Modeling Material Heterogeneity by Gaussian Random Fields for the Simulation of Inhomogeneous Mineral Subsoil Machining

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***Abstract*—In general, tools used in concrete machining operations are not adapted to the particular machining processes whereas tool wear and production time are the main cost causing factors. A geometrical simulation model describing cutting forces and wear of both diamond and workpiece had been proposed in the past. This model takes the abrasive nature of the machined material into account by modeling the microparts of diamond and workpiece as delaunay tessellations of points randomly distributed within the workpiece and simulating the process iteratively. By fitting the model to a series of real experiments, the general appropriateness of the model had been shown. An implicit assumption of these fittings is that the connected processes are stationary. However, after investigating real process data in the time domain, it turns out that this assumption does not hold. Instead, the forces are obviously affected by material heterogeneity which is not taken into account in the first stage model. To fill this gap, now, an extension of the simulation model is introduced, where the material heterogeneity is modeled and simulated by Gaussian Random Fields.**

Keywords-*Machining; Numerical Simulation; Gaussian Random Fields.*

I. Introduction

Tool wear and material removal rate represent two dominant cost factors in machining processes. To obtain durable tools with increased performance, these factors have to be optimized considering the process conditions. Unlike ductile materials such as steel, aluminum or plastics, material characteristics for mineral substrates like concrete are difficult to determine due to their strongly inhomogeneous components, the dispersion of the aggregates and porosities, the time dependency of the compression strength, etc. [2]. As a result of the brittleness of mineral materials and the corresponding discontinuous chip formation, there are varying engagement conditions of the tool which leads to alternating forces and spontaneous tool wear by diamond fracture.

Despite the manifold of concrete specifications, tools for concrete machining are still more or less standardized tools which are not adapted to the particular machining application. The following analysis is carried out in a subproject of the Collaborative Research Center SFB 823 [10]. In non-percussive cutting of mineral subsoil such as trepanning, diamond impregnated sintered tools dominate the field of machining of concrete due to the excellent mechanical properties of diamonds. These composite materials are fabricated powdermetallurgically [6]. Well-established techniques like vacuum sintering with a preceding cold pressing process or the hot-pressing, which is a very fast manufacturing route, are used for industrial mass production. Due to the premixing of metal powders and synthetic diamond grains, the embedded diamonds are statistically dispersed in the metal matrix. Additionally, the composition and allocation of different hard phases, cement and natural stone grit in the machined concrete are randomly distributed. Because of these facts, the exact knowledge of the machining process is necessary to be able to investigate for appropriate tool design and development.

To obtain a better understanding of these highly complex grinding mechanisms of inhomogeneous materials, which are hard to be described by physical means, statistical methods are used to take into account the effect of diamond grain orientation, the disposition of diamonds in the metal matrix and the stochastic nature of the machining processes of brittle materials. The first step to gain more information about the machining process is the realization of single grain wear tests on different natural stone slabs and cement.

This paper is organized as follows. Section II gives an overview of the setup used for the experiments under study. After that, Section III shortly describes the simulation model the extension of which is shown in Section IV. After the presentation of the results in Section V, the paper closes with the conclusion and a short outlook in Section VI.

II. Experimental Setup

To gain information about the fundamental correlations between process parameters and workpiece specifications, single grain scratch tests have been accomplished. Within these, isolated diamond grains, brazed on steel pikes have been manufactured (see Fig. 1 and 2) to prevent side effects of the binder phase or forerun diamond scratches as they occur in the grinding segments in real life application. To provide consistent workpiece properties, high strength

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Figure 1. Diamonds and brazed sample.

