Materials Science-Poland, Vol. 23, No. 3, 2005

A new simple fractal method for nanomaterials science and nanosensors*

W. KLONOWSKI[1, 2**], E. OLEJARCZYK[1, 2], R. STĘPIEŃ[1, 2]

[1]Institute of Biocybernetics and Biomedical Engineering, Polish Academy of Sciences, Warsaw, Poland

[2]GBAF, Medical Research Center, Polish Academy of Sciences, Warsaw, Poland

We proposed a very simple new method of quantitative assessment of surface roughness and texture. We have combined methods that have been used in medicine (histopathology) with methods used in nonlinear time series analysis. A greyscale 2-D image of a 3-D surface is used for calculations of the surface fractal dimension which is a good measure of surface roughness. In the pre-processing step, the image is transformed into 1-D signals ("landscapes") that are subsequently analyzed. The method draws from multiple disciplines and has multidisciplinary applications. One of the possible applications is quality assessment of nanosensors. The same methods of analysis may be used for processing of (bio)signals generated by these nanosensors.

Key words*: fractal dimension; nanosensors; nanomaterials; quality assessment; signal analysis*

1. Introduction

Calculating materials properties from structural models has been one of the most important problems in materials science [1]. There is still a need for relatively simple methods to assess properties of materials, especially surface properties, based on the analysis of experimental data such as microscopic images. Fractal and symbolic methods of image and signal analysis can be very useful for these purposes. The problem is that there exist very different definitions of fractal dimension and very different methods are implemented for their calculations [2]. As scientists become more specialized in narrow disciplines, frequently the methods which need to be applied in their research may have been used in other disciplines for a long time. When we learn this we are often amazed, like Molier's Mr. Jourdain (*Le Bourgeois Gentilhomme*

---

*The paper presented at E-MRS 2004 Fall Meeting, Warsaw, Poland, 6–10 September, 2004.
**Corresponding author, e-mail: wklon@ ibib.waw.pl

II.iv), who says: "Good heaven! For more than forty years I have been speaking prose without knowing it". What is needed is a very multidisciplinary approach to the problems and these methods both, draw from multiple disciplines and have multidisciplinary applications.

These methods may be used for assessing structural properties of materials as well as for quality assessment of nanosensors as their quality depends on surface roughness and texture. Nanotechnologies provide new sensors that enable easy acquisition of biosignals for monitoring of drivers, pilots, etc. and for clinical applications. But before any signal generated by a nanosensor can be used for monitoring or clinical assessment, the signal has to be appropriately processed and visualized. The same data-processing methods, based on fractal and symbolic computational methods, may be used for extraction, fusion, and visualization of multi-modal information from nanosensors for representing and managing signal complexity. These methods are computationally effective and may be applied in real time.

The symbolic method proposed for signal analysis leads to similar results as the fractal dimension method [3, 4], but needs greater sets of data (i.e. longer signals) than those considered here as examples.

2. Methods

The fractal dimension is a good predictor of people's perception of surface roughness [5, 6]. A new method of inferring fractal dimension of a 3-D surface (i.e., of a surface in 3-D physical space) from a 2-D greyscale image of that surface has been developed – the image data are preprocessed to produce 1-D *landscapes*, which are analyzed using signal analysis methods. In this way, the dimensionality of the problem and so its computational complexity is drastically reduced.

A digitized image can be viewed as a surface for which *x*- and *y*-coordinates represent position and the *z*-coordinate represents *grey* level (intensity). The fractal nature of this putative, statistically self-affine surface can then be characterized, both in the spatial domain with fractal dimension, and in the frequency domain with spectral exponent β.

Fractal dimension is invariant with respect to linear scale transformations and it is simply related to power spectrum exponent β. If a fractal Brownian surface embedded in 3-D space has fractal dimension D_s and the power spectrum proportional to f^{β}, its 2-D image shows power spectrum proportional to $f^{2-\beta}$, where $\beta/2 = (3 - D_s)$. Thus, one can use the power spectrum of the image to assess the fractal dimension of the surface. β is also simply related to the Hurst exponent [5, 6]. However, this method of calculation of fractal dimension is much simpler than the spectral or Hurst methods.

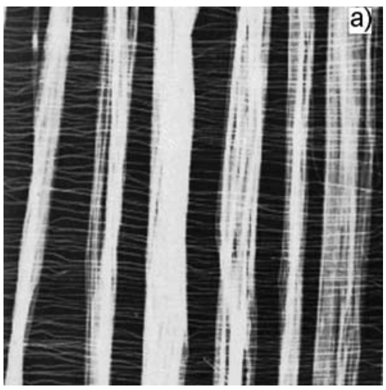
Epithelial roughness and texture play a central role in histopatological diagnosis of malignancy. Mattfeldt (1997) preprocessed microscopic 2-D images of tumor cells' epithelium into 1-D signals (*landscapes*) and then embedded these signals in a phase space, using a 'time-delay' method. He found that the *correlation dimension* differed considerably between benign and malignant mammary gland tumors [7]. Here we propose to use a similar simple method for preprocessing the surface's 2-D image to construct 1-D landscapes, but in the second step to use Higuchi's fractal dimension method [8] for analysis of the landscapes obtained.

