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Comparison of three multiscale methods for topographic analyses

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Keywords

Roughness, multiscale decomposition, polymer, abrasion

Abstract

There is a growing demand for high level surface characterization. The functionality of machine parts, such as tribological behavior, depends on the texture of contacting surfaces. The relation between texture parameters depending on the scaling of texture features, finishing process parameters, such as grain sizes for grinding, and functionality of a surface is investigated. Due to the fractal aspect of the studied surfaces, more advanced tools are used for characterization. This article presents a comparison of three different segmentation methods (patchwork, box, and motif) for multiscale decomposition, using different roughness parameters to analyse the texture of polymer samples finished with various abrasive papers from FEPA grade 80 to 4000 to represent varying abrasion on the different scales. The consistencies and discrepancies of the different procedures of multiscale decomposition in the relation between separability of macro and micro abrasions, identification of self-similarity and features or regions on varying scales and the finishing with different abrasive grain sizes have been investigated.

1. Introduction

There is a growing demand for high level surface characterization. The functionality of machine parts, such as tribological behavior, depends on the texture of contacting surfaces. The relation between texture parameters depending on the scaling of texture features, finishing process parameters, such as grain sizes for grinding, and functionality of a surface is investigated. However, this high number of variables make the tribological study complex. A divide-to-conquer strategy is then useful to simplify characterization. Some segmentation tools are then selected.

Segmentation is the process to divide an image or a topography map according to specified criteria such as similarity or dissimilarity, feature size respectively spatial band width respectively scales. Decomposition is a chain or tree of segmentation results of one image or map according to a sequence of different parameter values of a specified segmentation criterion such as feature size, spatial frequency, or scale. If a series of segmentations with varying parameters is performed on an image or topography map, this image or map is decomposed into a series of images or topography maps of various scales. The series obtained by the monotonous variation of segmentation parameters is called tree or chain. The procedure of constructing the tree or chain using scales respectively feature size respectively spatial band width for segmentation parameterization is called multiscale analysis.

The objective of this paper is to compare three multiscale decompositions of surface topographies, which use three different methods: patchwork, box, and motif. These are based on three different concepts, derived from fractal geometry [1], covering, space subdivision, and motif segmentation, respectively.

This is important because surfaces can have complicated, irregular topographies, which are special places for interactions. Functionality can be related directly to topographies [2], and functional topographic analyses can be difficult to characterize adequately for product and process design and quality assurance. Many physical phenomena can be involved in, and interact with, surface generation and performance. It is through the establishment of functional correlations with performance and processes, and by providing means for confidently discriminating surfaces, that surface metrology can be valuable for science and industry.

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4 Multiscale analyses and characterizations can elucidate relations in topographically dependent
5 phenomena, and discriminate surface properties, that are not evident with classical topographic analyses
6 [3]. They facilitate the understanding of superficial physical phenomena, such as sealing of machined
7 parts [4], and brightness [5]. Multiscale decomposition can separate topographically related phenomena
8 by their scales of interaction. Multiscale understanding can facilitate independent control and adjustment
9 of several topographically related phenomena, simultaneously, on the same surface.

10 In this work, “scale” refers to narrow bands of spatial frequencies, or wavelengths, in larger
11 spectra. There are many different expressions of scale. Scales are generally expressed as lengths or as
12 derived units, such as, areas, or spatial frequencies. Single topographic datasets contain ranges of scales,
13 from the smallest, the sampling interval or resolution limit, to the largest, the size of the measured region.
14

15 Multiscale analyses, characterizations, concepts, and decompositions methods have been
16 recently reviewed and categorized [3]. Four principles were proposed for discovering strong correlations
17 and confident discriminations: use appropriate scales, characterizations, measurements, and statistics.
18 Most importantly, scales provide a special kind of dimension where underlying relationships with
19 topographies and processing or performance can be found.

20 Topographic characterization parameters should be chosen for their physical relevance to
21 phenomena of interest, or for their strength of correlation. Average roughness, S_a , the most common
22 characterization parameter [6] and the other classic height parameters, found in ISO 25178 and ASME
23 B46.1 [7], are not multiscale characterizations, unless a series of filters are systematically applied to
24 define multiple, specific scales before they are calculated. Some new characterization parameters, such
25 as, fractal complexity (e.g., ISO 25178-2, ASME B46.1), can only be calculated over ranges of scales.
26 These are called multiscale parameters, because their values usually vary with scale, and a range of
27 scales is required for their computation. Furthermore, multiscale characterization is not limited to
28 topographic datasets of heights. Many kinds of data obtained from topographies can be used, for
29 example, surface curvature tensors [8], [9].

30 This paper is organized as follows. Section 2 summarizes the state of the art in multiscale
31 analysis. In Section 3, we describe segmentation methods (patchwork, box, and motif) for multiscale
32 decomposition. In Section 4, we provide the comparison of three multiscale methods by detaining the
33 materials and methods including the results and their comments. Finally, Section 5 concludes the paper.
34

35 2. State of the art in multiscale analysis

36 Several researchers have demonstrated and compared relevancy of different kinds of multiscale
37 analyses. Le Goïc *et al.* [10] studied topographies of engineering surfaces with the help of multiscale
38 analysis by using gaussian filtering, discrete wavelet transforms and discrete modal decomposition. The
39 relevance of the topographic characterization parameters [11] has been determined with the help of
40 Mesrug software, multiscale decompositions and bootstrapping [12]. Using wavelet multiscale
41 decomposition with various wavelet forms and orders, Deltombe *et al.* [4] have shown effects of
42 machining processes on seals, especially in case of leakage. Malshe *et al.* [13] highlighted the link
43 between multiscale properties and functionality in both natural and bioinspired engineering surfaces.
44

45 Multiscale decompositions are effective in finding strong correlations between surfaces and
46 their functionality. Through the use of the patchwork method, Moreno *et al.* [14] correlated oil retention
47 in fried foods with relative areas. Cantor and Brown [15] found strong correlations between chocolate
48 temperatures and the relative areas of fracture surfaces. In those two publications, the correlation
49 coefficient R as function of scale was shown. R values are greater when relative areas of the topographies
50 are calculated at the most relevant scales, whereas low R values are obtained for less relevant scales.
51 Multilayered steel sheet surfaces with coating and industrial paint were studied by Mezghani *et al.* [16]
52 with continuous wavelet multiscale decomposition, and the authors have shown the influence of each
53 layer over the final surface. More specifically, roughness is influenced by the last layer of paint while
54 waviness is more affected by the deeper layers.
55

56 Two kinds of multiscale analysis methods are considered here. In both kinds, a range of scales
57 and step intervals are selected, and multiscale characterization parameter values are calculated over this
58 range. One kind of method uses a series of sampling distance that are constant for each step of the
59 decomposition, such as, gaussian, wavelet, box, Richardson, i.e., compass, or classical area-scale
60

patchwork methods. The other kind uses an algorithm to find various scales during one step of decomposition, like the motif method. An example of the second kind, with variable sampling distance, is the slit island method designed by Mandelbrot [1] which detects isolated local roughness peaks by slicing a topography with a plane. Here, each isolated peak has its own scale based on its apparent area. Contrary to some of these earlier methods, where scales are based on arbitrary and fixed elementary entities and some variations of them, the main idea here is to find a pattern.

