-Cánovas, 1993; Barrett & Peleg, 1995; Dźiuba, Babuchowski, Smoczyński, & Smietana, 1999; Kerdpiboon, Devahastin, & Kerr, 2007; Nussinovitch, Jaffe, & Gillilov, 2004; Rahman, 1997; Tang & Marangoni, 2008). More specifically, the Fourier power spectrum method has been used previously in foods: in the assessment of the jaggedness of the stress-strain relationship of two kinds of puffed extrudates stored under different humidity conditions (Barrett, Normand, Peleg, & Ross, 1992); in the numerical description of various food surfaces and the microstructure of potato cells as well as in the detection of the bloom starting point in chocolates (Quevedo, López, Aguilera, & Cadache, 2002); in the quantification of the fractional dimension of fat crystal networks (Tang & Marangoni, 2006); in describing the visual appearance of bread crumb as well as obtaining correlations using trained panelists (Gonzales-Barron & Butler, 2008a; Gonzales-Barron & Butler, 2008b); and in determining the senescent spotting in bananas (Quevedo, Mendoza, Aguilera, Chanoa, & Gutiérrez-López, 2008). Other studies have implemented this method to determine the fractal dimension in medical imaging applications (Dougherty, 2001; Dougherty & Henebry, 2001; Einstein, Wu, & Gil, 1998), to explain plant structure information (Critten, 1997) and to assess surface topography changes (Perry, 2000). Lacunarity analysis has been proposed as a general method for the analysis of a number of spatial patterns (Butson & King, 2006; Cheng, 1997; Chmiela, Slota, & Szala, 2006; Feagin, Wub, & Feagin, 2007; Gan, 2005; McIntyre & Wiens, 2000; Melo, Vieira, & Conci, 2006a; Moghaddam, Hintz, & Stewart, 1991; Myint & Lam, 2005; Myint, Mesev, & Lam, 2006; Saunders, Chen, Drummer, Gustafson, & Broosofe, 2005; Witt & King, 1999). In particular, Keller, Chen, and Crownover (1989) introduced new features based on the concept of lacunarity which capture the second-order statistics of fractal surfaces. Smith, Lange, and Marks (1996) reviewed the concept of lacunarity as a potentially distinguishing measure in cellular morphology, while other studies involved lacunarity in medical applications (Einstein et al., 1998; Melo, Vieira, & Conci, 2006b) and in particular as a texture measure containing essential information on bone microarchitecture (Dougherty, 2001; Dougherty & Henebry, 2001; Zaia, Eleonor, Maponi, Rossi, & Murri, 2005; Zaia, Eleonor, Maponi, Rossi, & Murri, 2006). Dale (2000) examined the properties of lacunarity analysis and compared it with other methods of pattern analysis. Krasowska, Borys, and Grzywna (2004) did a systematic study of lacunarity as a supplement for describing texture. Lacunarity as a texture measure was used also by Plotnick, Gardner, and O’Neill (1993) for quantifying landscape pattern, by Henebry and Kux (1995) for connecting image phenomenology and scene dynamics, and by Facon, Menoti, and Araújo (2005) for address block segmentation. Furthermore, Dávila and Parés (2007) used lacunarity analysis to complement the microstructure description of heat-induced plasma proteins gels.

Image analysis techniques are capable of extracting descriptors of the visual and non-detected visual textural patterns from ham slice surfaces (Mendoza et al., 2009). These descriptors allow analysis and interpretation with precision and objectivity for the quality grading of hams. In addition, they may correlate well with physical and sensorial indicators of ham quality (Du & Sun, 2006). As a result, they could be used for the automation of ham inspection protocols. Therefore, the objective of this study was to investigate the potential usefulness of two fractal metrics; namely Fourier analysis fractal dimension based on 2D fast Fourier transform (FFT) using different colour scales, and lacunarity using binary images of pores/defects and fat-connective tissue structures, as quantitative descriptors of visual texture in ham slice images. To our knowledge this is the first reported use of lacunarity for the characterization of images of food surfaces.

