Quantitative assessment of machine tools precision states through fractal analysis of machine error parameters

Kanglin Xing[1, *], Xavier Rimpault[1,2], J.R.R. Mayer[1], Jean-François Chatelain[2], Sofiane Achiche[1]

[1]Department of Mechanical Engineering, Polytechnique Montréal, Montréal, QC H3T 1J4, Canada
[2]Department of Mechanical Engineering, École de technologie supérieure, Montréal, QC H3C 1K3, Canada

Abstract

The precision status of machine tools directly affects parts' quality. Therefore, periodical calibration of machine tools is desirable. Multiple machine error parameters can be acquired in one calibration using automated indirect methods, but to fully automate the calibration, the automation of the results is required. Fractals have been successfully used to process volumetric error vector similarity measures and volumetric error coordinates of machine tools. Herein, fractals are firstly attempted to process the machine error parameters for quantitative assessment of the machine tool precision state. The SAMBA method is used to measure the 13 machine error parameters of the experimental HU-40T five-axis machine tool. Repeated tests are conducted with the machine tool in its normal state, real C-axis encoder and pseudo pitch/straightness error faulty states. In addition, simulated faults with steep and gradual change caused by the manual correction of ISO230-1 error parameters are also considered. As a comparison, the change of machine tool precision state is also recognized by fractal analysis of volumetric error coordinates. Towards the same fault, the proposed method has been found to be an efficient approach to detect faulty states. The fractal analysis application in this study has a comparable performance as fractal analysis of volumetric error coordinates in machine tool precision state recognition. Therefore, fractal analysis of machine error parameters could be an effective tool to detect change in a machine tool status.

1 Introduction

The precision state of machine tools plays a decisive part in modern manufacturing. A stable precision state of machine tool is helpful to ensure the machining quality. However, in practice, factors such as the change of geometric errors, thermal errors, tool wear, etc can all contribute to the machining inaccuracy [1]. Therefore, it is of great importance to identify the precision state of machine tools.

The precision state of machine tools can be accordingly confirmed either by a single machine error or by a qualitative analysis of machine tool errors. A single machine error could be measured using direct methods such as the laser interferometer, laser tracker, or indirect methods such as the scale and master ball artefact (SAMBA) method [2]. Qualitative analysis of machine tool errors has been found in volumetric errors (VEs). For example, VEs have been processed by vector similarity measures and control chart for the identification of machine tools conditions fluctuation. In addition, VEs processed by K-means and principal component analysis can be used for machine tool precision states classification [3, 4]. Moreover, a novel method based on fractal analysis has been used to process VEs coordinates, and provides new measures for VEs feature extraction [5]. The advantage of this method is that the acquired VE vector coordinates are directly processed without any further data pre-processing. Technically, using this fractal analysis approach decreases the complexity in VEs data processing. In addition, similar attempts of fractal analysis could also be found in VEs VSMs. As an alternative method, could the measured/estimated machine error parameters be applied to quantitatively assess the precision state of a machine tool?

Fractal analysis is a technique allowing to quantify the shape pattern(s) of an object at different magnification scales. The complexity of shape pattern(s) can be reflected by the fractal parameters that have a the shape pattern can be reflected by the fractal parameters which have good correlation relationship with the change process of one monitoring object [6], for example, a machine tool evolving state, a machining process and the tool life [7, 8]. Based on the best performance in the above domain and the processing of VEs, therefore, fractal analysis is selected as the main method for processing the machine error parameters.

Therein, the research evaluates the performance of machine tools precision state indicator generated by fractal analysis of machine error parameters. To verify the performance of the proposed method, one published solution based on fractal analysis of VE coordinates has also been included. Validations of the proposed method are conducted using data of a real fault acquired from the experimental machine tool (C axis encoder fault), pseudo-faults (EXX, EYX and EZX) and the simulated faults caused by the gradual and steep change of the modelled "13" machine error parameters. Finally, the conclusions are drawn.