It appears that multiscale analysis of surface topographies could be in turmoil. Choosing one method over others could be baffling. Selection can depend on ease of implementation, instead of morphological justification. From 1980 to 2000, multiscale aspects were limited to computing fractal dimensions on one surface. Different calculation methods have been reported, and results compared with theoretical fractal dimensions with simulated curves and fractal functions. Many methods exist for generating simulated rough surfaces. They are generally equivalent to the generation of fractional brownian surfaces. On the other hand, mathematicians tried their methods on a wider range of fractal curves, such as Takagi surfaces [17]–[19], and proved that topological methods lead to better estimations compared with spectral methods.

Questions remain in surface metrology. Can a method, which relevantly estimates fractal dimension on ideal mathematical fractal curves, be applied, ipso facto, to topographic characterizations, and especially, their multiscale behavior? This legitimate question is still to be answered and leads surface metrologists to reconsider fractal dimensions as a tortuosity and irregularity indicator of rough surfaces over universal mathematical parameters [20].

Since 2000, multiscale analyses are more focused on decomposition, instead of summing up the object of decompositions with scaling laws, whose coefficients can be linked to the fractal dimension. Zahouani *et al.* [21] studied multiscale transfer functions using continuous wavelet decomposition and proved the relevancy of local scale approaches over the determination of a universal coefficient. Bigerelle and Iost [22] showed that a multiscale method is relevant if topographic differences can be demonstrated statistically. Though many multiscale decompositions exist, selecting the most relevant method to accurately identify multiscale signatures remains difficult. A classification system of different methods, although as questionable as any such system, is necessary then. This could be attempted by introducing their topographic implications.

Before constructing a multiscale classification system, consider continuous mathematical representations of rough surface types. Consider “rough” to be an interpretation of measured textures, or topographies, at certain scales that can include irregular components. Three types can be defined. First, a rough surface can be represented as a function of two parameters (type A), generally x and y , under the form $z = f(x, y)$. Another option (type B) is the use of parametric surfaces under the form $z = \Gamma(t)$. Last representation (type C) is from a collectivist point of view, based on the combination of multiple parametric curves. Then, roughness is under the form $z = \bigcup_{i \in I} \Gamma_i(t)$ where I is the index set of curves $\Gamma_i(t)$. In fact, type A is a special case of type B, which in turn is a special case of type C. Each type (A, B and C) is a morphological representation of the roughness, and surface topography as a measurement belongs to type A class (Figure 1).

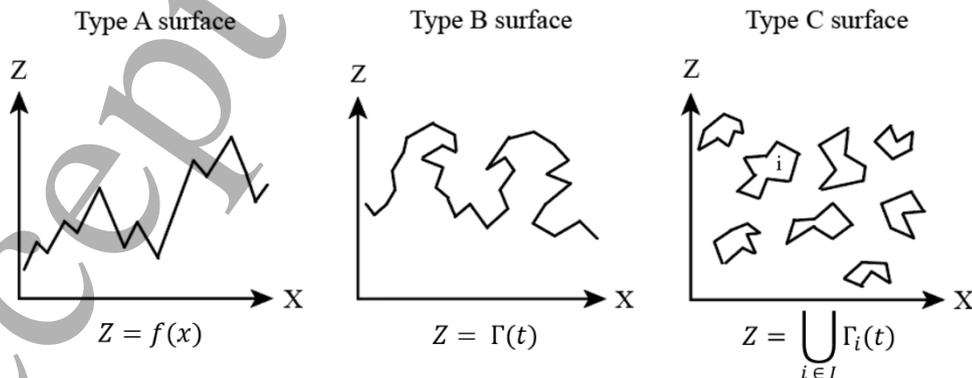


Figure 1: Surface types from a 2D sliced view

Obviously, parameterization of surface roughness facilitates the use of morphological methods related to type A surfaces for the study of type B surfaces. Then, two classes of fundamental

morphological methods can be defined: functional methods (FM) related to type A rough surface representations, and parametric methods (PM) linked to type B rough surface representations. However, a physical difference remains between FM and PM, with sometimes non-negligible implications in surface roughness characterization. The developed interfacial area ratio Sdr specifying a ratio between the size of the area of the surface skin of a topography and the size of the area of the projected surface, is a good example. The developed interfacial area ratio Sdr is calculated directly from the digitized measured data set, perhaps after filtering the shortest wavelengths, only at the scale of the sampling interval. It cannot be used to estimate a fractal dimension. In a way, it is not the true developed area, because developed area only has meaning when it is linked to the scales of measurement and calculation. ISO 25178-2 does not require that the sampling interval accompany the developed interfacial area ratio Sdr, which severely limits its usefulness.

3. Three multiscale methods for topographic analysis

Three kinds of functions can be used to describe topographies, convolutions, variations and coverings.

Convolutions decompose topographies with scalable functions and look for the highest similarity between them. Initial topographies are reinterpreted as combinations of elementary mathematical forms. Elementary, scalable forms are still to be defined. Ideally, scalable functions should fit morphology at every scale. A wavelet with a scalable form, similar to an elementary topographic form, could be relevant for search of multiscale physical mechanisms. Bigerelle *et al.* [23] showed that even a specific wavelet is relevant for characterization of an isolated topographic signature, but specific wavelets fail when used on surfaces generated by an assembly of multiple, elementary mechanisms, for example, an abraded surface. On the other hand, Le Goïc *et al.* [10] highlights that the choice of a convolution method depends on the surface type, such as, periodic, with defects, or spectral.

Variations create numerical indicators that characterize topographic variations locally at specific scales. The structure function is well-known. Most can robustly characterize topographic variations in scalable windows [24].

Finally, coverings estimate the Minkowski sausage to find the Minkowski-Bouligand dimension. Box, oscillation, and sphere are kinds of coverings. These can also be used in PM multiscale analyses. Mandelbrot [1] defined four classes of covering methods: fixed yardstick, variable yardstick, Minkowski, and Packing methods. Additionally, Mandelbrot proposed an original method to calculate fractal dimensions of topographies, applicable to either FM or PM, the slit island method. This method sections topographies horizontally to form islands and computes fractal dimensions from relations between their areas and perimeters. Assuming self-similarity of these islands, fractal dimensions of surfaces can be determined. Actually, this method is equivalent to the calculation of a length at a given scale by taking roughness peak of same area. By varying the area and by measuring with a fixed yardstick size the perimeter of the island, the multiscale roughness can be estimated. Even if this method can produce statistical artifacts [22], it is unique. First, a peak is isolated, and not an arbitrary sub-region. Also, the apparent area of a roughness peak at a given scale corresponds to a spatial scale of the roughness. Then, this multiscale method doesn't impose an observation, or gauge, scale. It can be classified as an object method (OM) which can analyse type C surfaces.