2. Materials and methods

2.1. Pork ham samples

Three pork ham qualities were manufactured in Dawn Farm Foods (Co. Kildare, Ireland), using different muscle sections and different percentages of brine solutions (wet curing by injection). Specifically, the high-yield ham (A1; low quality) had a 50% brine injection and the pork muscle used was Silverside PAD (biceps femoris) cut to 100 mm wide. The injected muscle was vacuum tumbled at 1500 rpm for 12 h and vacuum filled into PVC casings, clipped and cooked at 82 °C to a core temperature of 72 °C. The medium yield ham (A2; intermediate quality) had a 30% brine injection and it contained three leg muscles: Topside, Silverside and Knuckle. The injected muscle was vacuum tumbled at 500 rpm for 5 h and vacuum filled into PVC casings, clipped and cooked at 82 °C to a core temperature of 72 °C. The low yield ham (A3; premium quality) had a 12% brine injection, and the pork muscle used was Silverside PAD (biceps femoris) cut vertically in half. The injected muscle was not tumbled, but vacuum packed and cooked at 82 °C to a core temperature of 72 °C. All pork ham samples were chilled to 4 °C before slicing. Images were acquired immediately after slicing (200 slices per quality).

2.2. Image acquisition and processing

A colour calibrated computer vision system (CVS) as described by Valous et al. (2009) was used for image acquisition (spatial resolution of 0.0952 mm/pixel). The software package MAT(LAB (MathWorks, USA) was used for image processing, fractal computations and curve fitting. A polynomial transform for calibrating colour signals (Valous et al., 2009) was used to map the RGB primaries to sRGB (IEC., 1999), and to CIEXYZ and CIELAB (‘L*a*b*’), and from ‘as is’ (sRGB) to greyscale intensities (Grey) and the HSV colour space, using the image processing toolbox functions ‘rgb2gray’ and ‘rgb2gray’ of MATLAB, respectively. Since different colour channels could give different information about the colour patterns of hams, the intensity images from each colour scale (R, G, B, ‘L’, ‘a’, ‘b’, H, S, V, and Grey) were stored for further analysis. Due to the large variations in size and shape among the three
ham qualities, the images were subsequently cropped in the central region to produce 256 × 256 pixel images (equivalent to 593.96 mm²). The reason for the image cropping was based on the notion that for fractal dimension evaluation, a convenient and fast implementation of the computation is carried out if the image is square with a dimension in pixels that is a power of two, i.e. 2^8 = 256 (Russ, 1994). In addition, for the lacunarity analysis, cropping allowed better scrutiny and interpretation (all images had the same spatial pixel dimensions), and also kept computation times manageable. The intensity images from each colour scale were the input for the fractal dimension computation, while the segmented binary images of pores/defects and fat-connective tissue were used to compute lacunarity.

2.3. Pores and fat-connective tissue segmentation

For pores/defects segmentation a median filter [3 × 3] was applied to the saturation (S) intensity images (from HSV colour scale), to remove impulse noise (Russ, 2005). Contrast enhancement filtering [20 × 20] highlighted the pores/defects (dark features in ham slice image), and a histogram-based segmentation using a unique threshold value of 100 produced the binary image. Post-processing involved a flood-fill operation on background pixels, to fill the gaps present on the pore structures. For fat-connective tissue segmentation (Valous et al., 2009), the green (G) intensity image was pre-processed with a median filter [3 × 3] to remove impulse noise. Then, a morphological closing filter [3 × 3] was applied to remove pores and also to decrease the intensity variations of the background pixels (more ‘flat’ background in relation with the fat-connective tissue) was carried out. A hi-pass filter [15 × 15] was applied for increasing sharpness and contrast. This operation introduced some random noise which was removed using the median filtering operation [3 × 3], while a subsequent histogram-based segmentation using a unique threshold value of 200 produced the binary images.

2.4. Fractal analysis

2.4.1. Power spectrum method

The methods to calculate fractal dimension can be divided into two types: spatial and spectral. The first type operates in the spatial domain, while the second type operates in the frequency domain. The two types are unified by the principles of fractional Brownian motion (Dougherty & Henebry, 2001). To estimate the fractal dimension it is generally unified by the principles of fractional Brownian motion (Dougherty & Henebry, 2001). To estimate the fractal dimension it is generally assumed that the input image A is of size T² pixels with A(x, y) ∈ {0, 1, ..., 255} and x, y ∈ {0, 1, ..., T − 1}. Furthermore, the pixel intensity z of A(x, y) is considered as a point (x, y, z) in three dimensions, where x and y are the spatial dimensions. The power spectrum method is based on the power spectrum dependence of fractional Brownian motion. The 2D Fourier transform of the ham slice image is calculated first and then the 2D power spectrum is derived. The 2D power spectrum is reduced to a 1D radial power spectrum (direction independent mean spectrum, i.e. the average of all possible directional power spectra) by averaging values over increasingly larger annuli for each of the radial increments (Dougherty & Henebry, 2001). The power spectrum, P(f), varies with frequency, f, as:

\[ P(f) = k \cdot f^{(1 - 2H)} \]  

where k is a constant and H is the Hausdorff–Besicovitch dimension. When the log[P(f)] is plotted against log[f], a straight line can be fitted (Geraets & van der Stelt, 2000). According to the Fourier slice theorem, the 1D Fourier transform of a parallel projection of an image along a line with the direction θ is identical to the value along the same line in the 2D Fourier transform of the image. This means that the line through the spectrum gives the spectral information obtained from a projection with the same orientation in the spatial domain (Yi, Heo, Lee, Choi, & Huh, 2007). The directional fractal dimensions were calculated as a function of orientation based on this theorem, with 24 being the number of directions that the frequency space was uniformly divided. The data of magnitude vs. frequency are plotted in log–log scale and its slope is determined using linear least-squares regression (Issa, Issam, & Chudnovskiy, 2003). Thus, the Hausdorff–Besicovitch dimension H is computed from the slope c of the straight line: \( c = -(1 - 2H) \). The fractal dimension \( D_f \) of the ham slice surface is related to the slope c of the log–log plot by the equation below, with \( H = D_f - 3 \):

\[ D_f = \frac{7}{2} + \frac{c}{2} \]  

The slope and intercept for all directions and for all colour channels were computed. The algorithm used was originated from Russ (1994), written in Matlab by Zhang (1994) and was modified in the current study for our purposes.

2.4.2. Lacunarity

The algorithm for lacunarity computation analyzes deviations from translational invariance of an image’s intensity distribution using gliding box sampling (gliding box algorithm, GBA) (Pendleton, Dathe, & Baveye, 2005). In this method, a square structuring element or moving window of side length b is placed in the upper left-hand corner of the ham slice image of side length T (pixels), such that b ≤ T. The algorithm records the number or “mass” m of pixels that are associated with the image underneath the moving window. The window is then translated by one pixel to the right and the underlying mass is again recorded. When the moving window reaches the right-hand side of the image, it is moved back to its starting point at the left-hand side of the image and is translated by one pixel downward. The computation proceeds until the moving window reaches the lower right-hand edge of the image, at which point it has explored every one of its \( (T - b + 1)^2 \) possible positions. Allain and Cloitre (1991) defined lacunarity A measured with a moving window of side length b, as:

\[ A = \frac{\sigma^2}{\mu^2} + 1 \]  

where the ratio of \( \sigma \) (standard deviation) to \( \mu \) (mean) changes with window size which signify that lacunarity depends on the scale (window size relative to image size), as well as the complexity of the image. The Matlab implementation of the algorithm takes into account the pixel mass-based lacunarity not only of the foreground pixels (structures of pores/defects and fat-connective tissue), but also of the empty boxes (white background or lean of hams). Thus, to calculate lacunarity, the number of empties is added to the mass counted. Since the size of the analyzed images was 256 × 256 pixels, the code computes the values of lacunarity for each value of b between \( b_{\text{min}} = 1 \) and \( b_{\text{max}} = 256 \), with a step size of one. Once the computation is complete, lacunarity as a function of moving window b is presented as a 2D plot, which illustrates the scale dependency of spatial nonstationarity in the image. Also, the normalized lacunarity was computed from the following (Dougherty & Henebry, 2001):

\[ A_{\text{norm}} = 2 - \left( \frac{1}{} + \frac{1}{A} \right) \]  

where A is the complementary lacunarity (obtained by calculating the lacunarity of the complemented binary image), ensuring a lacunarity measure within the range of 0–1 that can be compared independently of image density.
3. Results and discussion

3.1. Texture appearance of ham slices

Fig. 1 shows representative images of the three evaluated pork ham qualities: (a) as well as a two-dimensional depiction of intensities (enhanced visual texture) in pseudocolor; (b) and the corresponding binary images; (c) of segmented pores/defects and fat-connective tissue structures (structures presented together). An intensity image in which each pixel is identified by two coordinates and conventionally scaled in the range of \( \{0, 1, \ldots, 255\} \) can be viewed as a surface. Thus, the terms image or surface can be used together when we refer to an intensity image. The 2D visualization of the sliced pork ham textured images in pseudocolor was derived from a 3D surface intensity plot with a viewpoint of 90° (viewed directly from above). The two main enhanced topographical structures are: (i) fat-connective tissue; which is depicted as a higher elevation surface feature, due to increased intensity levels (brighter regions), and (ii) pores; which are presented as crater-like structures, due to lower intensity values (darker regions). The textured images (Fig. 2b) enhance the differences in appearance among the three ham qualities. It is apparent that differences can be perceived (\( A2 > A1 > A3 \)) in the spatial distribution of pores/defects and fat-connective tissue, which defines the degree of heterogeneity and complexity of the observed visual texture.