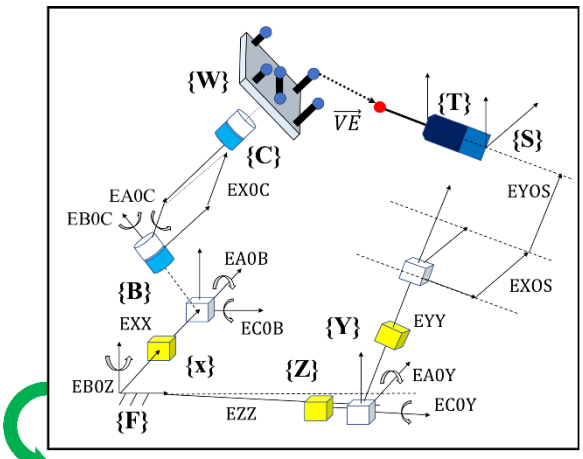
2 Machine tools precision state indicator data processing

Machine tool error parameters are usually acquired at variable times during machine tools maintenance pitstops. Then, these error parameters are be coupled

as the input for fractal analysis. The generated fractal results are be assessed in view of the precision state of machine tools.

2.1 Machine error parameters and their acquisition

An indirect machine tool calibration method, the SAMBA method is selected to estimate machine error parameters and volumetric errors of a five-axis machine tool. Usually, different machine error parameters could be estimated by the selection of machine error models. The detail of the SAMBA machine error model could be found in [9, 10]. Herein, a "13" machine error model (Figure 1) is selected owing to its advantages in measurement time and model stability. The meaning of each error parameter could be found in Figure 1.



EA0B	Out-of-squareness angle of the B-axis relative to the Z-axis
EC0B	Out-of-squareness angle of the B-axis relative to the X-axis
EX0C	Offsets between the B and C axes
EA0C	Out-of-squareness of the C-axis relative to the B-axis
EB0C	Out-of-squareness of the C-axis relative to the X-axis
EB0Z	Out-of-squareness of the Z-axis relative to the X-axis
EA0Y	Out-of-squareness of the Y-axis relative to the Z-axis
EC0Y	Out-of-squareness of the Y-axis relative to the X-axis
EY0S	Offset of the spindle relative to the B-axis in X-axis
EZ0S	Offset of the spindle relative to the C-axis in Y-axis
EXX1	Positioning linear error of the X-axis
EYY1	Positioning linear error of the Y-axis
EZZ1	Positioning linear error of the Z-axis

Figure 1. Kinematic chain of HU-40T five-axis machine tool and the meaning of the "13" machine error parameters [9]

After the SAMBA measurement, 13 machine error parameters are combined as a data series (Eq. (1) for the next fractal analysis.

$$\mathrm{ME_j} = [\mathrm{EA0B}, \mathrm{EC0B}, \mathrm{EX0C}, \ldots, \mathrm{EYY1}, \mathrm{EZZ1}] \tag{1}$$

2.2 Data processing using fractal analysis

Fractal analysis allows evaluating the fractal characteristics of a dataset, and it includes methods such as correlation and capacity dimensions [11]. Among numerous fractal analyses, the fractal regularization technique is chosen for this research thanks to its relatively good robustness and high degree of automation [11]. It relies on the convolution of a data series "s" with different rectangle sized kernels ga – affine function with a width of "a" (Eq. (2) [6]. Then, sa is presumed to have a finite length (la). Finally, a fractal dimension estimation, expressed as the regularization dimension D, is calculated as Eq. (3.

$$\mathbf{s}_\mathrm{a} = \mathbf{s} * \mathbf{g}_\mathrm{a} \tag{2}$$

$$\mathrm{D} = 1 - \lim_{\mathrm{a}\to 0} \frac{\log \mathrm{l_a}}{\log \mathrm{a}} \tag{3}$$

According to the referenced procedures for the preliminary evaluation [5], the range of the slope determination is obtained. After that, the following three fractal measures can be acquired: the fractal dimension D (slope estimation), the topothesy G (y-intercept) and R2 (auto-scale regularity) [6]. Besides, an index measure considering the above three measures is also used (Eq. (4) [12]:

$$\mathrm{Index} = \frac{\mathrm{D.G}}{\mathrm{R}^2} \tag{4}$$

In this research, except the fractal analysis of machine error parameters, fractal assessment of VEs coordinates (Eq. (5) is also conducted. By comparing of both results, the performance of the fractal analysis of machine error parameters could be investigated. The VE coordinates of one SAMBA measurement are combined as a data series for fractal processing (Eq. (5). For the detail, please refer to [5].

$$\mathrm{VExyz_i} = [\mathrm{VEx_{i,1}}, \mathrm{VEy_{i,1}}, \mathrm{VEz_{i,1}}, \ldots, \mathrm{VEx_{i,N}}, \mathrm{VEy_{i,N}}, \mathrm{VEz_{i,N}}] \tag{5}$$

3 Machine tools precision state indicator data processing

Machine error parameters for this research comes from the following four sources (Figure 2): A real fault in the continuous measurement of a HU40-T five-axis machine tool; Pseudo-faults generated by the modification of machine error compensation tables; Simulated steep or gradual change fault caused by the correction of one error parameter; A specific simulated fault caused by the manual

correction of EZX error parameter. Regarding the real fault, it is caused by a faulty in the C axis encoder. After detecting this fault, the C axis angular position was control by the C axis motor encoder, which may bring a slight change to positioning capability.