These three morphological analysis classes are compared in this article by using three methods adapted to topographic surfaces. Table 1 indicates in which class defined by Mandelbrot [1], pp. 25-26, the compared methods belong to.

Table 1: Classification of multiscale methods by five categories defined by Mandelbrot

		Mandelbrot Categories				
		Fixed Yardstick	Variable Yardstick	Minkowski	Packing	Slit Island
Methods	Box			X	X	
	Patchwork	X	X			
	Motif				X	X

The patchwork method for area-scale analysis extends Richardson's method with yardsticks, used by Mandelbrot to compute Britain coastline length [1], profiles to areal measurements and surfaces (ASME B46.1 ch10 [7], ISO 25178-2). In classical area-scale analysis, measured surfaces are decomposed into progressively smaller triangular patches, performing a succession of virtual tiling exercises covering a range of scales (Figure 2). Each tiling exercise uses triangles of the same area in 3D, representing the scale. The tiled area at that scale is the number of triangles times the area of the triangle. Only full triangles, with the prescribed area, are counted in the tiling exercises. This leaves some portions at the edges of the measured surface untilted with each exercise. Therefore, the nominal area, i.e. x - y area, floor, or projected area, of the tiling is different for each exercise. To calculate the area ratios, i.e. relative areas, at each scale the tiled area is divided by the corresponding floor, or nominal, area for that tile size [25], which corresponds with the developed interfacial area ratio Sdr. Here a patchwork-like method is used. The triangular tiling, with a succession of triangle sizes, is approximated by first doing a succession of fits to the topography at different scales, then using the developed area function, Sdr, in MountainsMap® (Digital Surf) on the fits. The fits are a low pass filter. By subtracting the fits from the original surface, a high pass filter can be obtained. Nonetheless, they appear to be a reasonable approximation of the classical tiling method, which essentially uses successive down samplings to achieve multiscale characterizations.

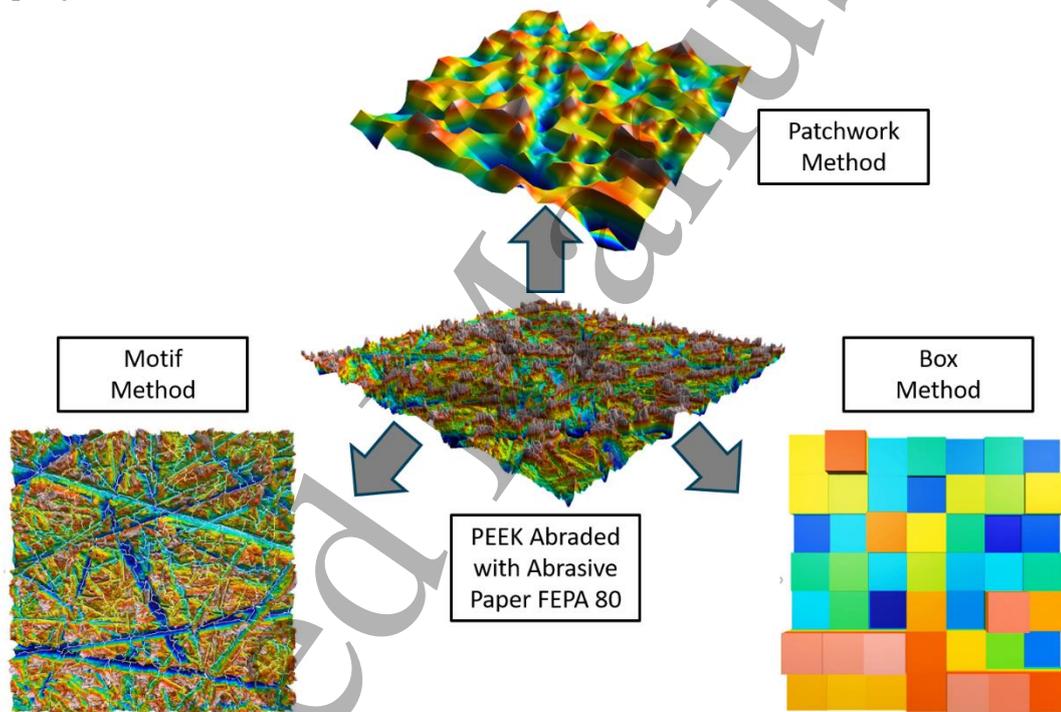


Figure 2: Concepts of the patchwork-like, the box and the motif multiscale decompositions

The box method evaluates topographic characterization parameters described in the ISO 25178 standard, like S_a and S_z , in a fraction of the original surface, i.e., a box (see Figure 2). In this study, the boxes are squares in x and y axes. Multiscale decomposition is obtained by systematically modifying the box size, i.e. the length of one edge of the square, and recalculating the parameters. The zero for the calculation of the height parameters is also recalculated with each box, so the values tend to decrease with box size.

The motif method considered here is based on a variation of Wolf pruning. Though Wolf pruning can be applied on many kinds of 2D data, it will be used on topographies in this paper. It detects topographic motifs, and computes parameters, such as, their height, their equivalent diameter and their orientation. In 2D, a motif can be defined as the segment between a succession of one peak, one valley and one peak - or alternatively, as in this study, a succession of one valley, one peak, and one valley, when summits are the object of the study. Furthermore, a second notion called the combination of motif needs to be added. Depending on user-defined height constraints, generally a S_z percentage (such as 5%

of S_z in ISO 25178 standard) or a percentage of total surface nominal area, motifs can be either merged or considered separately. When height constraint values get sufficiently small, motifs tend to be peaks (Figure 2). The 3D extension of the motif can involve neighboring points [26]. Figure 3 shows how motifs are merged, depending on the user-defined constraints, for various percentages of the total surface nominal area. Multiple scales are obtained during a decomposition, where each detected peak possess its own scale.

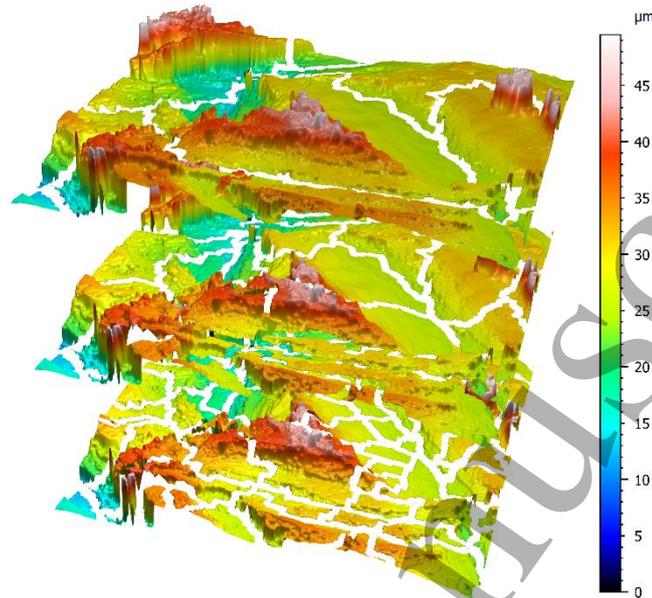


Figure 3: Motifs with three different area constraints

Box and patchwork methods belong to the fixed sampling distance category, whereas the motif method uses a variable sampling distance. These three multiscale analyses (Figure 2) are applied to abraded surfaces of PEEK, to evaluate their abilities to discriminate wear phenomena from topographies.