A digitized image is a pattern stored as a rectangular data matrix. Grayscale images are matrices where the matrix elements can take on values from 0 to $g_{max}=(2b-1)$, where b denotes number of bits (for $b = 8g_{max} = 255$). The rendering on a video screen is a presentation of the values from white (0) to black ($2b$ – 1). Most colour images are overlays of three grayscale images.

Stepping through a grey value image length of N pixels and height of M pixels *row by row* the sum of the grey values in each row, G_m (m= 1, …, M), are calculated and the numbers normalized by using the largest of those values G to produce the "horizontal" landscape

$$NGS_m = \frac{G_m}{G}$$

Similarly, stepping through the same image column by column (n = 1, …, N) another, "vertical" landscape is produced as shown in. Fig. 1.



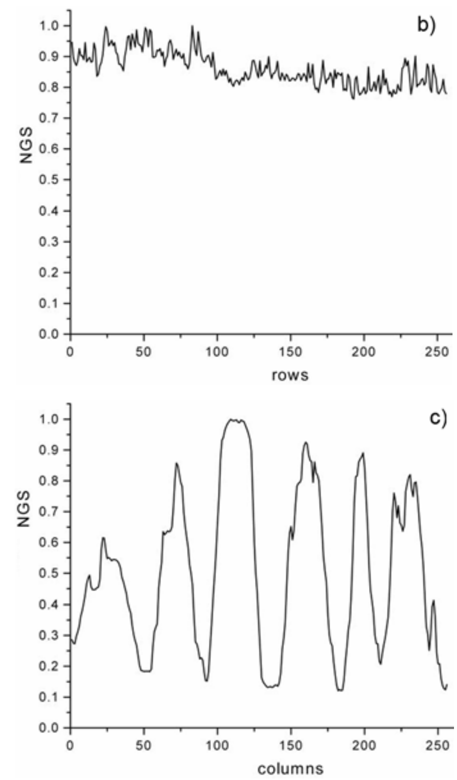
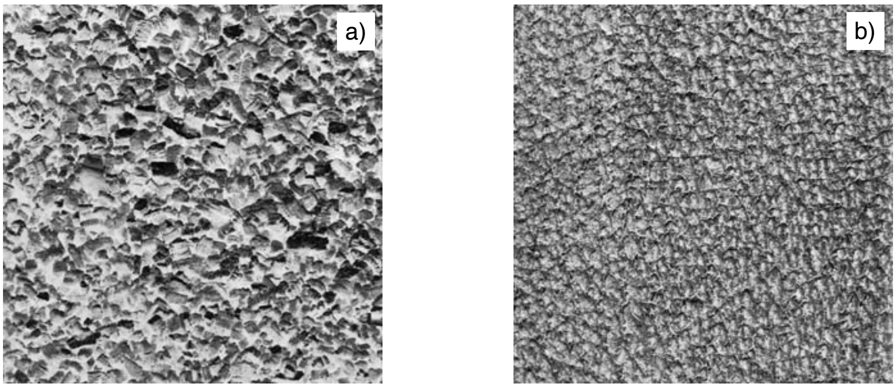


Fig. 1. Example of a surface with anisotropic roughness properties (texture); fractal dimension in the x and y image direction are unequal: a) the grey-scale image (D51.gif from [4]), 256×256 pixels; the landscapes were analyzed using 128 points window, moved in each step 1 point to the right, b) horizontal landscape (row by row) shows mean fractal dimension D_h = 1.84, c) vertical landscape (column by column) shows mean fractal dimension D_v = 1.07

If necessary, other landscapes may be constructed using a similar counting technique, stepping through the same picture in different directions, e.g. in diagonal directions, or in some rectangular frames. The resulting *NGS* series serve as an input for the subsequent signal analysis using Higuchi's fractal dimension or symbolic dynamics methods.



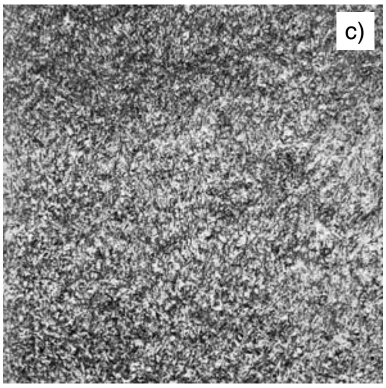


Fig. 2. Examples of surfaces with (nearly) isotropic and uniform properties of different roughness; fractal dimensions of the horizontal landscapes D_h and of the vertical landscapes D_v are nearly equal. The greyscale images, each 644×644 pixels from [4]; landscapes were analyzed using 128 points window, moved in each step 1 point to the right: a) D5.gif from [4], $D_h = 1.32$, $D_v = 1.32$, b) D92.gif from [4], $D_h = 1.42$, $D_v = 1.47$, c) D9.gif from [4], $D_h = 1.65$, $D_v = 1.70$

Higuchi's fractal dimension *D* is calculated directly from the time series, without embedding the data in a phase space as in the case of e.g., correlation dimension. D_f is, in fact, a fractal dimension of the curve representing the signal under consideration, and so it is always between 1 and 2. Since a simple curve has dimension equal 1 and a plane has dimension equal 2, the fractional part of D_f is a measure of the signal complexity. D_f should not be misled with fractal dimension of an attractor in the system's phase space.

