
Evaluation of Crunchy and Dried Food Products Using Fractal Analysis of Acoustic Parameters

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Abstract: - This study investigates the applicability of fractal analysis to acoustic signals generated during the fracturing of dry and crunchy food products, with the aim of supporting the quantitative characterization of textural properties. The fractal dimension and scaling exponents obtained from the fractal analysis of the sound impulses produced during the mastication of three categories of food products (caraway breadsticks, Mediterranean pretzels, roasted almonds) serve as particularly useful fractal indicators for assessing food quality, providing an objective alternative to conventional methods. The results obtained for the fractal dimension using the Higuchi method (DH), with values between 0.9776–0.9949, or for the fractal exponent β , with values of 0.7581 for breadsticks, 0.3754 for pretzels, and 0.1146 for almonds, highlight a notable correlation between the fractal complexity of the acoustic signal and the sensory perception of crispness, corroborated through auditory and instrumental experiments. The experimental results indicate consistent relationships between specific fractal descriptors and perceived textural attributes, particularly crunchiness. While certain fractal measures exhibit limited variability across products, others - such as DFA and spectral slope - show greater sensitivity to structural differences. These findings suggest that fractal analysis of food-related acoustic signals can provide complementary quantitative information to conventional sensory and instrumental evaluations, within controlled experimental conditions.

Keywords: - fractal dimension; crunchiness; acoustic analysis; food quality; texture

1. INTRODUCTION

Fractal analysis of food sounds, such as those generated during chewing, quantifies the complexity and texture of the acoustic signal. This approach enables indicators such as fractal dimensions to objectively quantify characteristics including crispness, tenderness, and brittleness, which are essential parameters in food quality control, product development, and texture assessment.

The fractal dimension of sound signals generated during food processing can be an extremely useful non-destructive method for assessing their freshness. At the same time, by analyzing the acoustic properties of foods, manufacturers or processors can create and develop new products with the desired

texture and crunchiness, widely loved by consumers. A representative example is provided by studies in which fractal analysis has been used to differentiate fresh from aged eggs based on the acoustic signals generated upon impact with a rigid surface.

A preliminary bibliometric analysis conducted on the Google Scholar platform, using the terms “Fractal analysis of food sounds”, indicated approximately 21,600 results. This high volume of publications confirms the interdisciplinary nature of the field, located at the intersection of food science, acoustics, signal analysis, and fractal methods. The results suggest a constant increase in scientific interest in the objective assessment of food texture and freshness by acoustic methods, as well as in the integration of fractal algorithms in quality control

and food product development. Even though the aforementioned platform shows an abundance of results due to the inclusion of related documents (doctoral theses, preprints, citations, articles from related fields), on a similar platform, Web of Science (WoS), we find that the actual number of articles with rigorous academic evaluation is extremely small. Only 9 WoS articles represent directly relevant publications, studies where fractals have been effectively applied to food sounds or research combining food acoustics and multifractals. It should be noted that this bibliometric overview is intended as an illustrative comparison rather than a formal quantitative bibliometric study. The search relied solely on keyword-based queries across the two platforms, without advanced bibliometric or citation network analyses. Its purpose is to highlight the relative scarcity of rigorously peer-reviewed studies specifically addressing fractal analysis of food-generated acoustic signals, thereby contextualizing the niche character of the present contribution.

The chewing sounds of different types of food such as potato chips, corn flakes, shrimp, and various low-calorie extruded starch snacks were investigated using advanced techniques by Belie et al. (2003). The researchers concluded that most of the incorrect classifications were generated by a certain type of product with a very irregular shape, which determines a wide variation in the sounds emitted during chewing [2]. Fractal dimension can be correlated with a sensation of anomaly in the sound signal, with drier foods generally presenting a much higher roughness.

At the beginning, some interesting research [3,4,5,6] that uses fractal analysis in the study of the mechanical properties of food products can be noted. Barrett et al. (1994) [3] applied a Blanket algorithm to calculate the fracturability of extruded corn products.

Analysis of the irregularities of filtered and compressed acoustic signals for dry cheese balls and croutons, as a function of water activity, was performed by Tesch et al. (1995) [4] in terms of an apparent fractal dimension of the Kolmogorov type. Edminster and Vickers (1985) [5] found a high correlation between crispness ratings made with and without auditory cues. They concluded that auditory information does not seem to be essential for determining crispness, and a better understanding of how crispness can be quantitatively assessed could lead to improved food quality control.

The research proposed by Vickers (1998) [6] states that force-strain curve evaluations or acoustic recordings, performed individually, can satisfactorily assess crispness, and suggests that a

combination of the two methods could better predict food fragility.

The method can also be used to understand how changes in the recipe, ingredient concentration or technological process influence the acoustic properties of the final product. Quantifying the complexity or “roughness” of an acoustic signal is often determined using the fractal dimension (Df), a very precise indicator. A high value of this reflects a more complex and irregular signal, often associated with a crispier texture.

For the prediction of properties such as crispness or freshness, data processing methods such as Fast Fourier Transform (FFT) or machine learning algorithms can often be used before fractal analysis. A more complete picture of the complexity of the acoustic signal can be obtained by examining its properties at multiple scales using advanced techniques such as multifractal analysis. Another fractal parameter, lacunarity, is often used to quantify the “discontinuities” or textural structure of the acoustic signal and has proven useful in detecting changes at different scales. In this regard, several studies can be mentioned that mention fractal analysis as a method to investigate how moisture content (water activity) influences the acoustic fractal dimension of cheese puffs or croutons [8,18,33,38].