4. Comparison of three multiscale methods

4.1. Materials and Methods

A PEEK rod, 30 mm in diameter, was cut into 20 mm thick disks. Each disk was polished to a mirror finish with a Tegramin 25 (Struers™) rotary grinding machine. Then each was ground with an abrasive paper. The FEPA grit sizes varied from 80 to 4000 as shown in Table 2.

Table 2: Abrasive grade (FEPA), mean grit grain diameter, and number of disks

Abrasive Grade	Mean Abrasive Grain Diameter (µm)	Number of Disks
80	201	1
120	125	2
180	82	2
320	46	2
500	30	2
800	22	2
1200	15	2
2000	10	2
4000	5	2

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Topographies were measured with a white light interferometer Zygo (NewView 7300™) with a 50X Mirau objective. To form each 2x2 mm topographic dataset, 432 individual measurements were stitched together with a 20% overlap. Each dataset has a spatial resolution of 0.219 μm along x and y axes and is composed of 83 million pixels. Stitching is essential as a wide scale range is obtained, allowing an enhanced detection of physical multiscale phenomena. Secondly, stitching has also the ability to stabilize roughness and morphological parameters, because stitched datasets contain more data and are statistically closer to a representative surface than a single elementary measurement would be. There are 10 such datasets per disk from randomly selected locations for a total of 170.

Initial measurements were processed with functions in MountainsMap®, consistent with ISO 25178. Form was removed with a 3rd order polynomial fit, providing a reference plane. Renderings of PEEK topographies are shown in Figure 4.

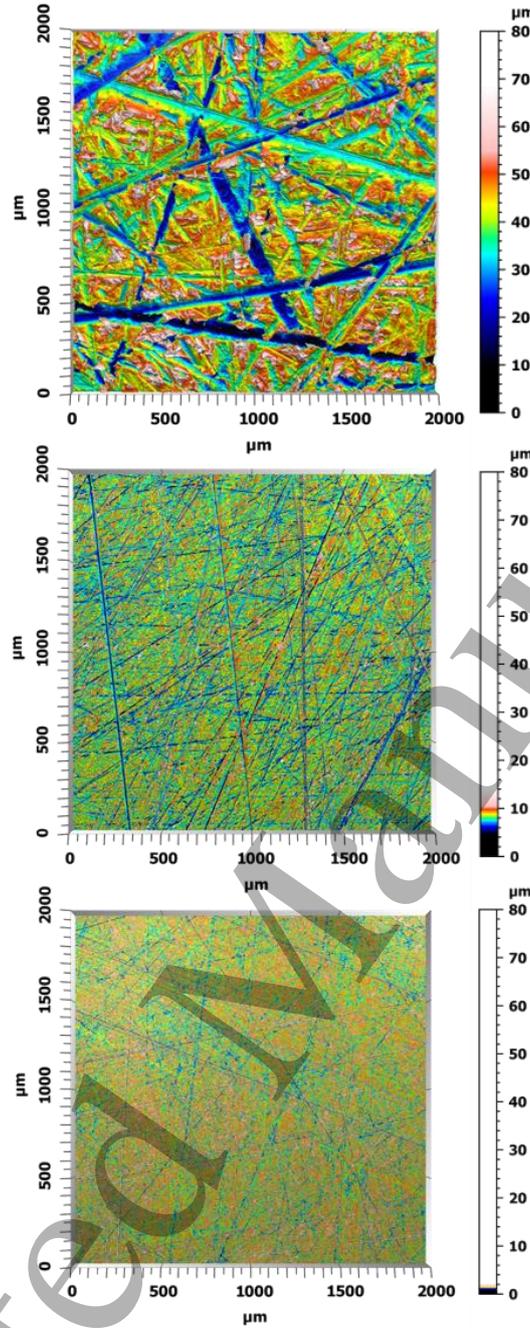


Figure 4: PEEK topographies after abrasion with abrasive papers FEPA 80 (top), 500 (middle) and 2000 (bottom)

In principle, performing analyses and characterizations at an appropriate scale facilitates the understanding of topographically related phenomena [3]. The topographies studied here consisted of intersecting grooves and scratches over a range of sizes, forming a kind of fractal pattern. Each surface was homogeneous at scales sufficiently larger than the grooves. Different wear mechanisms can be active at different scales. Different grits and mechanisms logically make grooves of different sizes and depths, peak sizes and densities. Although abrasive processes might seem simple, it is difficult to determine, a priori, an appropriate scale for elucidating mechanisms of abrasive wear. This difficulty suggests a multiscale approach. Many multiscale decompositions exist, with their own advantages and drawbacks [3].

Here the analysis methods described above, patchwork, box and motif Wolf pruning segmentation, are compared. The results of each multiscale decomposition are plotted below.

4.2. Computational Results

Common outputs of multiscale analyses are plots of characterization parameters as a function of gauge parameters, i.e., scales of observation. Though characterization and gauge parameters vary depending on the multiscale decomposition method and the scale sensitivity of the characterization parameter, common behavior patterns are sought. For example, scaling phenomena could be detected if the regimen shift is observed, delimiting macroscopic and microscopic, i.e., more local surface characteristics. Each multiscale method in this article has its own characterization and gauge parameters.

Figure 5 shows the evolution of the developed interfacial area ratio (Sdr, ISO 25178) as a function of the scale of the spline fit, the gauging parameter, for each abrasive grain size (FEPA grade). As expected, finer scales generally correspond to greater developed interfacial area ratios. Developed interfacial area ratios are also lower when abrasive grains are larger. Each abrasive paper is ranked from larger to finer abrasive grain sizes (FEPA grade 80 to 4000). Slopes of Sdr are clearly greater at the highest scales and smaller at the finest scales. This suggests that a crossover scale separating these two regimens might be identified.