These perceived dissimilarities between qualities emerge due to the differences in the raw material used and on processing conditions, which includes injection of brine, and tumbling (Casiraghi, Alamprese, & Pompei, 2007). Ham products of higher quality (A3) are manufactured with a low level of brine injection and no tumbling. Tumbling provides an intense mechanical action on the meat (suitable for medium and high-yield hams) resulting in considerable cellular damage, (i.e. cellular disruption) that facilitates extraction of the salt-soluble proteins. This is important to bind the individual muscles together during cooking (Arboix, 2004) and leads to changes in the original structure pertinent to the final product texture. Thus, the A3 ham which retains the original muscle structure was not tumbled, in order for the meat structure and natural texture appearance to be kept intact. The visual texture of this ham is quite smooth, with characteristic horizontal and diagonal surface fissures. By contrast, lower quality hams (A2) are often structured from several pieces or comprised of different muscle types that can reproduce the entire ham when they are put together before cooking. This also has an effect on the texture appearance and colour of the ham slices.

The intensity images resulting from the image acquisition of ham surfaces are related in some unique way to the perceived surface roughness. The ham surface shows a pattern of scattered intensities that exhibits variations; ergo the analysis of these variations can be used to quantitatively characterize and differentiate...
The individual data points fit the straight line well (R \log[f] for the terms in the Fourier series and the corresponding phase image, are depicted. As expected the log[f] falls off linearly with log[f]. Similar results and graphs were obtained from the intensity images of the other colour spaces and ham qualities (not shown). The individual data points fit the straight line well (R^2 \geq 0.975 for all channels and ham qualities), with a linear relationship of the form:

\[ \log(P(f)) = c \cdot \log(f) + IC \]  

where \( c \) is the slope and IC is the intercept. From Fig. 2 it can be observed that the phase of the terms is properly random which indicates fractality (Russ, 1994). This uniform randomness is more apparent in the phase images (Fig. 2c), having no cross pattern of horizontal and vertical lines that correspond to image edge mismatch. Moreover, there is no significant scattering of points from the main trend, which can affect the slope. The fractal dimension computed with the power spectrum method is not the same as other dimensions, i.e. the Fourier analysis dimension is less than or equal to the Hausdorff dimension (Russ, 1994), due to the images used not being ideal fractal surfaces (continuous and truly self-similar); only then the results would be equal.

Table 1 shows the values (average and standard deviation) of the Fourier analysis fractal dimension and the power spectrum intercept for the three pork ham qualities using R, G, B, L’, a’, b’, H, S, V, and Grey colour scales. The averaged fractal dimensions of the pork ham images show an increasing trend from the A2 to the A3 ham of the form: A2 < A1 < A3. On the other hand, the power spectrum intercept shows a decreasing trend from the A2 to A3 ham of the form: A2 < A1 < A3. The increasing and decreasing trends were manifested in all colour scales, but analysis showed that the H colour scale was not successful to demonstrate meaningful correlations with pork ham qualities. Nevertheless, statistical differences (P < 0.05) exist among the three ham qualities for all colour channels except for the H colour scale, where D\(_ f\) cannot differentiate in a statistically significant level, while IC cannot differentiate between high and low yield pork ham slices for the same colour scale.

The fractal dimension is a descriptor that characterizes the roughness of an image (Pentland, 1984). Higher values of fractal dimension usually indicate irregularity and a complex visual texture, which is a function of the spatial variation in pixel intensities. A surface may have a fractal dimension between 2 and 3 (close to two would be quite smooth but close to three would be very rough) and as the fractal dimension increases, heights of nearby points (intensity values) become more independent. In addition, the fractal dimension describes the scaling properties of the topography, expressed as intensity variations. The values of fractal dimension are larger for the A3 ham followed by A1 and A2, while

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**Table 1**

Values (average and standard deviation) of the Fourier analysis fractal dimension D\(_ f\) and the power spectrum intercept IC for the three pork ham qualities and for all colour scales.