The present study does not aim to introduce a paradigmatic innovation in the field of food acoustics or fractal signal analysis. Instead, its contribution lies in the systematic application and comparative use of multiple fractal and scaling descriptors—namely box-counting fractal dimension, Higuchi fractal dimension, detrended fluctuation analysis exponent, and spectral slope—to characterize acoustic signals generated during the fracturing of dry and crunchy food products.

By integrating several complementary fractal indicators within a unified analytical framework, this work provides an application-oriented methodological contribution that emphasizes interpretability, reproducibility under controlled conditions, and low computational complexity.

The proposed approach complements, rather than replaces, more recent data-driven techniques such as machine learning or multimodal evaluation. Both the theoretical principles of fractal analysis and its practical implementation will be discussed, including data preprocessing, fractal dimension estimation, and interpretation of the results in relation to the physical and sensory properties of foods.

2. THEORETICAL METHODS AND MATERIALS FOR FRACTAL ANALYSIS

2.1. Fractal Analysis

Fractal analysis aims to identify scaling properties (self-similarity) within signals. In the context of an acoustic signal, this involves examining how the variability of the signal evolves over different temporal scales. This approach allows for the characterization of subtle structural features in the acoustic signal that are often imperceptible to the human ear, providing objective insights into properties such as crispness, brittleness, or other textural attributes of food products.

The most commonly used methods in fractal analysis are:

a) Higuchi Fractal Dimension (HFD) Direct estimation of the fractal dimension for time series. Suitable for non-stationary signals. Applicable to discrete signals. $X(1), X(2) \dots, X(N)$, Higuchi defines k series constructed as follows:

$$X_m^{(k)} = \{X(m), X(+k), X(+2k), \dots, X(m) + [N - m]/k \cdot k\} \quad (1)$$

where, $k = 1, 2, \dots, k_{\max}$ is the scale, and $m = 1, 2, \dots, k$ are the offsets.

For each pair (m, k) , the following is calculated as the curve length: $L_m(k) = \frac{1}{k} \cdot \frac{(N-1)}{\left[\frac{N-m}{k}\right]_k^2} \sum_{i=1}^{\frac{N-m}{k}} |X_N(m - ik) - X_N(m + (i-1)k)|$ (2)

Then the meaning is calculated:

$$L(k) = \frac{1}{k} \cdot \sum_{m=1}^k L_m(k) \quad (3)$$

Fractal dimension estimation. $L(k)$ depends on scale as a power law:

$$L(k) \propto k^{-D} \quad (4)$$

where D is the fractal dimension. Therefore:

$$\ln(L(k)) = -D \cdot \ln(k) + C \quad (5)$$

and D is obtained from the slope of the linear regression of the plot $\ln(L(k))$ versus $\ln(k)$.

b) Detrended Fluctuation Analysis (DFA) obtain the exponent α (related to the Hurst exponent H), widely used in biomedical signals. In step 1, the signal is integrated using the relation:

$$Y(i) = \sum_{t=1}^i [x(t) - \bar{x}] \quad (6)$$

In step 2, the signal is divided into windows of length n . In step 3, the trend is removed by linear regression within each window. The root mean square (RMS) fluctuation is given by:

$$F(n) = \sqrt{\frac{1}{N} \sum_{i=1}^N [Y(i) - Y_{trend}(i)]^2} \quad (7)$$

The fractal exponent is the slope of the curve:

$$F(n) \simeq n^\alpha \quad (8)$$

c) Box-counting (adapted to a 1D signal) the method consists of transforming the signal into a 2D curve (time vs. amplitude) and counting boxes at multiple scales. The signal is represented as points in the plane (t, x) :

$$\text{Box_Size} \simeq \varepsilon \quad (9)$$

$N(\varepsilon)$ = the number of 2D 'boxes' that contain at least one point.

The fractal dimension is given by:

$$D_B = -\lim_{\varepsilon \rightarrow 0} \frac{\log N(\varepsilon)}{\log \varepsilon} \quad (10)$$

d) Spectral slope — The slope in the log-log scale of the power spectral density; β relates to fractal properties (the relationship between β , H , and D depends on the type of process). For a power spectral density approximated by:

$$S(f) \simeq f^{-\beta} \quad (11)$$

$$\log(S(f)) \simeq -\beta \cdot \log(f) \quad (12)$$

$$\beta = -d \cdot \log(S(f)) / d \cdot \log(f) \quad (13)$$

e) Wavelet-based multifractal analysis — detects multifractal behaviors (more advanced).

Steps required to perform fractal analysis:

- Recording / File reading — WAV, 16/24-bit, appropriate sampling rate (e.g., 44.1 kHz for food sounds, 48 kHz for general audio).

- Preprocessing: filter out unnecessary bands (e.g., band-pass 20 Hz–20 kHz or as needed); normalize (z-score or scale to $[-1, 1]$); remove silent sections if applicable.

- Feature extraction: envelope: demodulation (rectification + filtering or Hilbert); RMS in a moving window (e.g., 5–50 ms); divide into frequency bands (filterbank) and analyze per band.

- Application of fractal method: choose the method (Higuchi/DFA/box-counting/power spectral density-PSD) and scale (k for Higuchi; box sizes for box-counting; window sizes for DFA).

- Robustness assessment: estimate error (bootstrap, variance between segments); evaluate sensitivity to parameters (e.g., window length).

- Interpretation: compare between conditions (e.g., fresh vs. aged product); correlate with physical or perceptual measurements.