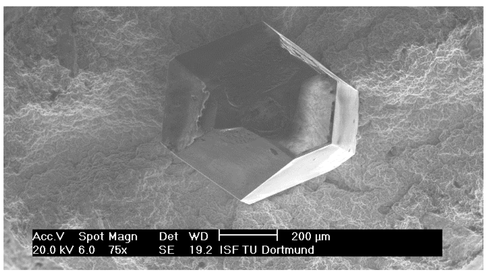

Figure 2. SEM picture of brazed diamond grain.

concrete specimens of specification DIN 1045-1, C80/90 [3] containing basalt as the only aggregate had been produced. Besides these the two phases, cement binder and basalt, were separately prepared as specimens for an analysis of their material specific influence on forces and wear.

To eliminate further side effects such as hydrodynamic lubrication, interaction of previously removed material and adhesion, the experiments have been carried out without any coolant. The brazed diamond pikes had been attached to a rotating tool holder which in turn had been mounted to the machine (see Fig. 3) to simulate the original process kinematic. Parameters for experimental design were chosen according to common tools and trepanning processes. To guarantee constant depth of cut the rotatory motion of the diamond pike had been superimposed by a constant infeed which generated a helical trajectory. To generate a measureable diamond wear, a certain distance had to be accomplished. Therefore, a total depth of cut of 250 μm had been achieved in every test.

III. Simulation Model

The general aim of the project at hand is the optimization of the machining process w.r.t. production time, forces affecting the workpiece and tool wear. For this aim, knowledge about the relationships between adjustable process parameters, measurable covariates and the outcome is inevitable. From this knowledge, optimal strategies and parameter settings can be derived. As the real machining experiments are very time consuming and expensive it is of primary interest to develop a realistic simulation model. This

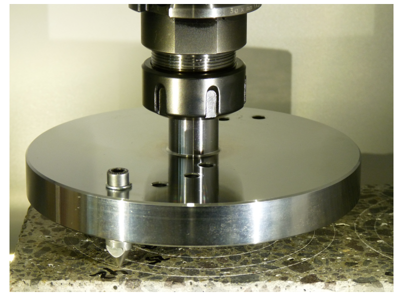

Figure 3. Scratch Test Device on Basalt.

compute (S_k, S_w)
$S_k^0 \leftarrow S_k R_x R_z R_y + (d_p, h_k, 0) \otimes 1_{n_k}$
for $i = 1 \rightarrow i_{max}$ **do**
  $S_k^i \leftarrow S_k^{i-1} R_r - (0, a_r, 0) \otimes 1_{n_k}$
  compute intersection volumes W_s
  for $j = 1 \rightarrow n_w$ **do**
    $m_{k;j} \leftarrow \sum_{l: w_{s;lj} > 0} w_{k;l} \rho_k$
    compute (γ_w, γ_k)
    $\gamma \leftarrow max(\gamma_w, \gamma_k)$
    $F_{ij} \leftarrow (v_p m_{k;j})/t_d$
    $(F_{n;ij}, F_{r;ij}) \leftarrow F_{ij}(sin\gamma, cos\gamma)$
    if $w_{w;j} \rho_w > \mu_k m_{k;j}$ **then**
      remove diamond simplices $l : w_{s;lj} > 0$
    else
      reduce heights of diamond simplices $l : w_{s;lj} > 0$ by η_k
    end if
    remove workpiece simplex j
  end for
  $(F_{n;i}, F_{r;i}) \leftarrow (\sum_j F_{n;ij}, \sum_j F_{r;ij})$
end for

Figure 4. Pseudocode Representation of Simulation Model. S_k and S_w: vertices of grain and workpiece; R_x, R_z and R_y: random rotation matrices for initial orientation; d_p: diameter of machined hole; h_k: initial grain height; R_r: rotation matrix of tool depending on angle per iteration; a_r: height change per iteration; W_s: matrix of intersection volumes $w_{l,j}$ between l-th grain and j-th workpiece simplex; ρ_k and ρ_w: diamond and workpiece material densities; γ_w and γ_k: angles of contacting workpiece and diamond simplices; v_p: cutting speed in rpm; t_d: time scaling parameter; μ_k: diamond specific threshold factor; η_k: diamond specific flattening factor.

model then can be used for the derivation and testing of such strategies and settings before verification in real processes.