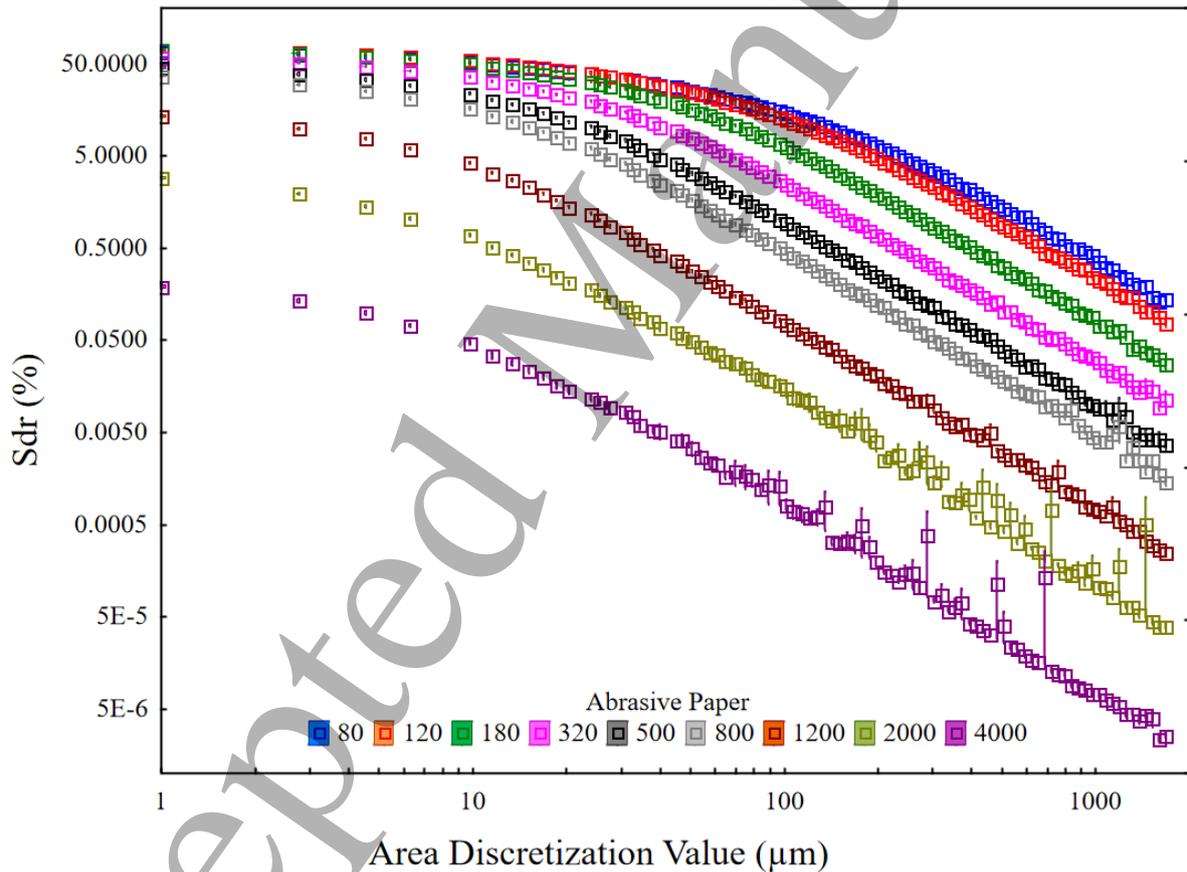


Figure 5: Patchwork-like method, developed surface areas (Sdr) as a function of scales of the spline fits

Figure 6 shows box multiscale decompositions, where peak-to-valley heights, S_z , are plotted as a function of box sizes, the gauging parameter, for each grit size. The height parameter decreases with box sizes and with higher abrasive grades. Two regimens and a crossover can be observed.

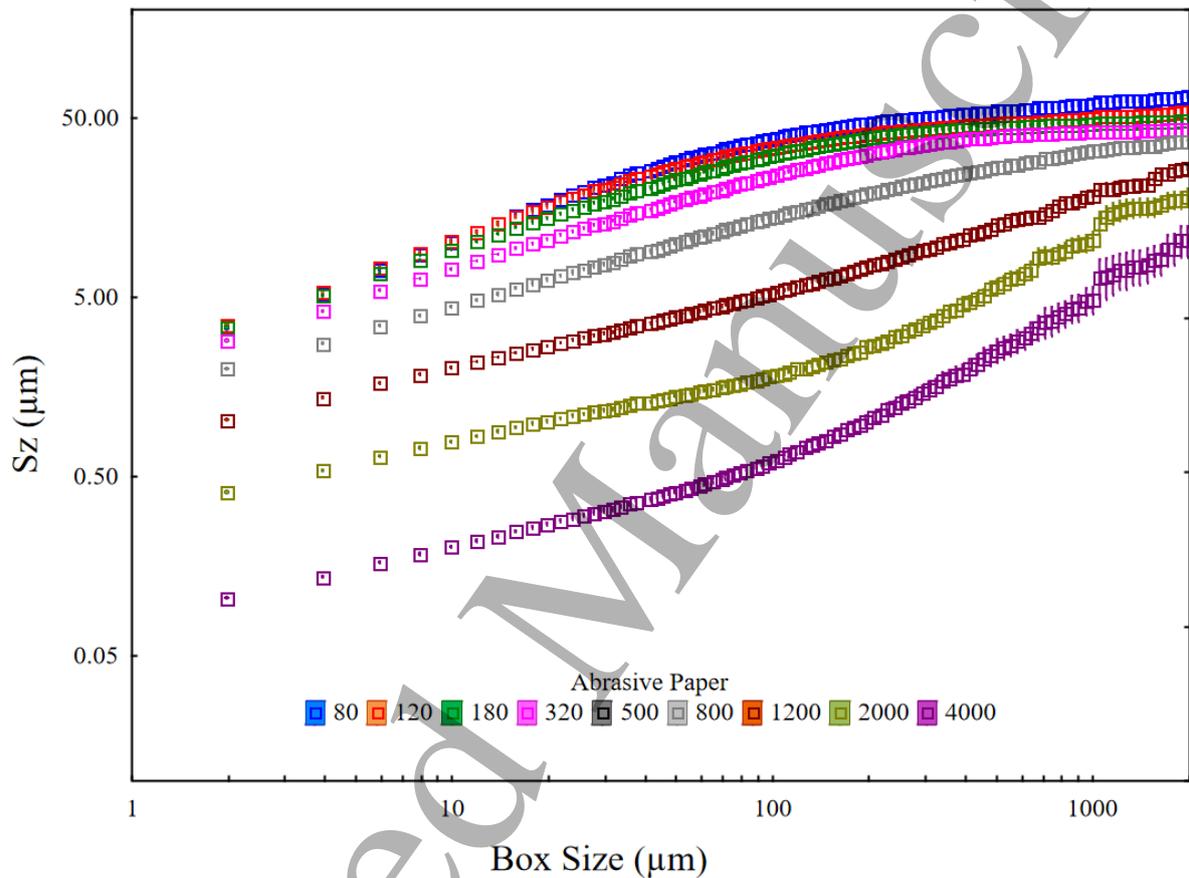


Figure 6: Box method, peak-to-valley height (S_z) as a function of box size

Lastly, for motifs, using Wolf pruning-like segmentation, motif height as a function of motif equivalent diameter, the gauging parameter, for different FEPA grades are shown in Figure 7, which highlights a crossover between two regimens. The crossover value changes depending on the abrasive paper. Overall, the motif height decreases as the motif equivalent diameter decreases.