2.2. Sound Card

The Logilink UA70098 USB sound card (Fig. 1) is designed around the Texas Instruments PCM2702 integrated circuit. The PCM2702 is a 16-bit digital-to-analog converter with two digital-to-analog output channels. The interface controller integrated in the PCM2702 is compliant with USB 1.0 standards. The integrated circuit can handle three sampling rates of 32, 44.1, and 48 kHz, and also incorporates a series of practical features, such as a built-in clock generator, digital attenuator, playback indicator, suspend indicator, zero indicator, mute function, and more. Most notably, this circuit is plug-and-play and does not require any software drivers for Windows or Linux operating systems.

The circuit receives control data and audio data from USB through the D+ and D- pins of the PCM2702, with data transfer occurring at full speed. The decoded audio signals are available at the VOUTL and VOUTR pins of the circuit. A 12 MHz crystal is connected between the XT0 and XT1 pins of the integrated circuit. The circuit also requires DC voltages of +5 V and +3.3 V for operation, both of which can be obtained from the USB port using a low-dropout (LDO) regulator.

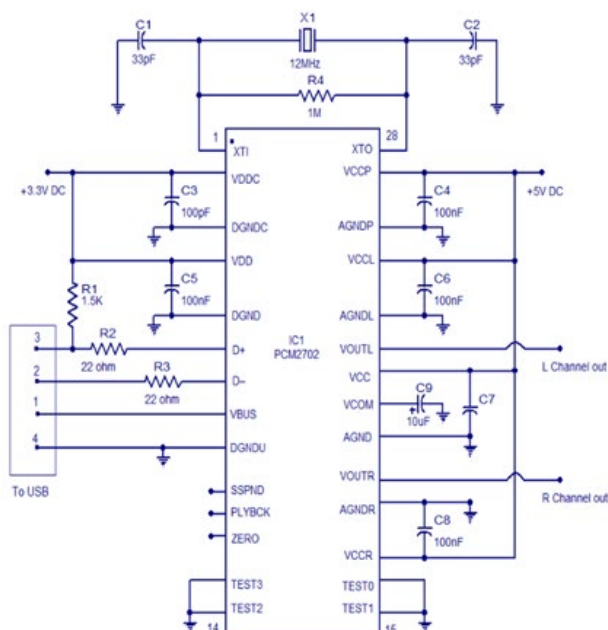


Figure 1. The architecture of the soundcard UA70098

The audio output signals available at VOUTL and VOUTR require additional amplification in order to drive low-impedance headphones or speakers.

2.3. The Microphone

The RØDE Lavalier II is an omnidirectional electret microphone with a 6 mm capsule and JFET preamplifier, designed for professional use. It has a frequency range of 20 Hz–20 kHz, sensitivity of –38 dB re 1V/Pa, signal-to-noise ratio of approximately 67 dB, and a maximum sound pressure level of 120 dB SPL. It is powered via plug-in power (1.8–5 V) and comes with a 1.2 m cable with a lockable 3.5 mm TRS connector. Accessories include a pop filter, clip, pouch, and colored mounting rings. Compact and lightweight (~9 g), it is suitable for a wide variety of video applications, presentations, and interviews.

The main characteristics of MEMS microphones are high performance density, compatibility with reflow soldering, minimal sensitivity variations with temperature, and very low susceptibility to vibrations compared to traditional microphones. Additionally, their easy integration with other MEMS devices makes them suitable for a wide range of applications [7].

The circuit of an electret microphone, illustrated in Figure 2, is simpler than that of an externally polarized microphone because the electret itself provides the polarization voltage for the capsule. However, the FET transistor's bias voltage usually drops close to zero due to leakage currents.

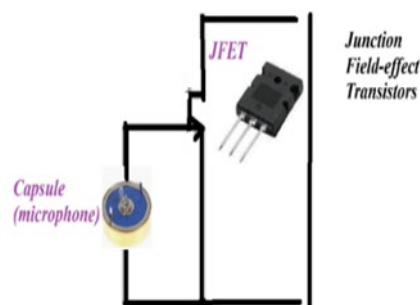


Figure 2. Circuit diagram for an electret microphone

Although the charge can be distributed throughout the electret, it can be modeled as a concentrated layer near the central region, depending on how symmetric the charge distribution is. Inevitably, some of the charge is lost both near the outer surface and near the coating layer, where some recombination of positive and negative charges occurs. Therefore, the concentrated charge layer and the coating can be treated as the two electrodes of a capacitor, between which a polarization voltage E exists, and the dielectric thickness is $h/2$, such that:

$$E = \frac{S \cdot \sigma_m}{2(C_M + C_G)} \quad (14)$$

where a and b are the dimensions of the rectangular plate. The distribution of acoustic pressure in a rectangular space with rigid walls is given by:

$$p = p_0 \cos(l\pi x/L_x) \cdot \cos(m\pi y/L_y) \cdot \cos(n\pi z/L_z) \cdot e^{i\omega t} \quad (15)$$

where l , m , and n are the modal indices (integers), and L_x , L_y , and L_z represent the length, width, and height of the space, in meters. In this way, the eigenfrequencies can be related to the elastic properties of the plate material [8].

The most important parameters for which this type of microphone was selected for our research are sensitivity, bandwidth, stability, dynamic range, and, last but not least, the cost of the manufactured device. The element that produces the sound is a flat radiating surface, namely the diaphragm, which is set into motion by an attached moving coil situated in a magnetic field. The diaphragm and the coil can be either circular or square [9-10].