To deal with this task, a simulation model based on Delaunay Tessellations [5] of the workpiece and the diamond was proposed. This approach had been chosen contrarily to the usually chosen discrete model types on regular grids for the simulation of grinding processes (see [1] and [11] for overviews) due to the abrasive nature of the used materials. Fig. 4 shows a pseudocode representation of the proposed simulation model. For full details of the model, see [9].

Beside the extension of the model, our work is focussing

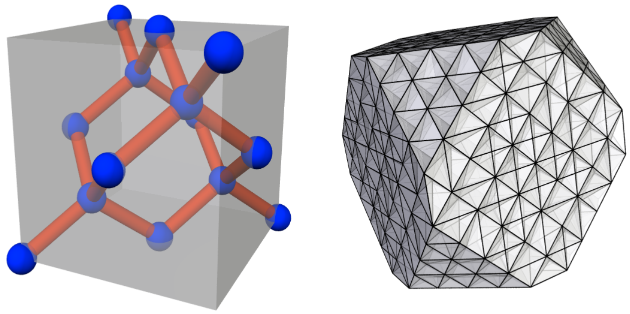

Figure 5. Left: Crystal structure of diamond, right: Simulated diamond grain

about, some slight modifications about how diamond grain and workpiece are modeled had been made. Up to now, the vertices in both grain and workpiece were generated by drawing coordinates from an independent uniform distribution within the material and tool shape. However, to get more realistic results by now the microparts are based on a jittered regular grid for the workpiece. For the tool, the vertices are aligned along the cubic crystal structure of the diamond and also (slightly) jittered (see Fig. 5).

IV. Modeling of Material Heterogeneity

In its latest version, the simulation model (described below) assumed both the diamond and the workpiece to consist of homogeneous material. While this assumption can be seen fulfilled in the case of the diamond it is obviously violated in the case of the workpiece as even relatively homogeneous materials like basalt show a high degree of local differences in hardness. These differences are to be assumed even higher in the case of concrete composites due to air pockets and the concrete additives.

This local heterogeneity in the machined workpiece obviously affects the force signals, as can be illustrated by forces measurements taken during each of the experiments of the basalt series the model had been fitted to in [9]. For better interpretation, Fig. 6 visualizes how the one-dimensional signals are transformed to spatial data. Subfig. a) shows a simulated workpiece with local differences in hardness heterogeneity visualized on a colour scale from blue (low) to red (high). The black arrow line in Subfig. b) shows the course the diamond tip takes during the process as the tool is rotated and shifted towards the workpiece with constant speed. When the tip enters the workpiece it takes force measures from the cylinder highlighted in Subfig. c). By assigning the force measurements to their coordinates on the cylinder and unrolling the resulting cylindral image (Subfig. d)), a two-dimensional image of the signal can be obtained. Note that even though visualizations in the following are partly presented in the plane, computations are always performed in 3D.