3. Results

As examples we present here analysis of surface images from [9]. If a surface shows anisotropic roughness properties (texture) then fractal dimensions of the horizontal and vertical landscapes differ one from another (Fig. 1). On the other hand, fractal dimensions of landscapes for surfaces that show isotropic roughness properties change appropriately with changes of surface properties – the smaller are unevennesses of the surface, the greater are fractal dimensions of its landscapes (Fig. 2).

4. Discussion

Fractal dimension of a surface is invariant with respect to linear transformation of the data and to transformation of scale. So, the normalization in Eq. (1) is convenient for presentation of the landscapes, but it is not really necessary since it does not change the value of Higuchi's fractal dimension; thus the time necessary for calculations may be even further reduced. Fractal dimension calculated from an image, by virtue of its independence with respect to scale, appears to be nearly independent of the orientation of the surface. If the fractal dimension in the x and y image direction are unequal the surface is anisotropic.

The fractal dimension of a natural surface depends on the dominant process at any particular scale. That is why a surface may need multifractal description [10]. The aim of measuring fractal dimensions is not only to add new structural parameters to already existing ones, possibly describing new structural characteristics but a more important aim is to get a deeper insight into the development of complex structures and the processes that contribute to structure forming.

Fractal methods are becoming increasingly more important in the study of materials characteristics and/or underlying processes' classification [10, 11] as well as in signal analysis [12] and image recognition [13].

5. Conclusions

The proposed method may serve for simple quantitative assessment of surface roughness and texture, in particular for comparative quality assessment of nanosensors. It is also attractive that the same fractal method may be used for processing of (bio)signals generated by nanosensors. Our philosophy is that to be applicable a method should preferably be really simple and easily understandable by non-specialists in the field. The presented fractal method is very simple and it both draws from multiple disciplines and have multidisciplinary application.

Acknowledgements

This work was partially supported by the Polish Ministry of Science and Information Society Technologies (formerly State Committee for Scientific Research (KBN)) grant No. 4 T11F 01 922 and by FP6. Integrated Project SENSATION (IST 507231).

References

[1] KLONOWSKI W., Can. J. Phys., 66 (1989), 1051, 1061; http://hrabia.ibib.waw.pl/~lbaf/PDF_Doc/k32.pdf; http://hrabia.ibib.waw.pl/~lbaf/PDF_Doc/k33.pdf.
[2] KLONOWSKI W., Mach. Graph. Vis., 9 (2000), 403; http://hrabia.ibib.waw.pl/~lbaf/PDF_Doc/gkpo2000.pdf.
[3] KLONOWSKI W., OLEJARCZYK E., STEPIEN R., N*ew Methods of Nonlinear and Symbolic Dynamics in Sleep EEG-Signal Analysis*, [in:] D.D. Feng, E.R. Carson (Eds.), *Modelling and Control in Biomedical System*, IFAC Publications, Elsevier, Oxford, 2003, pp. 241–244.
[4] KLONOWSKI W., OLEJARCZYK E., STEPIEN R., Physica A, 342 (2004), 701.
[5] PENTLAND A.P., IEEE Trans. Patt. Anal. Mach. Intel., 6 (1984), 661.
[6] KUBE P., PENTLAND A., IEEE Trans. Patt. Anal. Mach. Intel.,10 (1988), 704.
[7] MATTFELDT T., *Spatial Pattern Analysis using Chaos Theory: A Nonlinear Deterministic Approach to the Histological Texture of Tumours*, [in:] G.A. Losa, D. Merlini, T.F. Nonnenmacher, E.R. Weibel (Eds.), *Fractals in Biology and Medicine*, Vol. II, Birkhäuser, Basel, 1997, pp. 50–72.
[8] HIGUCHI T., Physica D, 31 (1988), 277.
[9] RANDEN T., Stavanger University College, http://www.ux.his.no/~tranden/brodatz/ or http://www.ux.his.no/sigproc/textures/brodatz/.
[10] STACH S., ROSKOSZ S., CYBO J., CWAJNA J., Mater. Charact., 51 (2003), 87.
[11] STASZCZUK P., MATYJEWICZ M., KOWALSKA E., RADOMSKA J., BYSZEWSKI P., KOZLOWSKI M., Rev. Adv. Mater. Sci., 5 (2003), 471.
[12] KLONOWSKI W., Solitons and Fractals, 14 (2002), 1379.
[13] TANG Y.Y., TAO Y. AND LAM E.C.M., Pattern Recognition, 35 (2002), 1071.

Received 9 September 2004
Revised 22 November 2004