The distribution of natural mode frequencies and the corresponding modal shapes is of particular importance in noise control within enclosed spaces, such as anechoic chambers. In the specialized literature, there are numerous studies and research works that associate the natural frequencies of bodies with specific shapes (beams, plates, cylinders) with the elastic properties of the materials from which they are made, which allows the application of the presented method. Significant results in this field can be found in important works such as [11-15,19,20,21,26,27].

To evaluate the robustness of the extracted fractal and scaling parameters, multiple independent recordings were analyzed for each product category. Inter-experimental variability was quantified using standard deviation, while parameter distributions were examined using boxplot representations. This procedure allows assessment of parameter stability across repeated measurements under identical experimental conditions. After mastication, each food sample was either swallowed or disposed of, making repeated chewing of the same specimen physiologically unrealistic and experimentally infeasible.

2.4. Sound recording

In accordance with the method proposed by Belie et al., 2003 [2], the mastication sounds were recorded by placing a microphone (Lavalier II, Rode) under the ear canal on the side where the products were to be chewed. Microphone position, orientation, and distance relative to the ear were kept constant across all recordings to minimize variability unrelated to the food structure. During chewing,

different sound signals typical of dry and crunchy products can be distinguished. In the experiment, three food products with distinct textural properties were analyzed: cumin crackers, a crispy and friable product made from thin dough; Mediterranean pretzels, with a moderately crunchy texture and homogeneous structure; and roasted almonds, a rigid product with low crunchiness and dense structure, typical of nuts.

The selected sound waves were imported into a Python program using the `scipy.io.wavfile` library to read the WAV files. The audio signals were automatically converted to mono and normalized so that the amplitude ranged between -1 and 1.

For the spectral analysis, a spectrogram was used, calculated with a 1024-sample window and a 512-sample overlap, as well as the power spectral density (PSD) estimated using Welch's method (`scipy.signal.welch`) with a 2048-sample window and a 1024-sample overlap. This allowed for sufficient resolution to analyze the relevant acoustic components. The sampling resolution was 16 bits. In addition, the signals were analyzed using four fractal methods: Box-counting, Higuchi FD, DFA, and spectral slope, to quantify the temporal and spectral complexity of the sound waves generated by the fracturing of crunchy food products. The corresponding plots (waveform, spectrogram, fractal graphs, and PSD) were shown in individual windows for interactive visualization [2,14,33].

For the fractal and spectral analyses, frequency components below 100 Hz were removed so that the analysis would reflect only the acoustic characteristics relevant to the perception of crunchiness [2,6,12]. This approach allowed the extraction of objective quality indicators for food products, complementing traditional sensory tests.

3. RESULT AND DISCUSSION

As an application in the food industry, it can be noted that fractal analysis can provide an objective and automated method for quality control, replacing subjective sensory evaluations. For example, an apparent fractal dimension can track the degree of drying of a snack-type product. In this section, the audio signals obtained from the fracturing of crunchy food products were analyzed using fractal methods and the spectral slope.

Each recording was made at a sampling frequency of 44,100 Hz with a unidirectional microphone, directly in the analysis program, and was subsequently saved as an audio file [23]. All processing parameters and analysis settings were kept constant across recordings to ensure consistency of the extracted descriptors. The

signals were loaded from WAV files, converted to mono, and normalized. It was found that using normalized datasets, any frequencies can be estimated [22,24]. Fractal parameters, as well as the scaling exponents obtained via DFA, were calculated for each signal. Additionally, the spectral slope β was estimated from the power spectral density.

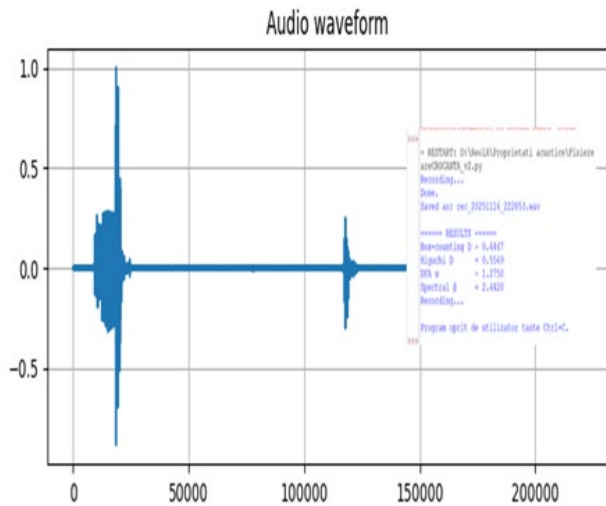


Figure 3. Plots and numerical results generated by the Python script

These measurements of acoustic parameters can also be combined with force–deformation measurements, through mechanical compression tests, to predict the perception of crunchiness [29,30].

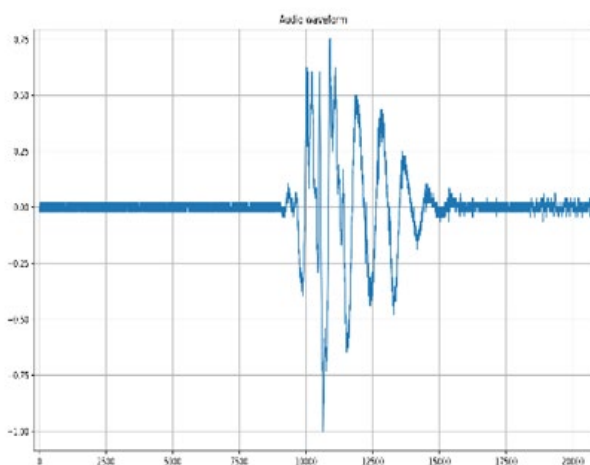


Figure 4. Raw data of breakout acoustic sound.