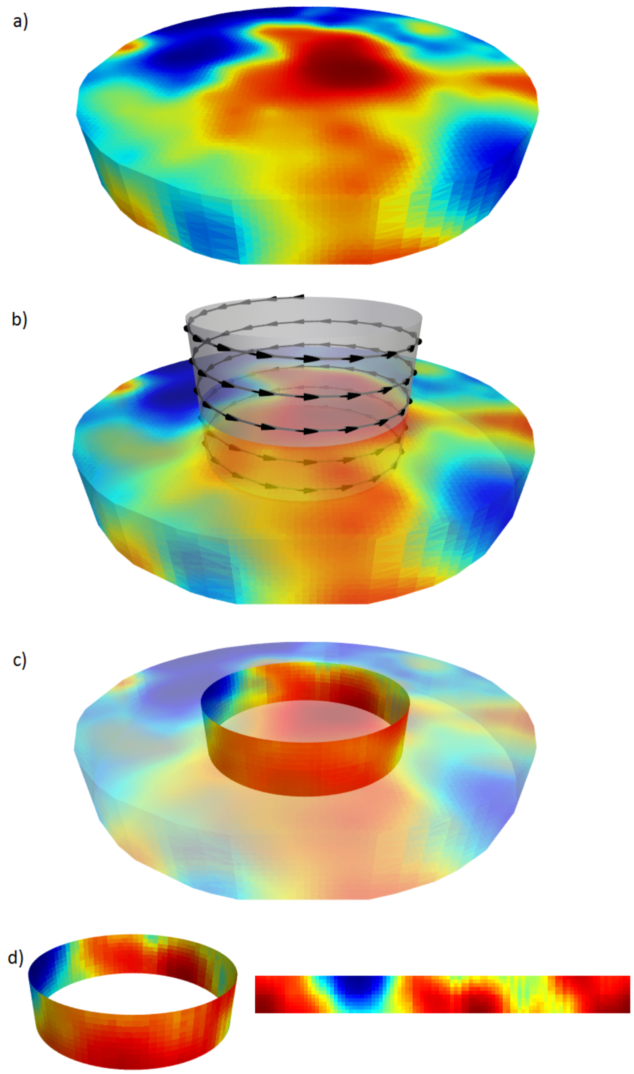

Figure 6. a) Simulated workpiece, b) Course of diamond during process, c) Cylindric bore hole, d) Cylinder cut free (left) and unrolled (right).

Fig. 7 shows exemplary 2D-images for two of the basalt experiments. Obviously, the forces reflect local differences. However, they are disturbed by both random and systematic noise. The random part of the noise is measurement error mainly caused by different chip sizes. The systematic part of the noise appears to be periodic on the one hand and reflects frequencies like gear wheel mesh frequencies which are prominent in the engine spectrum. Another part of the systematic noise is global trend being active during the start of the process while the diamond enters the material.

A. *Robust Statistical Estimation of Local Heterogeneity*

By making the force data accessible for an estimation of the material heterogeneity means the separation of the

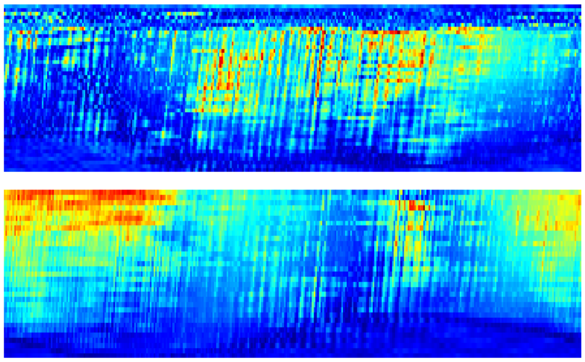

Figure 7. Two-dimensional force images of two basalt machining experiments. Color scale from blue/low force to red/high force.

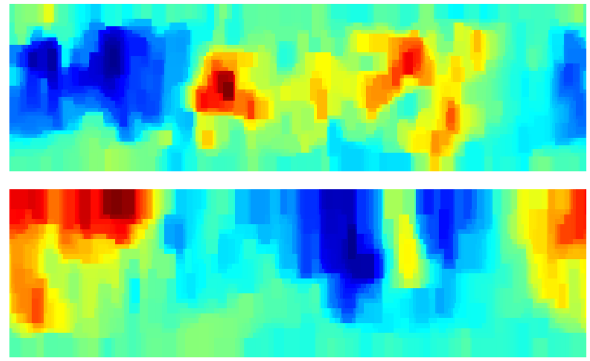

Figure 8. Two-dimensional heterogeneity of two basalt machining experiments. . Color scale from blue/low heterogeneity to red/high heterogeneity.

smooth local heterogeneity and noise. Due to the high variability between the experiments and the severe presence of outliers and possible sudden shifts in the force measurements robust techniques are applied to solve this task.