To increase the diversity of the fault types, two pseudo-faults EXX and EYX were applied. For theEXX fault, a U shape error with magnitudes of 35 µm was inputted to the pitch error compensation table for the X axis to decrease the positioning capability of the X- axis. This operation could be reflected in the estimated machine error parameters. The second pseudo-fault EYX was generated by the manual modification of the raw SAMBA probing file. The Y-axis coordinate of each probing position is corrected as a function of its X-axis coordinate [6].

The simulated faults caused by the gradual or steep change of one of the "13" machine error parameters were generated by the AxiSAMBATM simulator software. The change tendency of one modelled error parameter was set accordingly as the paper [4], while the change of remaining error parameters is in a range of 15% of its normal reading. The same simulation rule has also been applied in the fault simulation of an un-modelled EZX error.

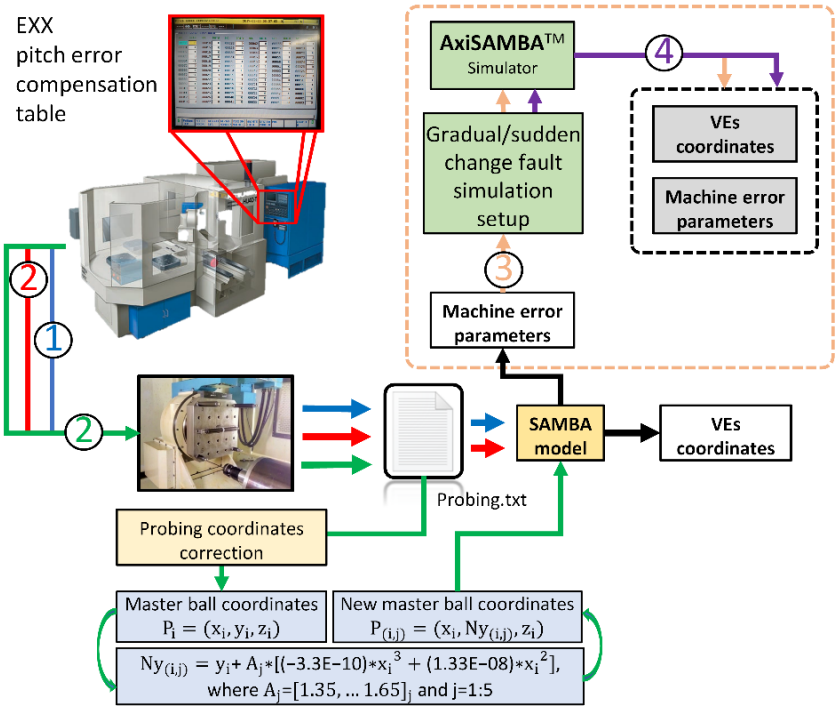


Figure 2. faults generated from four paths. Path (1) stands for the real C-axis encoder fault; Path (2) pseudo EXX and EYX faults; Path (3) simulated gradual/steep change fault; Path (4) simulated EZX fault.

4 Results and discussion

The fractal measures of machine error parameters and VE coordinates of each SAMBA measurement were calculated, respectively. After that, the detected fault occurrence time using the fractal analysis of two inputs were compared with the known occurrence time.

4.1 Real C-axis encoder fault analysis

Four presented fractal measures were used to process the data serials of machine error parameters and VE coordinates (Figure 3). The known fault occurrence time is the 13th and it could be well recognized by fractal assessment of VE coordinates and machine error parameters (except the fractal parameter R2). However, a slightly different normal machine condition could only be suggested by the fractal parameters of VE coordinates rather than the machine error's fractal parameters.