For investigating the acoustic characteristics of crunchy food products, a dedicated Python script was developed, which allows both real-time recording of audio signals and loading of existing WAV files. The audio signals are converted to mono (if stereo), normalized, and digitally processed to extract information about their dynamics and

complexity. The script implements multiple fractal and spectral analysis methods. Based on these approaches, it generates several graphical representations and corresponding numerical results (Fig. 3):

- The waveform represents the signal amplitude over time and allows visualization of the acoustic impulses. An example of a time-domain signal for a roasted almond product is shown in Fig. 4.

- Spectrogram plots show the time–frequency distribution of the signal (Fig. 5) and accentuate the frequency components related to the rupture of the product.

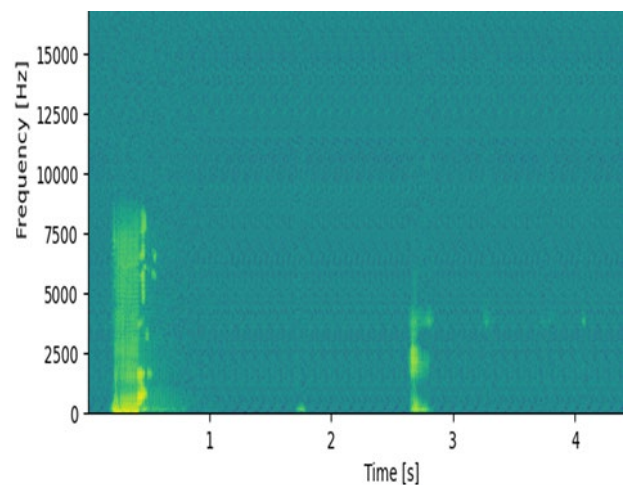


Figure 5. Raw signal spectrogram for Mediterranean pretzels

- Fractal plots for Box-counting (Fig. 6), Higuchi FD, and DFA are on a logarithmic scale and allow the estimation of the fractal dimension and scaling exponents.

- Spectral slope represents the signal's PSD and the logarithmic scale trend line for estimating the slope β (Fig. 7).

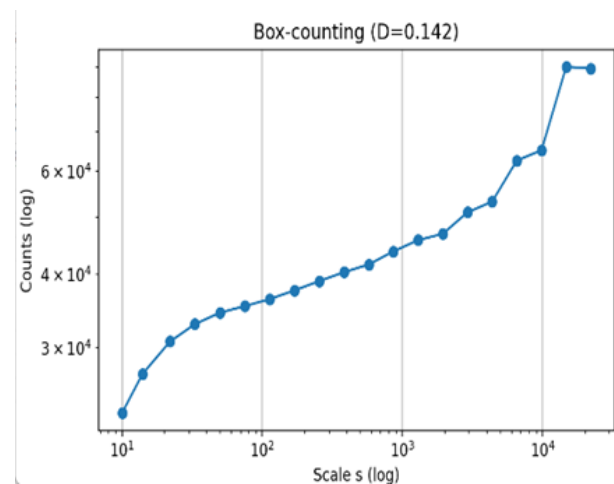


Figure 6. The variability of the fractal dimension of the signal is highlighted by the Box-counting graph.

The strong relationship between the fractal complexity of the acoustic signal and the sensory perception of crispiness is very clearly highlighted by the obtained results. In this way, complex signals, with increased fractal dimension values and steeper spectral slopes, are generally more suitable for crispier products, as demonstrated by sensory and instrumental evaluations.

Therefore, the easy use of a Python script proposes an objective and reproducible method for evaluating the quality of crispy food products.

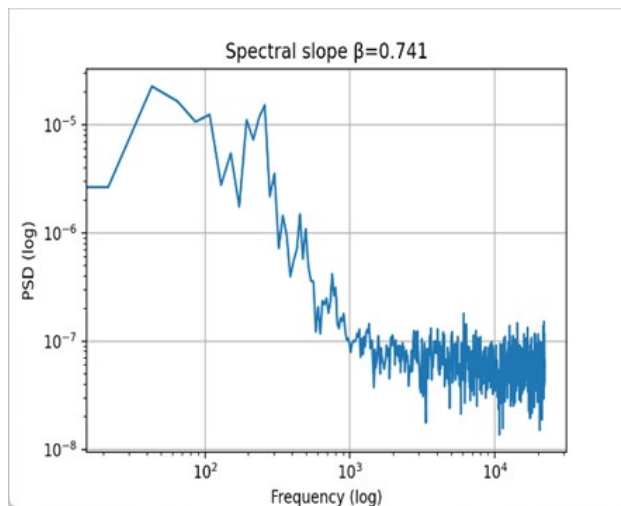


Figure 7. Power spectrum of mastication sound “Saratele cu chimen” - experiment 3.

The platform allows rapid analysis of multiple audio files, comparison of fractal and spectral parameters, and integration of the results into broader studies for the development or quality control of food products. Additionally, the obtained plots and numerical values can be used for generating reports, comparative evaluations, or statistical studies.

The compressive stress–strain relationships for most cellular materials and solid foams have a characteristic sigmoidal shape, reflecting three deformation mechanisms: elastic distortion dominant at small strains; collapse and/or fracture of the cell walls; and densification. The exact form of this relationship is primarily determined by the composition of the materials, including moisture content; the size and geometry of the cells and cell walls; and the type of cells (open or closed). Under repeated loading, as in mastication, the nature of the relationship may change due to irreversible changes in the solid matrix (particularly rupture).