<table>
<thead>
<tr>
<th>Ham qualities</th>
<th>R</th>
<th>G</th>
<th>B</th>
<th>L’</th>
<th>a’</th>
<th>b’</th>
<th>H</th>
<th>S</th>
<th>V</th>
<th>Grey</th>
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<tbody>
<tr>
<td>Fourier analysis fractal dimension D(_ f)</td>
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</tr>
<tr>
<td>A1</td>
<td>2.552 ± 0.08*</td>
<td>2.316 ± 0.09*</td>
<td>2.333 ± 0.11*</td>
<td>2.359 ± 0.09*</td>
<td>2.362 ± 0.10*</td>
<td>2.434 ± 0.12*</td>
<td>2.550 ± 0.12*</td>
<td>2.251 ± 0.11*</td>
<td>2.525 ± 0.08*</td>
<td>2.354 ± 0.09*</td>
</tr>
<tr>
<td>A2</td>
<td>2.492 ± 0.11*</td>
<td>2.252 ± 0.10*</td>
<td>2.293 ± 0.11*</td>
<td>2.302 ± 0.10*</td>
<td>2.252 ± 0.11*</td>
<td>2.398 ± 0.09*</td>
<td>2.593 ± 0.21*</td>
<td>2.219 ± 0.10*</td>
<td>2.493 ± 0.11*</td>
<td>2.296 ± 0.10*</td>
</tr>
<tr>
<td>A3</td>
<td>2.619 ± 0.07*</td>
<td>2.358 ± 0.07*</td>
<td>2.385 ± 0.07*</td>
<td>2.402 ± 0.07*</td>
<td>2.433 ± 0.08*</td>
<td>2.504 ± 0.07*</td>
<td>2.563 ± 0.06*</td>
<td>2.309 ± 0.07*</td>
<td>2.620 ± 0.07*</td>
<td>2.563 ± 0.06*</td>
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<tr>
<td>Power spectrum intercept IC</td>
<td></td>
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</tr>
<tr>
<td>A1</td>
<td>20.502 ± 0.76*</td>
<td>22.640 ± 0.81*</td>
<td>22.850 ± 0.90*</td>
<td>21.992 ± 0.82*</td>
<td>19.872 ± 0.82*</td>
<td>19.648 ± 0.95*</td>
<td>7.362 ± 0.71*</td>
<td>11.976 ± 0.97*</td>
<td>9.420 ± 0.76*</td>
<td>22.156 ± 0.83*</td>
</tr>
<tr>
<td>A2</td>
<td>21.259 ± 1.09*</td>
<td>23.552 ± 1.08*</td>
<td>23.441 ± 1.05*</td>
<td>22.810 ± 1.09*</td>
<td>21.033 ± 1.06*</td>
<td>20.044 ± 0.78*</td>
<td>7.699 ± 1.04*</td>
<td>12.523 ± 1.00*</td>
<td>10.176 ± 1.08*</td>
<td>22.981 ± 1.09*</td>
</tr>
<tr>
<td>A3</td>
<td>19.751 ± 0.66*</td>
<td>22.087 ± 0.62*</td>
<td>22.213 ± 0.60*</td>
<td>21.420 ± 0.61*</td>
<td>19.230 ± 0.62*</td>
<td>18.910 ± 0.64*</td>
<td>7.372 ± 0.41*</td>
<td>11.221 ± 0.65*</td>
<td>8.669 ± 0.66*</td>
<td>21.561 ± 0.61*</td>
</tr>
</tbody>
</table>

\( (a, b, c) \) values in the same column for \( D_f \) with different letters are significantly different \((P < 0.05)\).

\( (a, b, c) \) values in the same column for IC with different letters are significantly different \((P < 0.05)\).
the intercept values are exactly the opposite, being the lowest for the premium quality ham (A3) which in general exhibits an apparent smoother visual texture (Fig. 1). The estimated fractal dimensions revealed unexpected characteristics in textural pattern for the A2 ham images than what we expected visually; it was expected to find fractal dimension values higher for the A2 ham. The reverse indicates that nearby points on the smoother surface (A3) are more independent while nearby points on the rougher surfaces are more correlated, therefore, the smoother pork ham slices have a more equal distribution of all manifestations of roughness (Kierein-young, Kruse, & Lefkoff, 1992). Similar results were obtained in Mendoza et al. (2009) concerning the directional fractal dimensions with the variogram method in commercial wafer thin ham slice images. Their results indicated that the visually rougher ham slices had smaller fractal dimension values, which meant that it was not simply the magnitude of the intensity or brightness variation that describes the roughness of the surface, but also the spatial organization. Furthermore, they pointed out that when the edges of the structures in the image (such as small particles or grit size structures) are rougher the fractal dimension increases. The pores/defects as well as the slight colour variations on the visually smoother ham are in fact smaller structural clusters, and therefore their edges are expected to be more irregular.