Mapped back to the time domain, the local heterogeneity can be interpreted as the gradually changing periodic component (seasonality) γ_t in the model

$$Y_t = \mu_t + \gamma_t + u_t + v_t, \quad t = 1, ..., N = l \cdot p, \tag{1}$$

where the other components building up the specific force signal Y_t are the global trend μ_t, the sum of systematic and random noise u_t and the spiky noise v_t caused by outliers. The period of one revolution is denoted by p, while the number of total observed revolutions is given by l. For the interesting heterogeneity γ_t general smoothness meaning $\gamma_t \approx \gamma_{t-p}$ is assumed while for identifiability the condition $\sum_{i=1}^{p} \gamma_{t+i} = 0, t = 0, p, ..., N-p$ is stated.

Our proposed method for the robust estimation of γ_t is a two-step procedure, the first step of which is the estimation of the trend by $\hat{\mu}$ using running medians of length $2 \cdot \lfloor \frac{p+1}{2} \rfloor + 1$:

$$\hat{\mu} = med\{y_{t-\lfloor \frac{p+1}{2} \rfloor}, ..., y_{t+\lfloor \frac{p+1}{2} \rfloor}\},$$
$$t = \lfloor \frac{p+1}{2} \rfloor + 1, ..., N - \lfloor \frac{p+1}{2} \rfloor.$$

In the second step of our procedure, the moving seasonality γ_t is iteratively estimated by alternating between smoothing the signal in rotational and in feed direction. The smoothing again is obtained by the application of running medians, while the initial heterogeneity estimator is based on the detrended signal meaning

$$\hat{\gamma}_t^{(0)} = med_{j \in J_0}\{y_{t+j} - \hat{\mu}_{t+j}\}, \quad t \in T_0$$
$$\hat{\gamma}_t^{(i)} = med_{j \in J_i}\{\hat{\gamma}_{t+j}^{(i-1)}\}, \quad i \in 1, ..., 2I, t \in T_i$$
$$J_i = \begin{cases} \{-k_h, -(k_h - 1), \ldots, (k_h - 1), k_h\}, \frac{i+1}{2} \in \mathbb{N}_0 \\ \{-k_v p, -(k_v - 1)p, \ldots, (k_v - 1)p, k_v p\}, \frac{i}{2} \in \mathbb{N} \end{cases}$$
$$T_i = \begin{cases} \{k_h + 1, k_h + 2, \ldots, N - k_h\}, \frac{i+1}{2} \in \mathbb{N}_0 \\ \{k_v p + 1, k_v p + 2, \ldots, N - k_v p\}, \frac{i}{2} \in \mathbb{N} \end{cases}$$
$$i = 1, ..., 2I, \hat{\gamma}_t = \hat{\gamma}_t^{(2I)},$$

where k_h and k_v are the half window widths in rotational and in feed direction and I is the total number of iterations. Values of $\hat{\gamma}_t$ for $t \notin T_i$ are estimated by extrapolation from the closest window.

Within the investigations of the basalt series, it turned out that a common half window width of $k_h = k_v = 7$ gave stable results and that the results converge after the iteration number exceeds the value $I = 16$. Hence, these parameter values had been chosen for the global fitting. Fig. 8 exemplarily shows the 2d-images of $\hat{\gamma}_t$ for the two experiments shown in Fig. 7.

B. Simulation of Local Heterogeneity by Gaussian Random Fields

One aim of our actual work is a realistic simulation of the material heterogeneity within the machining process simulation. A straightforward way for doing so is to simulate the heterogeneity by samples of Gaussian Random Fields, the parameters of which are based on the estimations of γ_t obtained in the way described in the last section.

For this purpose, a joint variogram based on random patches of the in total 73 cylinders derived from each $\hat{\gamma}_t$-series had been computed. The moment estimated variogram based on 50 equally spaced bins from 0 to 130 mm is shown in Fig. 9.