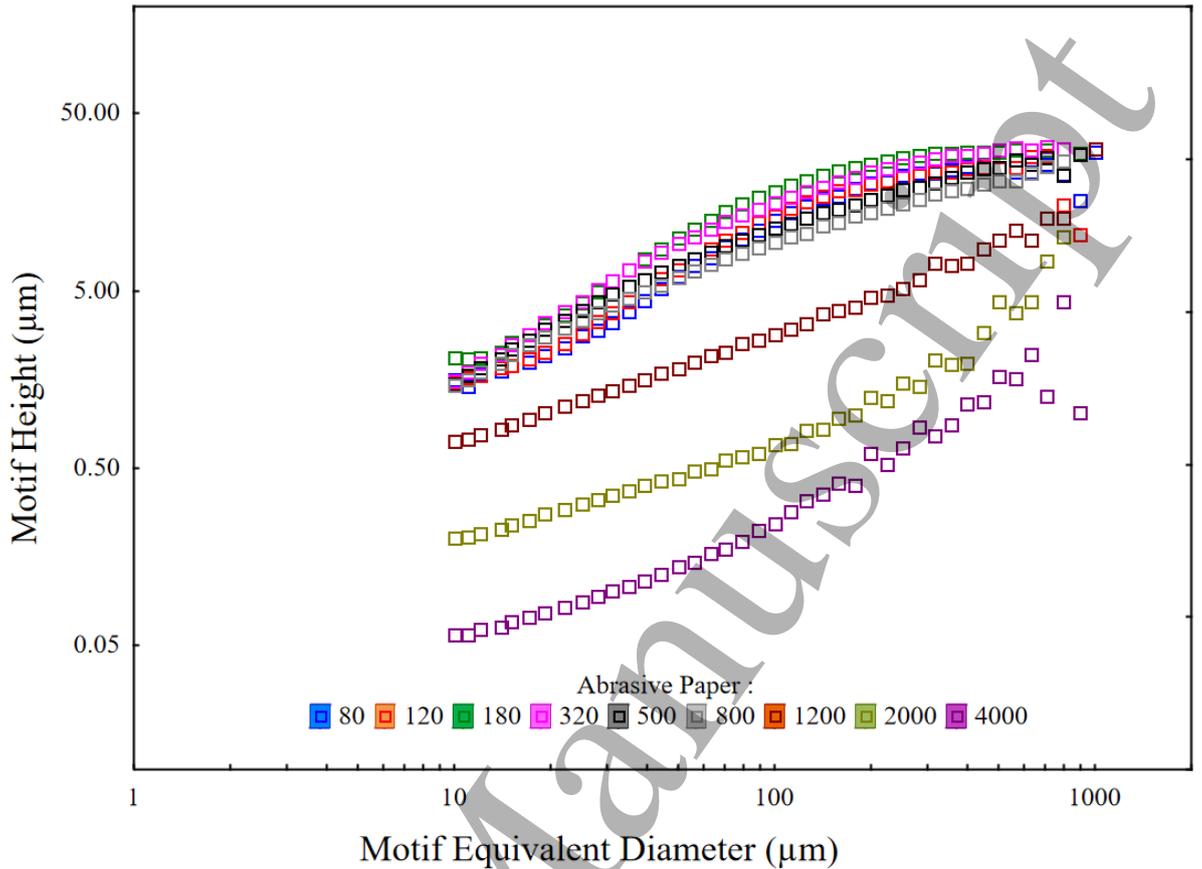


Figure 7: Motif height as a function of motif equivalent diameter

As a crossover can be found with the patchwork method, the box method and the motif method, an optimization process helps in its determination for each method and each abrasive paper grade. Crossover values are detected by minimizing standard deviation of residuals r for different abscissa values. Figure 8 shows an example of crossover detection. A system of equations needs to be solved in order to know the parameters A , B , C and D in Equations 1 and 2:

$$\begin{cases} \log(y) = A * \log(x) + B & \text{if } x \leq \text{crossover} \\ \log(y) = C * \log(x) + D & \text{if } x \geq \text{crossover}, \end{cases} \quad \text{Eq. 1}$$

with

$$D = A * \log(\text{crossover}) + B - C * \log(\text{crossover}), \quad \text{Eq. 2}$$

where x and y values are respectively area discretization value and the developed interfacial area ratio S_{dr} for the patchwork method, box size and the peak-to-valley height S_z for the box method and motif equivalent diameter and motif height for the motif method. Also, the standard deviation of residuals r is computed, and is used as an objective value for optimization.