Since the material of the cell walls is very fragile, the power spectral density curve can become highly irregular and jagged [18,35], often masking an underlying sigmoidal shape. Acoustic characterization of such fragile or crunchy products requires methods for evaluating the degree of

irregularity and smoothing procedures, which are currently available and have also been successfully applied to expanded extruded food products [33,34].

Similarly, the tested bulk food products under compressibility or shear loading may exhibit such patterns, even if they do not have a cellular structure themselves. Although the tensile properties of spongy baked products, such as breadcrumbs, can be determined experimentally, they have so far not proven useful as indicators of texture quality, primarily, it seems, due to structural non-uniformity.

Table 1. Fractal and scaling parameters – cumin crackers

<i>Cumin crackers</i>				
Exp.	Box-counting D	Higuchi D	DFA α	Spectral β
1	0.135	0.9808	0.797	0.7406
2	0.1645	0.9843	0.742	0.6271
3	0.2241	0.9668	0.953	1.0146
4	0.1663	0.9782	0.774	0.6327
5	0.1464	0.9782	0.785	0.7767
6	0.1421	0.9775	0.787	0.7568
Mean	0.1631	0.9776	0.8062	0.7581
StDev	0.0324	0.0059	0.0743	0.1409

Table 1 presents the fractal and scaling parameters determined for cumin crackers, highlighting the geometric complexity of the signal, local irregularity, long-term correlations, and the spectral distribution of energies generated during the fracturing of the product.

Data analysis for the cumin crackers category using the Box-counting method for the fractal dimension D (mean 0.1631, StDev 0.0324) indicates a moderate fractal complexity of the acoustic signal during fracturing, suggesting a crunchy structure with local variations.

Although the Higuchi fractal dimension values are clustered within a narrow range ($DH \approx 0.97$ – 0.99), this behavior reflects the high stability and robustness of local micro-fracture dynamics across dry and crunchy food products rather than a lack of sensitivity of the method. In this context, product differentiation is primarily provided by complementary descriptors, particularly the DFA exponent and spectral slope, which capture differences in long-term temporal correlations and spectral energy distribution.

In the Detrended Fluctuation Analysis (DFA) method, the scaling exponent $\alpha = 0.8062 \pm 0.0743$. Values above 0.7 suggest medium-term correlations in the acoustic signal, reflecting that the fracturing noise is not completely random but retains repetitive structures. In the spectral slope method

(with $\beta = 0.7581 \pm 0.1409$), the spectrum indicates a predominance of low- to mid-frequency components, which can be correlated with the perception of crunchiness during chewing.

Cumin crackers thus exhibit a crunchy and uniform texture, with acoustic signals that are predictable and relatively stable between experiments. The variability (StDev) is moderate, indicating good reproducibility between samples.

Table 2. Fractal and scaling parameters – Mediterranean pretzels

<i>Mediterranean pretzels</i>				
Exp.	Box-counting D	Higuchi D	DFA α	Spectral β
1	0.1014	0.9954	0.6666	0.3654
2	0.1039	0.9956	0.678	0.3494
3	0.1121	0.9948	0.6836	0.3769
4	0.0984	0.9958	0.6726	0.3456
5	0.1066	0.9928	0.6979	0.3946
6	0.1056	0.9949	0.7031	0.4202
Mean	0.1047	0.9949	0.6836	0.3754
StDev	0.0047	0.0011	0.0143	0.0284

Data analysis from Table 2 for Mediterranean pretzel-type products, using the Box-counting fractal method ($D = 0.1047 \pm 0.0047$), shows that the signal's fractality is lower than that of the cumin crackers, indicating a more homogeneous and denser structure, less complex acoustically.

In the Higuchi method ($D = 0.9949 \pm 0.0011$), the very high self-similarity suggests that the produced noise is highly uniform and predictable between experiments. Medium-term correlations are lower than in the cumin crackers ($\alpha = 0.6836 \pm 0.0143$, DFA method), indicating a less elastic or denser structure. The spectral power slope of the signal ($\beta = 0.3754 \pm 0.0284$) is flatter, with less pronounced high- and mid-frequency components, which may indicate a weaker and more uniform crunchy texture.

Mediterranean Italian pretzels are more uniform and homogeneous, with predictable acoustic noise, but exhibit a milder crunch compared to cumin crackers.

For roasted almonds, data analysis presented in Table 3 shows moderate fractality, similar to cumin crackers, but with smaller variation (Box-counting method, fractal dimension $D = 0.1462 \pm 0.0113$). The acoustic signal is relatively simple, but with slight variations. Using the Higuchi method, where the fractal dimension $D = 0.9841 \pm 0.0070$, a high self-similarity is observed, indicating that the noise structure is consistent and repetitive between experiments.

In the DFA algorithm, with exponent $\alpha = 0.5591 \pm 0.0083$, medium-term correlations are lower, approaching 0.5, indicating noise closer to random, reflecting a more rigid and fragile texture. The power spectrum slope $\beta = 0.1146 \pm 0.0684$ shows a signal spectrum with more pronounced high frequencies, but with greater variability, indicating more 'uneven' acoustic noise during fracturing.

