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FREE-FORM SURFACE DATA REGISTRATION AND FUSION. THE CASE OF ROUGHNESS MEASUREMENTS OF A CONVEX SURFACE

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Abstract

Combining surface measurement data from individual measurements of surface fragments is an issue that has been recognized for flat surfaces. The connection takes place on the principle of making 'overlap' measurements according to a specific measurement strategy, and then the algorithm synthesizes the measurement data for the common part (data fusion).
This paper presents a method of combining partial data into one larger set using image processing methods. The purpose of the analysis is to combine surface data of a more complex shape in terms of surface roughness and waviness. A successful attempt was made to combine surface measurement data located on a cylindrical surface – convex surface. A rotated table was designed and used for surface data acquisition. The datasets were acquired with the use of CCI 6000 (366 μm – 366 μm) with the assumed overlapping of at least 20%. The measurement datasets were first pre-processed: filling in non-measured points, levelling and form removing were applied. For such processed datasets, the common part was identified (data registration) and then the data fusion was performed. An example of stitching the surface datasets shows usefulness of the presented methodology.

Keywords: stitching data, surface measurement, free-form surface.

1. Introduction

In today's industry, functional surfaces are produced as free-form surfaces of different forms of data and different levels of computational complexity. The typical forms of data can be derived from surface measuring instruments describing degrees of freedom for a dataset and its processing [24]. The lowest level of measurement data format is obtained in surface measurement methods such as confocal or stylus. In the measurement instruments developed for given measurement methods, a maximum of 2.5D is obtained for the range data. This means the coordinate z depending on (x, y). More complex forms of data include a profile set (2.5D), scattered data (2.5D), grid data (3D), a point cloud (3D) and volume data (3.5D). Along with the complexity of data form, the way they are processed and their fusion become more complicated. Fig. 1 presents the spatial data fusion methods indicating the direction of growth of the complexity of these methods [12, 17].

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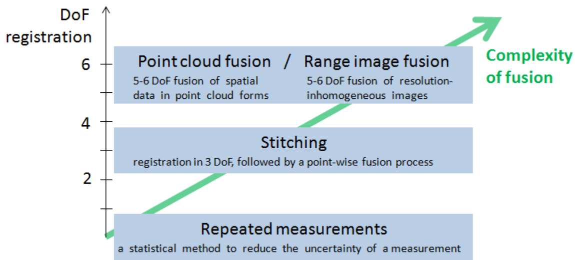

Fig. 1. Spatial data fusion methods.

At the lowest level – repeated measurements – a sequence of measurement data from the same sensor can be obtained and averaged using the arithmetic mean (weighted mean) minimum or maximum. If each individual dataset contains random noise or defects caused by temperature, illumination or vibration, then a lower uncertainty can be achieved by taking the mean output of repeated measurements.

A completely different case is when the surface characteristic features can be revealed depending on the scale of observation. In order to fully characterize the machined surface, both macro- and micro-scale measurements should be performed at the same time. The measurement, in which both a large measurement area and high-resolution data are simultaneously expected, is a challenge in the surface metrology. To fully characterize multi-scale surfaces, the high-resolution data from a large area are needed, which is provided by applying the stitching procedure. In the case of stitching, however, more complex methods than the weighted average are often required. First the data are registered and only then the data fusion can be carried out [5, 6, 15–17].

This paper refers to the measurement (2.5D) of a surface after longitudinal turning. It is an example of surface with a multi-resolution characteristic, which reveals the presence of both macro- and micro-scale changes in the field [4]. The macro scale refers to the analysis of machined surface formation taking into account the tool geometry and the position of the tool in relation to the workpiece. The micro scale, however, results from the observation of the micro-topography of the tool and its impact on the workpiece with other disturbing factors [8]. For the purpose of obtaining a large measurement area, the partial data are combined along the feed direction. The aim of the paper, however, is to present a procedure of combining these partial data along the main direction. This approach consists in first joining the curved surfaces for which the data registration procedure should be determined, and only then fusing the data.

2. Theory

Due to the limitations of the measurement instruments, which in the case of a large observation field (field-of-view FOV) offer a lower resolution, and in the case of a high resolution – a small observation area, it is difficult to obtain a satisfactory result in a single measurement for the aforementioned surfaces. The most common solution in this case is to perform multiple measurements and then fuse the data to create a larger dataset of a resolution suitable to characterize micro- and sub-micro-roughness [24]. One possibility of widening the spatial range of measurement is combining partly measured three-dimensional data according to the following activities:

– measurement of the surface of an object by changing the position or direction of measurement and obtaining several datasets with overlapping parts;

– for each set of partly measured data, registration of the overlapping area for the neighbouring datasets, taking into account differences in measurements;
– for the overlapping area, fusion of the data of each set of partly measured three-dimensional data [15, 16].