Fig. 9 also shows a theoretical variogram in green which is based on an exponential covariance model (see [12]) with

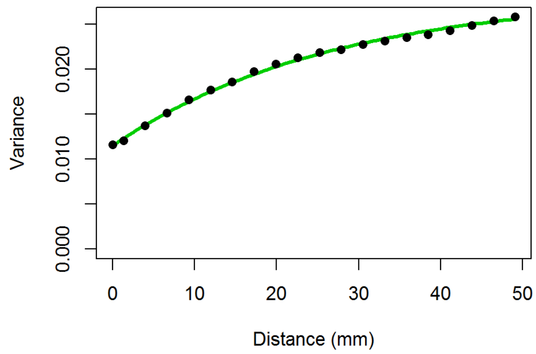

Figure 9. Joint variogram of fitted local heterogeneity. Green: fitted exponential covariance model.

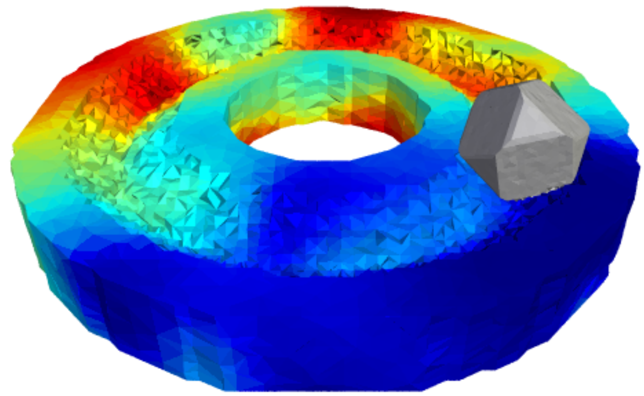

Figure 11. Simulated machined workpiece.

parameters fitted to the empirical variogram by Ordinary Least Squares [7]. These parameters are given by the values 0 for the mean, 0.0168 for the standard deviation, 0.0112 for the nugget and 26.852 for the scale. The corresponding theoretical variogram obviously meets the empirical one very well so it can be used to base the heterogeneity simulations on.

For the simulations between the geometrical initialization of the workpiece and the process simulation, a step is added to the model, where each workpiece simplex gets a heterogeneity value assigned to. To do so, an isotropic Gaussian Random Field [12] is sampled based on the fitted covariance model on a equidistant grid within the workpiece. Then, each workpiece simplex gets the heterogeneity value assigned to that results from interpolating the specific Random Field realization to its center by ordinary Kriging [12].

As the covariance function parameters are based on the additive decomposition of the original signal into trend, seasonality and error, the implementation of the simulated material heterogeneity is simply obtained by adding γ_t to the homogeneously simulated signal y_t.

V. Results

The procedure described in the previous section had been applied to re-simulate a process series with parameter settings defined by the Central Composite Design the basalt experiments were based upon. The simulated output had been compared to the corresponding real data sets and a high degree of accordance between simulated and real data was observed. Fig. 10 shows an exemplary comparison of simulated and measured forces, while Fig. 11 displays a simulated heterogeneous workpiece after machining.

The main remaining differences between the simulated and the real data by now seem to be a periodic noise. As the dominating frequencies of this noise are the same for processes with the same parameter settings, this noise is not caused by material heterogeneity but by the engine and therefore extends the scope of this paper. Obviously, the noise is stationary and by this does not affect the heterogeneity estimation. However, further analysis of this systematic noise type and appropriate model extensions will be made in separate work.

VI. Conclusion and Future Work

In this paper, a major extension of an efficient, flexible and valid model for the simulation of the machining process of inhomogeneous mineral subsoil had been proposed. This extension consists of the shift from static to dynamic modeling where it turned out that material heterogeneity has to be taken explicitly into account. It had been shown that for the integration of this heterogeneity in the case of a comparably homogenous material with presumably continuous heterogeneity structure like basalt the usage of Gaussian Random Fields is appropriate. This result is very feasible since it yields a parsimonious and well identifiable parametrization of heterogeneity.