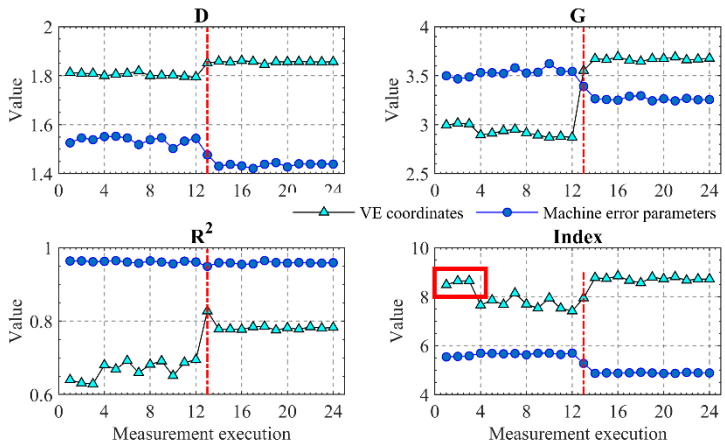


Figure 3. Fractal analysis of machine error parameters acquired before and after the occurrence of C axis encoder fault

4.2 Pseudo faults EXX and EYX analysis

Figure 4 displays the recognition results of pseudo fault EXX using fractal analysis of VEs coordinates and machine error parameters, respectively. The exact pseudo-fault of EXX occurred at the 7th SAMBA measurement, and it could be well detected by the fractal assessment of VE coordinates (D, R2, Index). While the fractal of machine error parameters-R2 and Index parameters had a worse performance in the change detection. This change could only be detected by the D and G measures. Similar conclusions were also drawn from fractal of VEs coordinates and fractal of machine error parameter results for the induced pseudo fault caused by the change of EYX.

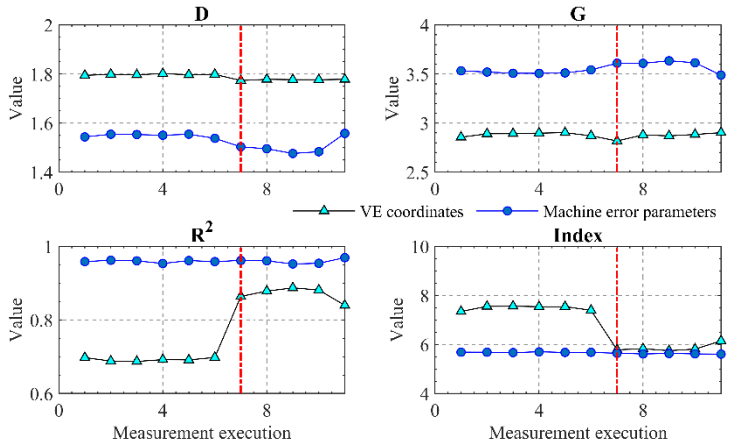


Figure 4. Fractal analysis results of pseudo faults EXX

4.3 Simulated EZX fault analysis

To deeply verify the performance of fractal measures of machine error parameters, a fault caused by the gradual and steep change of EZX error, which is not included by the estimated result of the AxiSAMBA™ software, was also simulated. Figure 5 reveals the fractal analysis of EZX fault using the inputs of VE coordinates and machine error parameters.

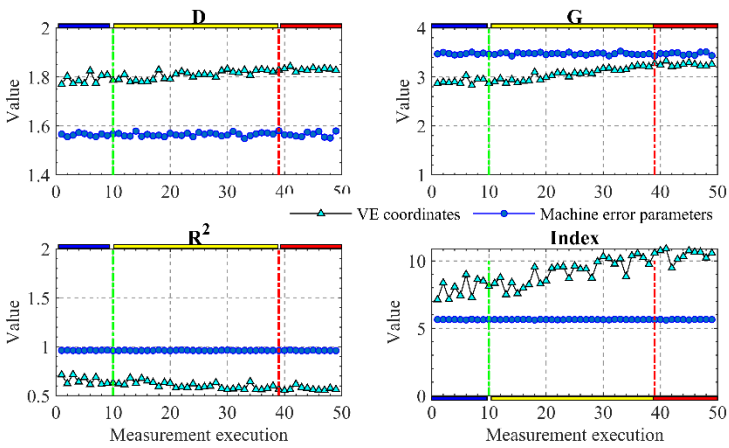


Figure 5. Fractal analysis results of simulated EZX fault using machine error parameters and VEs coordinates; the blue, yellow and red bars show the development of a fault from its normal state, transition state (gradual change) to faulty state; This procedure also works for Figure 6.