In this study, fractality is represented by the slope and intercept of the Fourier power spectrum analysis. The intercept of the power spectrum is independent of the slope and is a description of the overall magnitude of the roughness (Perry, 2000; Russ, 1994). The increasing and decreasing trends towards the smoother premium quality ham (A3) shows that the Fourier analysis dimension and intercept are clearly important fractal parameters that describe the irregularity and complexity of the sliced ham surfaces and capture information embedded in the spatial structure of the underlying image texture. In addition, the power spectrum intercept correlates well with the overall magnitude of roughness of the observed texture appearance of the ham images.

### 3.3. Lacunarity analysis

Fig. 3a–b presents a scatter plot of the averaged values of Λ, as a function of moving window b for pores/defects and fat-connective tissue binary images. Due to the lower resolution of the graphs, and in order to discern differences among the computed lacunarity values for the three ham qualities, two smaller graphs showing the inward-curving were embedded in the main scatter plots, providing better visualization of the trend and quicker understanding regarding the differences among lacunarity profiles. The gliding box size (pixels) range, represented in the smaller graphs, is 16–64 for pores/defects and 2–24 for fat-connective tissue.

Lacunarity plots explicitly characterize the spatial organization of the image (texture) and can measure space filling capacity and heterogeneity. Pores/defects and fat-connective tissue binary images exhibit random spatial patterns in a relatively wide range of structural dimensions (Valous et al., 2009). Lacunarity is smaller when the binary image is nearly translationally invariant, being made of “diffuse” clumps separated by smaller empty lacunas, like in the case of the A2 ham. Lacunarity is higher when the image consists of structures in the form of “tight” clumps separated by larger empty gaps. Having this in mind, differences can be perceived (A2 < A1 < A3) regarding the spatial organization of structures in the images (Fig. 1), with increasing lacunarity towards the premium quality sliced ham (A3). In this sense, the more lacunar A3 images could be called fractally crowded, while lower lacunarity images could be called fractally uncrowded (Mandelbrot, 1983). In addition, the A3 ham (for both pores/defects and fat-connective tissue) has bigger lacunarity values, because the sizes of the structures in the images are distributed over a wider range (not shown in Fig. 1). The lower values of lacunarity for the A1 and A2 pork hams relate to the lower deviation from translational invariance. The additional discriminating effect of lacunarity among the three ham qualities is more apparent in the pores/defects binary images, where the curves differentiate the ham qualities better than in the fat-connective tissue images. In the latter, the structures for A1 and A2 seem to have similar but nevertheless distinguishable lacunarity values. Texture appearance is strongly affected by lacunarity due to spatial heterogeneity of the structures. More lacunar images (A3) signify that there are fewer structures in the image, consequently pixel intensity variations are decreased, resulting in a smoother surface.

Additionally, from the graphs it can be deduced that for all the images analyzed, the behaviour of lacunarity, with $b \in [1,256]$, resembles the one of an exponential decay. Considering this manifestation, the fitting of the scatter plots of the averaged values of lacunarity was carried out using a three-parameter single exponential decay function. A quantity is said to be subject to exponential decay if it decreases at a rate proportional to its value. Symbolically, this can be expressed with the following equation:

$$A = m \cdot e^{-bn} + q$$

where $A$ is the quantity and $n$ is called the decay constant. In Eq. (6) $m$, $n$, and $q$ are coefficients. The model fits all the lacunarity data...
Cally differ from each other (followed by a post hoc Tukey HSD test, confirmed these differences of data that has approximately normal distribution. Then, ANOVA addition transformed the non-normally distributed data to a set was performed (minimizing the mean squared error), which in addition transformed the non-normally distributed data to a set of data that has approximately normal distribution. Then, ANOVA followed by a post hoc Tukey HSD test, confirmed these differences (P < 0.05). Results showed that the three qualities of ham statistically differ from each other (P < 0.05) with respect to parameter m and q for the pores/defects binary images. In the case of the fat-connective tissue images, no statistical differences were found between A1 and A2 ham qualities for all parameters, while the differentiation was between A3 and the higher yield pork hams (A1 and A2). These results signify that the high and medium yield ham exhibit relatively similar patterns in spatial organization as regards the binary structures, which translates to somewhat similar values of space filling capacity of the fat-connective tissue present in those ham slices, probably due to raw material and process conditions.