Table 3. Fractal and scaling parameters – roasted almonds

<i>Roasted almonds</i>				
Exp.	Box-counting D	Higuchi D	DFA α	Spectral β
1	0.1465	0.989	0.5617	0.0819
2	0.1322	0.9885	0.5641	0.1307
3	0.1375	0.9928	0.5425	-0.0085
4	0.1558	0.9807	0.5607	0.1739
5	0.1427	0.9751	0.564	0.1454
6	0.1625	0.9785	0.5618	0.1642
Mean	0.1462	0.9841	0.5591	0.1146
StDev	0.0113	0.0070	0.0083	0.0684

Roasted almonds have a denser and more rigid texture, with less structured and more variable acoustic noise between samples, suggesting a lower and 'rougher' crunchiness.

Table 4 presents a comparative overview of the data obtained for the three product categories, from which the following observations can be drawn:

Cumin crackers have the highest perceived correlation and crunchiness, highlighted by high DFA α and Spectral β values.

Pretzels are more homogeneous, with predictable noise, but less crunchy.

Roasted almonds have a more random and less structured acoustic signal, correlated with their rigidity.

Table 4. Comparative conclusions

Product	Box-counting D	Higuchi D	DFA α	Spectral β	Texture
Cumin crackers	0.1631	0.9776	0.8062	0.7581	Uniform crunch, predictable noise
Mediterranean pretzels	0.1047	0.9949	0.6836	0.3754	Moderate crunch, homogeneous noise
Roasted almonds	0.1462	0.9841	0.5591	0.1146	Rigid, low crunch, more random noise

This fractal and spectral analysis provides a quantitative and reproducible method for characterizing the crunchiness of food products.

Figure 8 shows the distribution of the fractal and scaling parameters for the three analyzed products—Caraway Breadsticks, Mediterranean Pretzels, and Roasted Almonds—using a boxplot representation. This visualization allows the assessment of inter-experimental variability and the stability of each parameter by highlighting the median, the interquartile range (IQR), and the extremes.

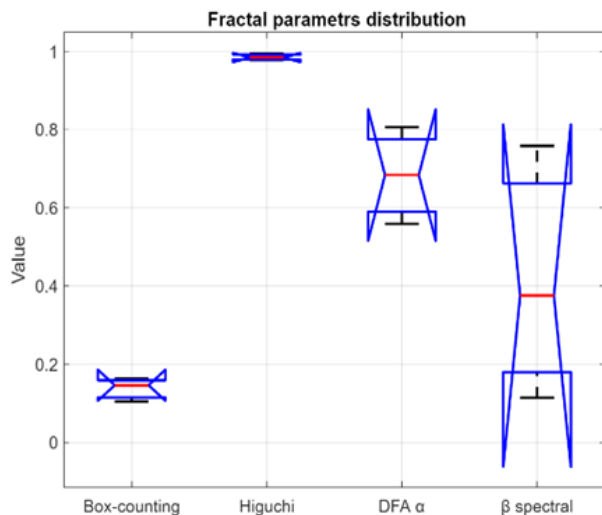


Figure 8. Boxplot chart – the distribution (median, quartiles) of each determined parameter.

The interpretation of the results, based on the values obtained for each product, is as follows:

a) *Fractal dimension using Box-counting D.* The values obtained are relatively close across the three products (0.1631 for Sărățele, 0.1047 for Covrigei, and 0.1462 for Roasted Almonds), indicating low variability in the geometric structure of the signal. This stability suggests that the general fluctuation pattern of the waveform is similar among the products, with no major differences in the geometric complexity of the fracture events.

b) *Higuchi Dimension D.* Higuchi D shows the lowest variability among all analyzed parameters (0.9776–0.9949–0.9841). This consistency confirms the robustness of the method and the high reproducibility of the local irregularity estimation. Regardless of the product, the signal exhibits a comparable level of temporal roughness, suggesting similar mechanisms of micro-fractures at the local scale.

c) *DFA exponent α.* The DFA α values vary significantly between products: chimen breadsticks: 0.8062; Mediterranean pretzels: 0.6836; roasted

almonds: 0.5591. The first two values (≈ 0.80 and ≈ 0.68) indicate behavior typical of crunchy products, with moderate long-term correlations—granular, impulsive signals with rapid variations. In contrast, the lower value for almonds (≈ 0.55) suggests a more temporally coherent signal, with slower and more orderly fluctuations. This result is consistent with the denser and more rigid texture of almonds, which leads to more uniform and less fragmented breakage. Thus, DFA α clearly separates the Almonds from the two dough-based crunchy products.

d) *Spectral exponent β.* This parameter shows the largest dispersion among the three products: Chimen Breadsticks: 0.7581; Mediterranean Pretzels: 0.3754; Roasted Almonds: 0.1146.

Higher values for the Breadsticks and Pretzels (≈ 0.75 and ≈ 0.37) indicate a relatively flatter spectrum, with energy distributed more evenly across higher frequencies—typical of crunchy, short, impulsive sounds. In contrast, the low value observed for Almonds (≈ 0.11) suggests a more “mature” and stable spectral profile, with energy concentrated in lower-frequency regions. This spectral behavior is consistent with the more rigid and “cohesive” fracture of almonds, which generates a less fragmented acoustic signal.

Comparing the boxplots clearly shows which parameters are stable (Higuchi D, Box-counting D) and which are sensitive to the product’s texture (DFA α, spectral β). The figure thus provides a solid visual basis for distinguishing food products according to the acoustic characteristics of their fracture, highlighting the overall structural similarity (Box-counting and Higuchi) but pronounced differences in temporal and spectral dynamics (DFA α and β), which directly correspond to the textures described sensorially.