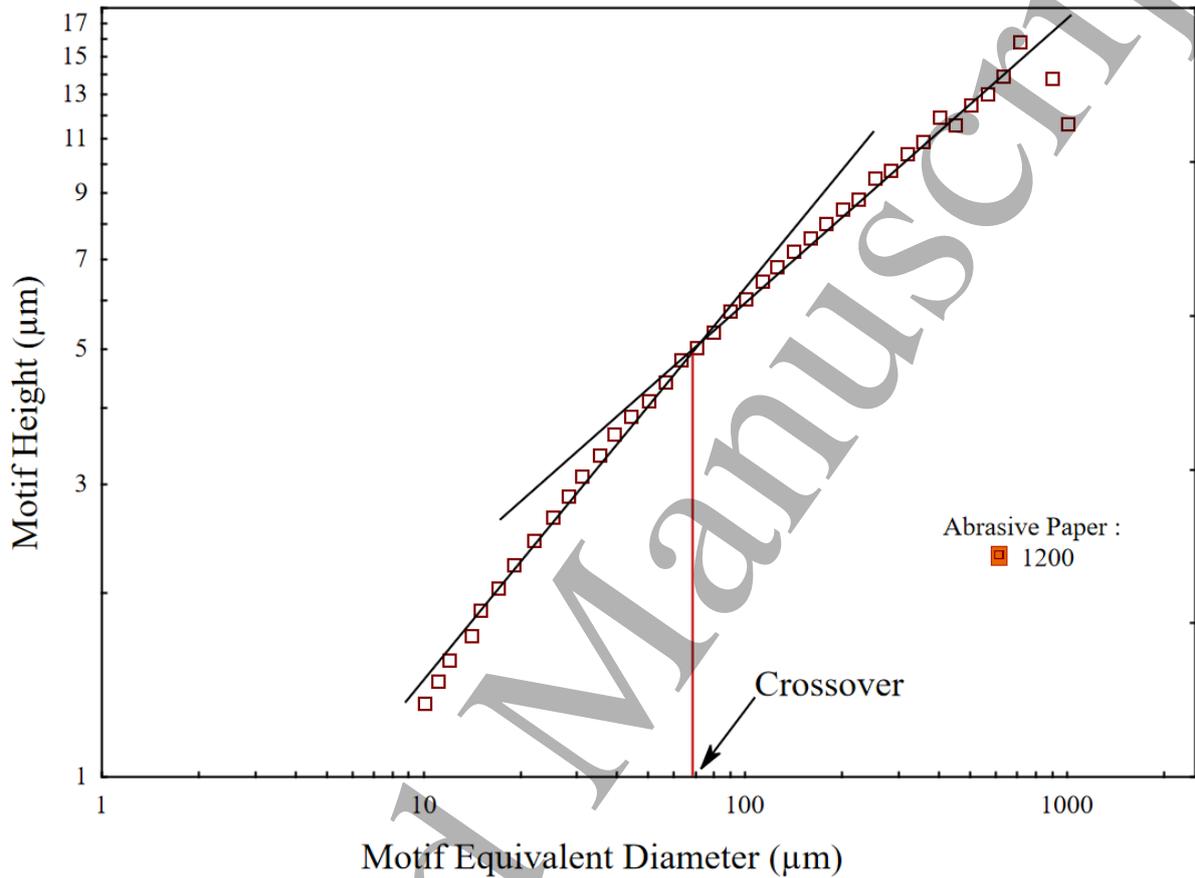


Figure 8: Crossover detection with motif detection for abrasive paper 1200

As two linear regimens can be detected for each grit paper in the multiscale decomposition direct output, it is necessary to compute the crossover at the behavior shift to find A , B , C and D parameters. Nonlinear regression was the selected tool in this study, as the hypothesis was made that the crossover should have the minimum standard deviation of residual r . An example of the optimization curve for the motif method for one abrasive grade is shown in Figure 9.

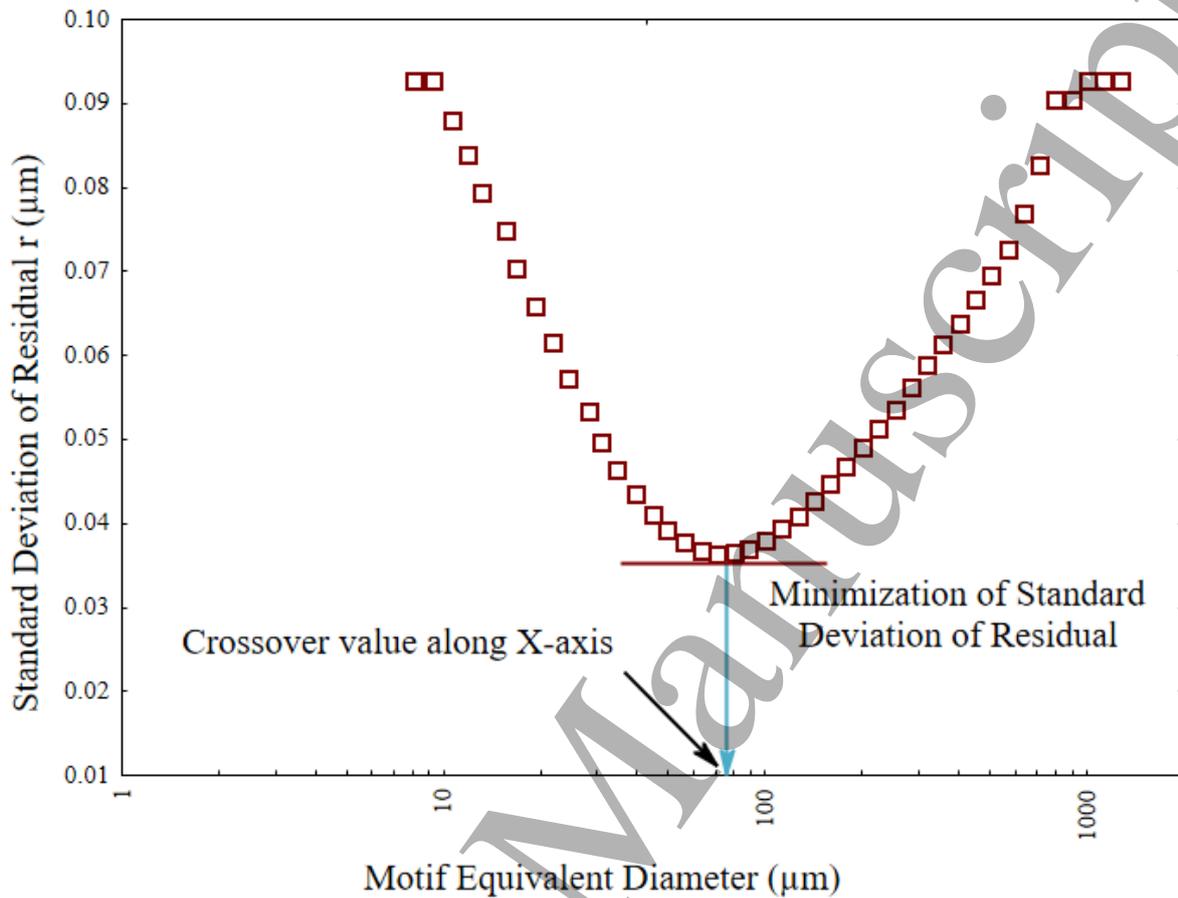


Figure 9: Optimization curve to find crossover for one abrasive grade with motif method

From here, D parameter corresponds to the intercept of the crossover value along y-axis. Parameters A and C are respectively the slopes of the left and right linear parts of the curve. Parameter B is the intercept of the left linear part.

Crossover values, plotted as a function of mean grain diameters for all three multiscale decompositions, are compiled in Figure 10. Abrasive paper grades have been converted to mean abrasive grain diameter using the FEPA standard. With all methods, the crossover values change with the mean abrasive grain diameter. Quantitatively, crossover values of box and patchwork methods converge, whereas crossover values from motif decomposition are higher. Although, the quantitative difference observed with motif method compared to the two others, crossover evolution follows the same tendency in all three cases over a critical mean grain diameter value of $15 \mu\text{m}$. For grains less than $15 \mu\text{m}$, the motif method presents a high divergence in crossover values compared to the two other methods, that could be outliers. An explanation could be that the Wolf pruning segmentation performs well at most scales but has difficulties in finding peaks at the smallest and the largest scales. True peaks and noise get confused, and a few motifs with small equivalent diameters present larger dispersion. At largest scales, as only a few peaks are found, summary statistics are more sensible to extreme values, and lack of statistical stability. As the crossover detection algorithm relies on minimal standard deviation of residual, those unstable values may influence the detected crossover value, and result in outliers.