The simulated EZX fault could be well recognized in the transition period by the VEs fractal measures D, G and Index. While it cannot be detected by the

fractal analysis of machine error parameters. Similar results could also be found from the EZX fault with steep change.

4.4 Simulated gradual/steep change fault analysis

13 simulated faults with the gradual/steep change of the modelled error of the AxiSAMBA™ software were also included. The recognition result of EC0Y fault with steep change is shown in Figure 6. The occurrence time of the simulated steep change fault is 11th and it could be mostly detected by the fractal of VE coordinates and machine error parameters expect fractal measure of VE coordinates Index.

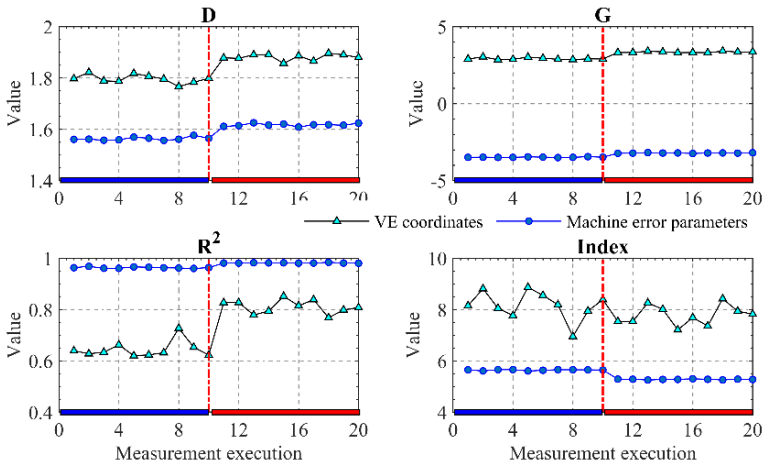


Figure 6. Fractal analysis results of simulated EC0Y fault using machine error parameters and VEs coordinates

Similar findings could also be obtained from the un-shown recognition results of gradual/steep change faults. Figure 7 shows the statistical results of the performance of fractal measures in the simulated gradual/steep change faults. "1" and "0" are used to represent if a fault can be detected. Take the "0" of EA0B as an example, it means that fractal measure of VE coordinates cannot detect the fault caused by the gradual/steep change of EA0B.

The successful detection number of faults using fractal measures is shown at the bottom of Figure 7. The performance of fractal measure is related to its input. Compared with the fractal measures of VEs coordinates, the fractal measure of machine error (ME) parameters has a better performance in fault detection and the four fractal measures perform equally. As for the fractal measures of VE coordinates, G and R2 can detect more faults.

	D				G				R^2				Index			
	VE		ME		VE		ME		VE		ME		VE		ME	
EA0B	0	0	1	1	0	0	1	1	0	1	1	1	0	0	1	1
EC0B	0	0	1	1	0	1	1	1	0	1	0	0	0	0	0	0
EX0C	0	0	1	1	1	1	1	1	1	1	1	0	1	1	1	1
EA0C	0	0	1	1	1	1	1	1	0	1	0	0	0	0	1	1
EB0C	0	0	1	1	0	0	1	1	0	1	1	1	0	1	1	1
EB0Z	0	1	0	0	0	1	1	1	0	0	1	1	0	0	1	1
EA0Y	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1
EC0Y	1	1	1	1	1	1	1	1	1	1	1	1	0	0	1	1
EY0S	0	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1
EZ0S	0	1	1	1	1	1	1	1	1	1	1	0	1	1	1	1
EXX1	0	0	1	1	0	0	1	1	1	0	1	1	0	0	1	1
EYY1	0	1	1	1	1	1	1	1	1	1	1	1	1	1	1	1
EZZ1	0	0	1	1	1	1	1	1	0	1	1	1	0	0	1	1
	1	4	12	12	8	10	13	13	7	11	11	9	3	6	12	12

Figure 7. Statistical results of fractal measures in fault recognition

5 Discussion

In this paper, a novel application of fractal analysis in machine error parameters has been proposed to quantitatively assess the precision state of machine tools. This new method was validated by the real C-axis enc1oder fault, simulated gradual and steep change fault, and pseudo-faults EXX and EYX. As a comparison, fractal assessment of volumetric error coordinates was also conducted. Four fractal measures perform differently in the detection of machine tool precision state. It may be related to the fault type, and it is not recommended to select one based on some cases. For example, G measure has different performances in the real, simulated and pseudo faults. The simulated faults demonstrated that fractal analysis of machine error parameters could have better performance than fractal analysis of VEs coordinates when the fault is caused by the change of one modelled error parameter. However, when the fault is caused by the unmodeled error parameter, fractal analysis of machine error parameters may be ineffective. In this case, fractal assessment of VE coordinate is needed. Therefore, in practice, the two data processing methods could be used together to access the precision of machine tools.