In the case of surface measurement instruments, the spatial data fusion is based on sewing data obtained for a relatively flat surface [20]. The accuracy of the lateral movement control of the sample influences the stitching process. Good stitching results are a consequence of the calibrated high-accuracy translation of a sample. If the translation is poorly defined, then the stitching lacks accuracy [24].

For a precisely defined translation the registration is characterized by three degrees of freedom (tip, tilt and piston). After the registration all the data are described in the same co-ordinate system. For two datasets, the first one is the reference. The points from the second set, after the transformation, are the sum of the original co-ordinates and of the product of the error modelling matrix and the vector of parameters. For each measurement the vector of parameters is calculated as a minimization of correspondence of each individual point. After the registration process, the data fusion is performed for each individual dataset at each overlapping position [21].

For the measurement devices the positions of measurement points of partial data can be determined manually or automatically. Even if the system has a built-in algorithm of the measurement strategy, the initial and final system settings are performed manually, and the data connection area is determined based on the dimensions entered. When the size of the measurement area is already known, the number of rows and columns covering the area is calculated automatically [4]. The locations of measurements are determined automatically – the recommended overlapping area is 16 to 30%.

The surfaces to be joined by the stitching procedure must be measured on a rectangular grid with regular spacing between the lines and between the columns. Each surface should have the same size and be measured at the same resolution. Adjacent surfaces must have an overlapping area [10]. The strategy of stitching is presented in Fig. 2.

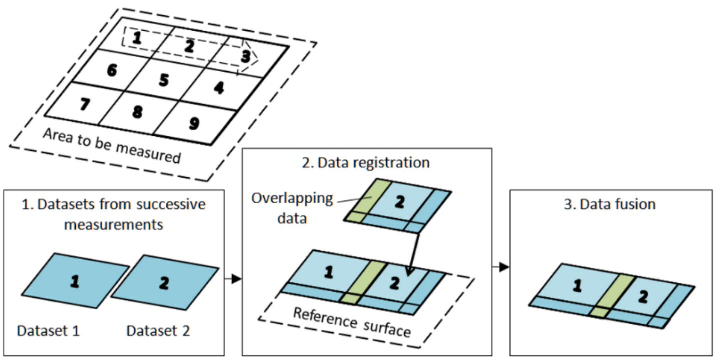

Fig. 2. The strategy for measuring a flat surface.

The measured convex or concave surfaces are more difficult for stitching due to the data registration problem [1, 13, 27]. In the case presented in Fig. 3a, the stitching procedure can be performed according to the earlier described strategy (Fig. 2). The problem arises for stitching of the datasets shown in Fig. 3b. It is not possible to perform stitching on the data obtained directly from the measurement. The alignment of the data introduces large changes to the output data for both surfaces and the program examining the similarity of the data encounters difficulties to determine the overlapping part and successfully perform the data registration [2, 10, 14].

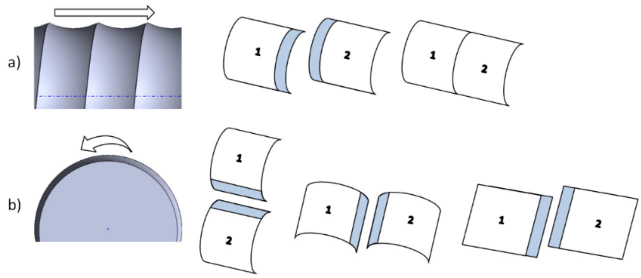

Fig. 3. The strategy for measuring a convex (concave) surface.

For two datasets arranged according to Fig. 3b there is no natural point-pair correspondence in the overlapping datasets. The registration and fusion algorithms need to be developed to accurately perform the data fusion. Such a spatial data fusion can be said that goes beyond the scope of stitching.

Registration of two datasets into a common coordinate system is usually the first task before the fusion of data. Many registration methods have been developed to guarantee for the individual datasets to be represented in the same coordinate system so that they can be properly fused [10, 22, 27]. Most methods use six degrees of freedom to register points in the overlapping areas, and their computational complexity is relatively large [17]. For a convex surface a five-degrees-of-freedom registration is necessary. After the registration, the fusion is carried out to combine the datasets in each overlapping region so that an enhanced output is produced.