However, for more complex materials like concrete, overall continuous heterogeneity cannot be assumed as, e.g., aggregates and air pockets cause rapid shifts in heterogeneity. For this reason, heterogeneities of different material phases will have to be modeled separately as, e.g., done in [4] for two-phase materials. For the fit of the correspondingly extended simulation model a procedure for automatic identification of phases is needed, which is actually being developed in the project the work presented here is part of.

Acknowledgment

This work has been supported in part by the Collaborative Research Center Statistical Modelling of Nonlinear Dynamic Processes (SFB 823) of the German Research Foundation

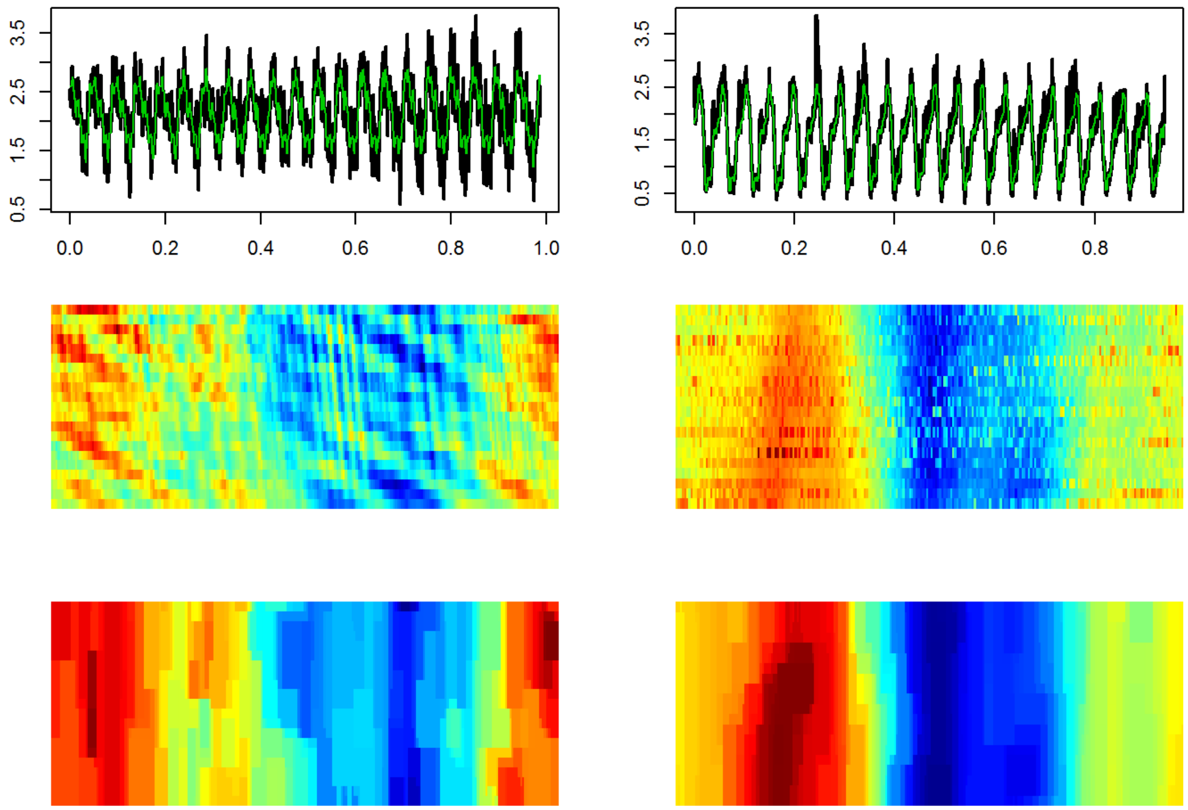

Figure 10. Comparison of real (left) and simulated data (right). Top: signals in time domain with estimated heterogeneities in green. Middle: Signals in 2D-representation. Bottom: estimated heterogeneities in 2D-representation. Note that color scales between signals and heterogeneities are not comparable.

(DFG), within the framework of Project B4, Statistical Process Modelling for Machining of Inhomogeneous Mineral Subsoil.

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