6 Conclusions

Therein, fractal analysis of machine error parameters has been found to be a useful solution for the assessment of machine tool precision state. The proposed solution

shows a relatively good detection of the faults related to the modelled or contained machine error parameters. Combined with the fractal assessment of VE coordinates, the change of machine tool precision state could be well detected. Furthermore, the uncertainty and various fault detection performance of the proposed method will be substantially examined with simulated faults caused by the change of multiple machine error parameters rather than one single error parameter.

Acknowledgments

The authors express their sincere thanks for G. Gironne and V. Mayer for conducting the experimental results and supporting in the SAMBA simulation work. This research is supported by the Natural Sciences and Engineering Research Council of Canada (NSERC) and China Scholarship Council.

References

[1] R. Ramesh, M. A. Mannan, and A. N. Poo, Error compensation in machine tools — a review: Part I: geometric, cutting-force induced and fixture-dependent errors, International Journal of Machine Tools and Manufacture, vol. 40, no. 9, pp. 1235-1256, 2000.

[2] H. Schwenke, W. Knapp, H. Haitjema, A. Weckenmann, R. Schmitt, and F. Delbressine, Geometric error measurement and compensation of machines—An update, CIRP Annals, vol. 57, no. 2, pp. 660-675, 2008.

[3] Kanglin Xing, Sofiane Achiche, and J. R. R. Mayer, Five-axis machine tools accuracy condition monitoring based on volumetric errors and vector similarity measures, International Journal of Machine Tools and Manufacture, vol. 138, pp. 80-93, 2019.

[4] Kanglin Xing, J. R. R. Mayer, and Sofiane Achiche, Machine Tool Volumetric Error Features Extraction and Classification Using Principal Component Analysis and K-Means, Journal of Manufacturing and Materials Processing, vol. 2, no. 3, p. 60, 2018.

[5] Kanglin Xing, Xavier Rimpault, J. R. R. Mayer, Jean-François Chatelain, and Sofiane Achiche, Five-axis machine tool fault monitoring using volumetric errors fractal analysis, CIRP Annals, vol. 68, no. 1, pp. 555-558, 2019.

[6] Kanglin Xing, Xavier Rimpault, J. R. R. Mayer, Jean-François Chatelain, and Sofiane Achiche, Quantitative assessment of machine tools condition through fractal analysis of volumetric error vector similarity measures, Procedia CIRP, vol. 86, pp. 145-150, 2019.

[7] Maryam Jamshidi, Xavier Rimpault, Marek Balazinski, and Jean-François Chatelain, Fractal analysis implementation for tool wear monitoring based on cutting force signals during CFRP/titanium stack machining, The International Journal of Advanced Manufacturing Technology, vol. 106, no. 9, pp. 3859-3868, 2020.

[8] Xavier Rimpault, Marek Balazinski, and Jean-François Chatelain, Fractal Analysis Application Outlook for Improving Process Monitoring and Machine Maintenance in Manufacturing 4.0, Journal of Manufacturing and Materials Processing, vol. 2, no. 3, p. 62, 2018.

[9] J. R. R. Mayer, Five-axis machine tool calibration by probing a scale enriched reconfigurable uncalibrated master balls artefact, CIRP Annals, vol. 61, no. 1, pp. 515-518, 2012.

[10] N. Alami McHichi and J. R. R. Mayer, Axis Location Errors and Error Motions Calibration for a Five-axis Machine Tool Using the SAMBA Method, Procedia CIRP, vol. 14, pp. 305-310, 2014.

[11] G. Losa, Ristanović, D. , Ristanović, D. , Zaletel, I. and Beltraminelli, S., From Fractal Geometry to Fractal Analysis, Applied Mathematics, vol. 7, pp. 346-354, 2016.

[12] Xavier Rimpault, Jean-François Chatelain, Jolanta Ewa Klemberg-Sapieha, and Marek Balazinski, Burr height monitoring while drilling CFRP/titanium/aluminium stacks, Mechanics & Industry, vol. 18, no. 1, p. 114, 2017.