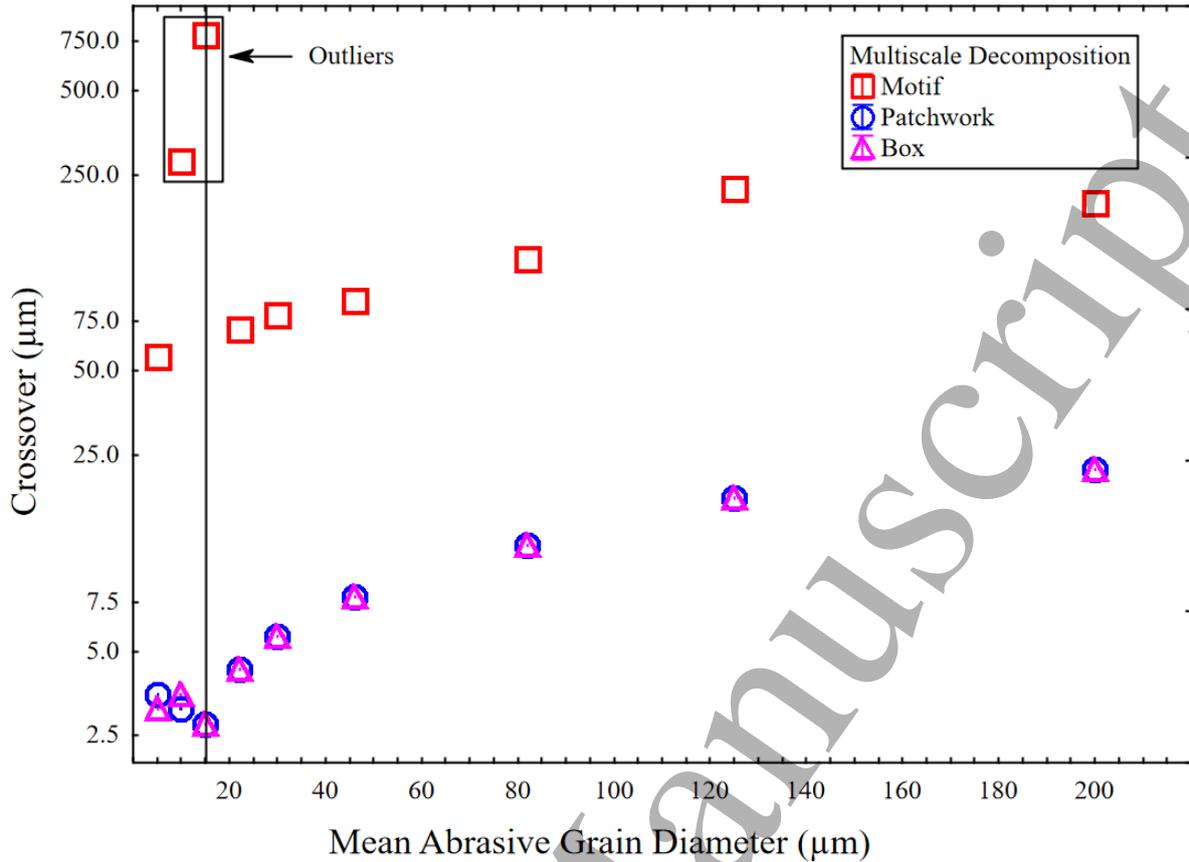


Figure 10: Crossover values depending on mean grain diameter for the three multiscale decompositions

Also, small differences are observed at the smallest scales between crossovers from the box and patchwork method. It results from the difference in the computation method of roughness parameter peak-to-valley height S_z for box method, which is an extremum parameter greatly influenced by measurement noise, and the developed interfacial area ratio S_{dr} parameter, which is based on the computation of interfacial developed areas and is less influenced by extremum height values.

4.3. Discussion

Three multiscale decompositions have been compared, highlighting the presence of a crossover scale separating two regimens. This crossover could represent limits between abrasion regimes: a larger one could be due to chip formation and removal, while smaller one is perhaps due to plowing. Furthermore, the fractal aspect of the surface is generated by the presence of little peaks on bigger peaks on abrasive grains over a range of peak sizes, resulting in a spectrum of scratch sizes on abraded surfaces.

Also, slopes of multiscale plots are interesting, because fractal dimensions, or Minkowski-Bouligand dimensions, can be calculated from the slopes. Ganti and Buschan [27] described this pattern on a plot composed of two fractal regions. Scaling laws can be found, generally based on a power law mode.

Quantitative differences between the motif method, and the box and patchwork methods, are linked to their underlying concepts. While box and patchwork algorithms detect peaks locally, the motif segmentation finds homogeneous regions at specific scales. Therefore, the motif tends to give higher crossover values than the two other methods with local perspectives. This observation is also linked to fixed sampling distances used for the box and patchwork methods, which do not rely on morphology, like the motif does. The three methods complement each other: a lower crossover is indicated by the box and patchwork methods, and an upper with the motif method. A true crossover value might be located between those given by these methods.

1
2
3 Finally, the motif method has another advantage over box and patchwork methods. By detecting
4 peaks and homogenous regions, the motif can discriminate heterogeneous topographies. Computing
5 roughness parameters over motifs is possible because homogeneities required for calculating such
6 parameters are verified inside a motif, while this is not true of sub-regions in patchwork and box
7 methods, which use a fixed and arbitrary sampling distance.

8 This study highlights needs for new tools in the analysis of heterogeneous topographic datasets.
9 Fixed sampling distance multiscale decompositions fail to correctly separate two distinctive sub-regions
10 due to the arbitrary slicing of datasets. These methods often rely on summary statistics tools, such as
11 means and median, which are not appropriate in the study of heterogeneous datasets. Hence, it is
12 necessary to leave global techniques to a more local decomposition, and to consider spatial positions of
13 each sub-area, like a motif, when studying heterogeneous surfaces.
14

15 16 **5. Conclusion**

17
18 Three segmentation methods, patchwork, box and motif multiscale decomposition, have been
19 used for analysis of texture features and have been compared. The characteristics of the three multiscale
20 analysis procedures has been investigated with the help of a study of PEEK polymer abrasion, using
21 abrasive papers, with FEPA grades 80 to 4000. The texture of the topographies is homogeneous with
22 fractal aspects. The topographies have been measured with a white light interferometer.

23 A crossover scale, separating larger and smaller abrasion regions in scale, has been detected
24 with each technique, though a quantitative difference appears with the motif method, contrary to the
25 other two. Nonetheless, evolutions of crossovers with mean abrasive grain diameters follow similar
26 trends for all three.
27

28 Evaluations of the discriminating power revealed that the box and patchwork methods detect a
29 lower bound for crossover, while the motif technique can find an upper bound, due to its ability to detect
30 homogeneous regions inside of a topography. Thus, the three techniques complement each other in the
31 detection of the true crossover value, which is probably contained between the previously described
32 boundaries.

33 Motifs achieve scale-based decompositions of surfaces based on morphology of surface
34 topography, e.g., peaks, unlike the patchwork and box methods that are based on measurement sampling
35 without any consideration for surface morphology. This highlights a special contribution of the motif's
36 approach, using summary statistics for local analyses, relying on spatial positions of each motif in
37 heterogeneous topographic datasets.
38

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