In addition, the parameters n and q have smaller numerical values that slightly differ among the three ham qualities (especially for the fat-connective tissue binary images) while the m parameter assumes values within a more wide numerical range. Moreover, it can be observed that, among the three coefficients, the parameter m undergoes the most significant variation. In particular, a correlation between parameter m and the three qualities of ham exists, while an increasing trend can be observed (A2 < A1 < A3) with the A2 ham having a low m value. Similar trends can be observed for coefficients n and q (for the pores/defects binary images only). Standard errors are a function of the number of data points, the distance of the points from the curve, and the overall shape of the curve and provide information about the certainty of the best-fit parameter values. Standard error being small indicates that a slight variation in the parameter would produce a curve that does not fit the data satisfactorily. On the other hand, with bigger standard errors, a relatively larger variation of that parameter would not spoil the fit much. This effect can be observed in Table 2, where the decay constant n has the smallest SE. Larger decay constants make the lacunarity curve to vanish much more rapidly, which in other words mean that lacunarity becomes smaller.

Table 2
Coefficients with standard deviations (SD), and standard errors (SE) of best-fit from the implementation of the exponential decay function to the binary images of pores/defects and fat-connective tissue for the three ham qualities.

<table>
<thead>
<tr>
<th>Ham qualities</th>
<th>m ± SD</th>
<th>SE</th>
<th>n ± SD</th>
<th>SE</th>
<th>q ± SD</th>
<th>SE</th>
</tr>
</thead>
<tbody>
<tr>
<td>Pores/defects binary images</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A1</td>
<td>587.475 ± 692.17a</td>
<td>5.736</td>
<td>0.185 ± 0.07a</td>
<td>0.003</td>
<td>3.015 ± 1.51a</td>
<td>0.330</td>
</tr>
<tr>
<td>A2</td>
<td>246.032 ± 309.05b</td>
<td>2.665</td>
<td>0.156 ± 0.06b</td>
<td>0.003</td>
<td>2.296 ± 1.10b</td>
<td>0.184</td>
</tr>
<tr>
<td>A3</td>
<td>1168.232 ± 1406.63c</td>
<td>11.967</td>
<td>0.192 ± 0.10c</td>
<td>0.003</td>
<td>4.308 ± 2.50c</td>
<td>0.636</td>
</tr>
<tr>
<td>Fat-connective tissue binary images</td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
<td></td>
</tr>
<tr>
<td>A1</td>
<td>41.636 ± 30.76a</td>
<td>0.518</td>
<td>0.110 ± 0.03a</td>
<td>0.002</td>
<td>1.417 ± 0.29a</td>
<td>0.046</td>
</tr>
<tr>
<td>A2</td>
<td>37.092 ± 29.73a</td>
<td>0.533</td>
<td>0.107 ± 0.04a</td>
<td>0.002</td>
<td>1.427 ± 0.26a</td>
<td>0.046</td>
</tr>
<tr>
<td>A3</td>
<td>78.313 ± 65.55a</td>
<td>0.924</td>
<td>0.134 ± 0.04b</td>
<td>0.002</td>
<td>1.605 ± 0.36c</td>
<td>0.070</td>
</tr>
</tbody>
</table>

(a, b, c) values in the same column for (1) with different letters are significantly different (P < 0.05). (α, β, γ) values in the same column for (2) with different letters are significantly different (P < 0.05).

Fig. 4 presents a log–log scatter plot of the averaged values of A, as a function of moving window b, for pores/defects and fat-connective tissue binary images. From the plot it can be inferred that the sparser spatial patterns of A3 have higher lacunarity than the denser patterns of A1 and A2 for the same gliding box size. As the moving window increases, lacunarity decreases due to the bigger level of translational invariance of the larger size gliding boxes. Moreover, in the log–log plot it is observed that a section

![Figure 4](image-url)
(in gray; approximately 10–90 pixel range) exhibits a linear mono-
tonic decrease ($R^2 \sim 0.995$) showing a large amount of self-similar-
ity or constant textural pattern regarding the structures in the
binary images. A thorough examination of the binary images and
the lacunarity curves confirm that the structures are randomly dis-
tributed clumps and in this case lacunarity can be used to detect
scales. The curve declines gradually to a point (box size in the order
of $5\sim15$) which corresponds to a characteristic size range of the
clumps. It then declines more rapidly, with the final concave up-
wards portion of the curve corresponding to the scales above that
of random behaviour (Plotnick et al., 1996).