Fusion algorithms convert 3D problems into 1D problems, by projecting a 3D dataset onto a reference surface so that the 3D geometry can be described by the surface height as a function of (x, y) coordinates. In this way the data fusion is reduced to fusion of surface heights. The fusion algorithms approximate the residuals between two reliability-differentiated datasets using Gaussian process models [13, 14, 18, 24].

The paper describes a procedure of combining the measurement data using the image processing method. First, the procedure for obtaining the raw measurement data is described, followed by the method of their processing (removal of noise and shape, identification of the common part – data registration) and then the data synthesis (data fusion) for connecting two successive measurement datasets of the convex surface.

3. Experimental procedure

The turning tests were carried out on an NEF 400 machining tool of high stiffness with the parameter values according to the tool manufacturer's recommendations (Sandvik TNGA 160408 S01020 CB7020): cutting speed 165 m/min, feed rate 0.15 mm/rev and cutting depth 0.1 mm (Fig. 4a). The workpiece was EN 41Cr4 steel, hardened at temperature of 850°C. The average hardness of samples was 40 HRC.

To research on stitching of the convex surfaces, a rotary table device has been developed (Fig. 4b). After the measurement of the first dataset, the workpiece was rotated by an angle enabling to obtain the overlapping data at a level of 20%. The data were registered and then fused in Matlab [7].

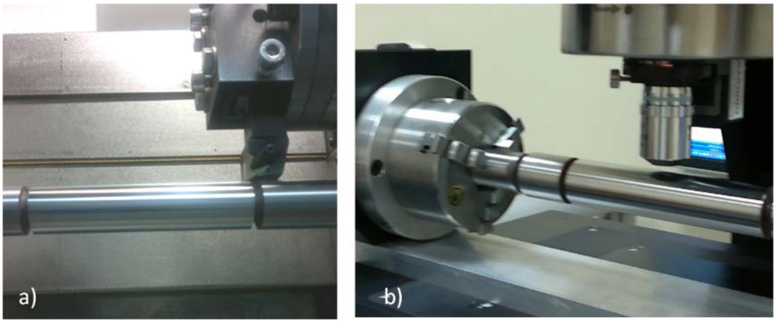

Fig. 4. a) The tool orientation relative to the machined surface; b) the orientation of the machined object in respect of the measuring lens.

Stitching of the successive fragments of the surface of a cylindrical workpiece fixed in the three-piece holder is a complex measurement, which is also influenced by the eccentric location of the centre of the measured surface fragment in respect of the axis of rotation caused by the retaining system. It forces the necessity to align the surface in z direction (translation in z axis).

4. Measurement and stitching procedure

For successive turns of the machined workpiece, 366×366 μm^2 surface topography data were measured at a resolution of 1024×1024 points [21]. First, the dataset was converted into a two-dimensional intensity image, and then the pre-processing was performed (Fig. 5b M1).

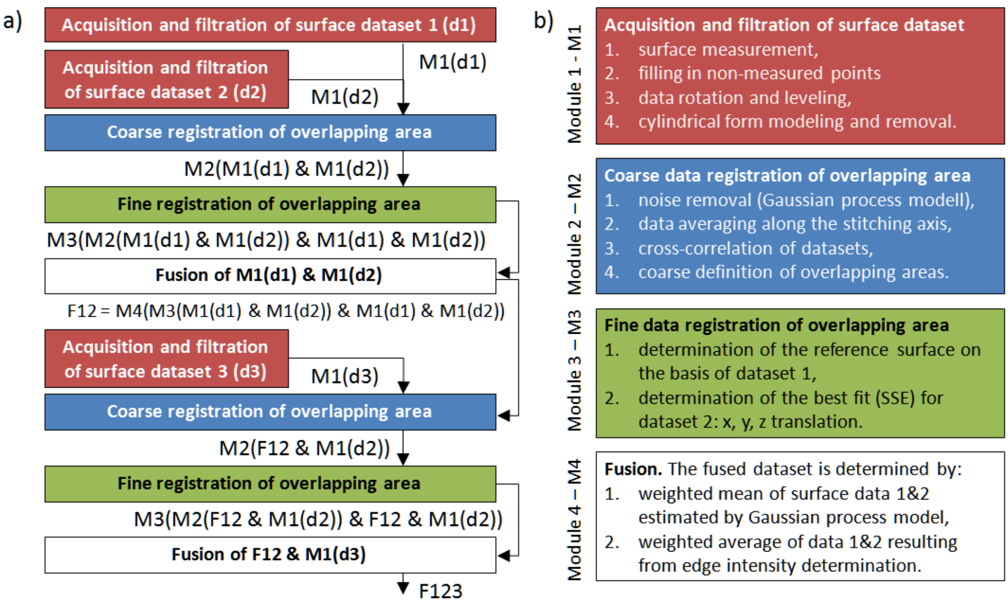

Fig. 5. a) A flowchart of data in the stitching procedure; b) data processing modules.