To verify whether the observed differences in fractal and spectral parameters among food categories are statistically significant, **non-parametric Kruskal–Wallis tests** were applied to three independent groups (Mediterranean pretzels, cumin crackers, and roasted almonds), each represented by six experimental repetitions. The analysis revealed **statistically significant inter-group differences** for **Box-counting D** ($\chi^2 = 11.79$, $p = 0.0028$), **DFA α** ($\chi^2 = 15.16$, $p = 0.0005$), and **spectral β** ($\chi^2 = 15.16$, $p = 0.0005$), confirming that these variations represent quantitative effects rather than descriptive trends, as summarized in **Table 4**. In contrast, **Higuchi D** showed lower discriminatory relevance despite reaching statistical significance ($\chi^2 = 12.08$, $p = 0.0024$), due to its limited dynamic range across food categories.

According to research conducted by Maruyama et al. (2008), the sound produced during chewing exhibits multiple nonlinear components and displays numerous abrupt changes over time [35]. Temporal instability and spectral nonlinearity are well-defined characteristics of this type of signal. Several studies on extruded corn-based food products have shown that neither density nor the mean specific surface area of the granules, considered individually, can serve as indicators of the product's mechanical resistance [21]. However, certain sensory scores could be quantified by applying Fourier analysis and fractal analysis to the compression curve. At the same time, the relationship between structural properties and acoustic sensory properties has not yet been investigated [17]. This represents a necessary research direction for achieving a deeper and more comprehensive understanding of the textural properties of these products. In the case of detecting breakage or fracturing, it is important that the frequencies are estimated accurately, and DFA-based methods provide amplitude–frequency pairs that can be applied to any signal length and any signal amplitude [22].

According to expectations and the results reported by Zhang et al. (2005), for drier products, as drying progressed, they exhibited increased crispness (indicated by bending resistance) and greater toughness (which can be reflected by fracture energy) [34].

In engineering practice, other more complex situations can also be encountered, involving effects of moisture content, thermal factors, or other influences that cannot be neglected. Acoustic studies on food products have generally developed two approaches to “crunchy and fracturable” textures. The first involves recording the sounds produced when a force is applied to a product, in order to obtain quantitative information about “crunchy,” “crispy,” or “crackly” sounds. The second approach involves measuring the perception of sounds transmitted through the air, to determine the contribution of these sounds to the sensation of crispness, brittleness, fragility, tender-rigidity, and fracturability of food products.

It has been found that the combination of acoustic and mechanical techniques describes food sounds more effectively than either technique used individually [29]. In this work, this fundamental idea of the aforementioned method was adopted, but instead of experimentally determining the natural frequencies of a material specimen, a rapid calculation is performed using fractal analysis. In this way, it is possible to quickly determine the quality characteristics of materials. This method has the advantage of being applied rapidly and at a very

low cost compared to traditional experimental laboratory methods, which require significant material resources, sophisticated equipment, and lengthy time [11].

The results reported by Acosta-Ramírez et al. (2024) on food breakage showed that samples characterized by less irregular acoustic fracture patterns exhibited higher spectral amplitudes and lower values of lacunarity (Λ) and generalized fractal dimension (GFD) [36]. Furthermore, da Cunha Rodrigues et al. (2025) showed that acoustic emissions captured by a microphone can be directly related to discrete-time acoustic pressure signals; however, due to the nonlinear and complex spectral nature of these signals, time-domain descriptors used alone cannot adequately represent the coupled energy–frequency content of fracture events [37]. Therefore, in full agreement with the results reported by Dias-Faceto et al. (2020) [38], strong correlations were identified between the sensory attributes and the acoustic properties of dry and crispy foods. These findings indicate that the method proposed in the present study may contribute both to the advancement of scientific literature and to practical applications in the food industry.

4. CONCLUSIONS

The results of this study indicate that fractal and scaling analysis of acoustic signals generated during the fracturing of dry and crunchy food products can contribute to the quantitative characterization of textural properties. By combining time–frequency analysis with multiple fractal descriptors—namely box-counting fractal dimension, Higuchi fractal dimension, detrended fluctuation analysis exponent, and spectral slope—it is possible to capture different aspects of signal complexity, temporal correlations, and spectral distribution associated with food fracture mechanisms. Future work may investigate the combination of fractal descriptors with deep feature extraction approaches, allowing the integration of interpretable acoustic metrics with learned representations to improve texture discrimination performance. Moreover, this methodology can be easily used to assess the freshness and degree of crispness of crunchy food products.

In the research conducted, we propose a review of the procedures that allow the quantification of the acoustic constants of a polymer food material, using classical theories of homogeneous bodies to calculate natural frequencies. In addition to spectral analysis, the signals were evaluated using four fractal methods: box-counting fractal dimension,

Higuchi FD, detrended fluctuation analysis (DFA), and spectral slope (β). These methods enabled the quantification of temporal complexity and the degree of irregularity in the signals produced during mastication. The fractal dimensions reflect the granularity and intensity of micro-fractures, while the DFA exponent and spectral slope characterize long-term dependencies and power-law-type spectral structure.

Perhaps, in the future, as a research direction, it is necessary to develop an integrated approach for assessing food quality, which would include the mechanical-acoustic analysis of force-deformation curves, of sounds generated during deformation and even of the acoustic behaviour of products during drying processes.

Overall, the proposed approach should be regarded as a complementary analytical tool that supports traditional sensory and mechanical evaluations. Under controlled experimental conditions, fractal analysis provides a reproducible framework for comparing acoustic signatures associated with food fracture mechanisms.

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