The normalized lacunarity (range from 0 to 1) plots for the bina-
rized ham images are shown in Fig. 5 for the whole range of sam-
pling windows (256 pixels). The three qualities are easily
distinguished in the case of the binarized images of pores/defects.
The normalized lacunarity of the binarized fat-connective tissue
images for the three ham qualities is relatively similar for small
moving window sizes (up to ~5 pixels) and for large moving win-
dow sizes (greater than ~190 pixels), but differs in the intervening
range. The same applies to the pores/defects images but for differ-
ent gliding boxes (small: up to ~10 pixels; large: greater than
~240 pixels). In the plot of normalized lacunarity all the typical
features found in lacunarity plots are more emphasized. For a given
structure mass and box size, higher lacunarity indicates greater
clumping (A3), so if the gliding box size reaches a characteristic
size range of the clumps (gray section in Fig. 5), the curve declines
more rapidly, however lacunarity decreases more slowly with
increasing gliding box size for irregular structures (Marwan, Sapa-
rin, & Kurths, 2007).

3.4. Overall assessment of fractal metrics

The visual texture of pork ham slices reveals a great deal of
information about the different qualities and the perceived image
roughness. This roughness is encapsulated as spatial variations in
groupy and spectral characteristics that occur on a smaller scale.
The perceived variations could be due to spatial dissimilarities in
directional or spectral scattering characteristics, or due to distribu-
tions of structures such as pores/defects and fat-connective tissue.

The application of two fractal metrics as quantitative descrip-
tors of visual texture in sliced ham images reveals interesting re-
sults. Fourier analysis fractal dimension is already being used to
characterize patterns on a great number and kind of applications;
while lacunarity as a textural analysis index has many advantages,
i.e. simpler implementation, exhaustively sampling of image to
quantify changes, etc. Fractal geometry can be a powerful descrip-
tor of texture in images, and the power spectrum method is able to
characterize complex surfaces. The results revealed unanticipated
characteristics in textural pattern, but both Fourier analysis fractal
dimension and power spectrum intercept emerge as descriptors
that capture information of irregularity and complexity.

On the other hand lacunarity as a multi-scale measure of tex-
ture provides information about the shape and distribution of gaps
within images, where self-similarity is not a pre-requisite. Lacuna-
arity which is a high-order fractal descriptor was employed to dif-
erentiate textures with the same fractal dimension (Krasowska
et al., 2004), but from the results, it is apparent that these fractal
metrics: dimension, intercept and lacunarity complement each
other in assessing visual variation, and are able to provide informa-
tion about the overall magnitude of visual roughness and heteroge-

4. Conclusions

Distinctive topographical features were observed in all three
qualities. The visually rougher high and medium yield ham slices
(A1 and A2) were cured with increased percentages of brine solu-
tions, comparing to the smoother A3 sliced ham. Texture appear-
ance was characterized using the Fourier power spectrum
method and gliding box lacunarity. The use of the power spectrum
method in this work revealed unexpected characteristics in the
textural pattern: the values of fractal dimension are larger for
the smoothest surface (A3).

Fourier analysis dimension and power spectrum intercept are
significant fractal parameters that describe the irregularity and
complexity of the sliced ham surfaces. Moreover, the intercept cor-
relates well with the overall magnitude of roughness of the ob-
served texture appearance of the ham images. The results of
lacunarity as a descriptor of visual texture indicate the characteris-
tics of space filling capacity and heterogeneity in the images.
Lacunarity plots appear more representative for the characterization of
texture appearance, due to the changes of lacunarity over different
boxing sizes. The experimental results suggest that lacunarity
has a discriminating effect among the three types of ham which is
more apparent in the pores/defects binary images, where the
curves differentiate the ham qualities better than in the fat-con-
nective tissue images. Additionally, the behaviour of lacunarity
resembles the one of an exponential decay and the fitting of the
scatter plots was carried out using a three-parameter single expo-
nential decay function. The parameters of this function can better
represent the variation of mass density of pixels in the images.
This investigation confirmed the usefulness of the Fourier analysis dimension, power spectrum intercept and gliding box lacunarity as quantitative descriptors of visual texture in sliced ham images.

Acknowledgements

The authors gratefully acknowledge the Food Institutional Research Measure (F.I.R.M) strategic research initiative, as administered by the Irish Department of Agriculture and Food, for the financial support.

References