The image registration was then carried out, which involved two stages: a coarse registration (Fig. 5b M2) and a fine registration (Fig. 5b M3). After x, y, z alignment of datasets, the final step was applied – the data fusion (Fig. 5b. M4).

4.1. Pre-processing of surface data

Three-dimensional datasets of surface roughness were modelled as images, in which the brightness level referred to the micro-roughness value. Before the levelling and form removal procedure, non-measured data points were filled in and the main direction of texture was identified. The direction of texture of the dataset was a result of the cutting process and the identified relative movements of the tool and the workpiece. It was a constant distortion that was filtered out by rotating the data in the xy plane. The data aligned in the y direction were levelled and then they were approximated to be a fragment of the surface of the cylinder. This form resulted from the convex shape of the measured surface and was assumed a priori approximation [2]. This form was filtered out. The data prepared in the described way constituted the input data for further processing.

4.2. Data registration

The data registration was used to make the input data transformed into the same coordinate system and to identify the overlapping area. The literature indicates two stages of the registration processes: the initial coarse registration and the fine registration [9, 19]. The coarse data registration aims to initially place a dataset into the same coordinate system as the reference model. The fine data registration is usually applied to all the sample points to determine the final registration parameters by minimizing the distance between two sets of data.

Due to the fact that the registration process accuracy can be affected by noise [17], the datasets were pre-processed using the image reconstruction method, in which random and out-of-range data were filtered out. The Gaussian process model was used and the mean value and variance were determined for image data blocks. The mutual dependence of these two values was the basis for inference and selection of the noise removal threshold. The purpose of the noise removal was to estimate the signal from noisy measurement data, which by definition is a function of these data. For this purpose, the MAP probability estimator (maximum a posteriori) was used to determine the most probable value of the signal modelled with the Laplace probability density function. The signal was filtered in such a way that part of the noised signal identified as noise was zeroed. The mathematical background of the procedure is discussed in [26].

The coarse data registration was necessary because the raw datasets after transformation lost their original character and there were no reference points (common, corresponding points) to be matched to. In the coarse registration module the average profiles of filtered datasets were computed. These profiles were then analysed with the use of a cross-correlation function to identify the similarity of a pattern. The coarse registration was used for data pre-matching.

The fine data registration enabled to establish a point-correspondence relationship for the following fusion stage [20]. The image translation (x, y) was used for dataset registration, which consisted in fitting two images based on the distribution of brightness levels first in the x direction (large periodic changes resulting from the feed) and then in the y direction (the direction of data stitching). The fine data registration is an iterative process. An overlapping area for fixed and moving images is defined. There is also defined a comparative measure (distance measure) and optimizer. After the transformation of the moving image was completed, comparative measures for each iteration were calculated. The process of matching the moving image to the reference image was stopped when the optimization criterion was reached [3]. Upon completion of the iteration process on achieving the optimization criterion, the datasets were additionally z aligned to eliminate a possible eccentricity of positioning of the measured surface.

4.3. Data fusion

The data fusion was carried out on the data points within the overlapping area of neighbouring datasets. After specifying the translation (x, y, z) of the moving dataset, the transformation was performed and both datasets were then fused with the use of the Gaussian process model [17, 18, 23, 25]. The datasets undergo the modelling procedure. In this way, a single dataset is divided into the part being a Gaussian model and the remaining part (residuals of the model). The Gaussian process model is presented in [25] and in [26].

For the stitching procedure the fusion of datasets was performed by summing up the average (weighted mean) of each pair of correspondent points of the model dataset and the weighted mean of edge intensity of the residuals [18]. For each of the data points in the overlapped area, the vertex intensity value was determined. This value was the basis for calculating the weight in the summation process.

Figure 6 shows an example of data fusion of 2 and 3 datasets of the measured surface. The overlapping areas in which datasets have been fused do not stand out of the stitched datasets. For comparative purposes, black spots visible from the movement of datasets in the x direction are left in the periphery.

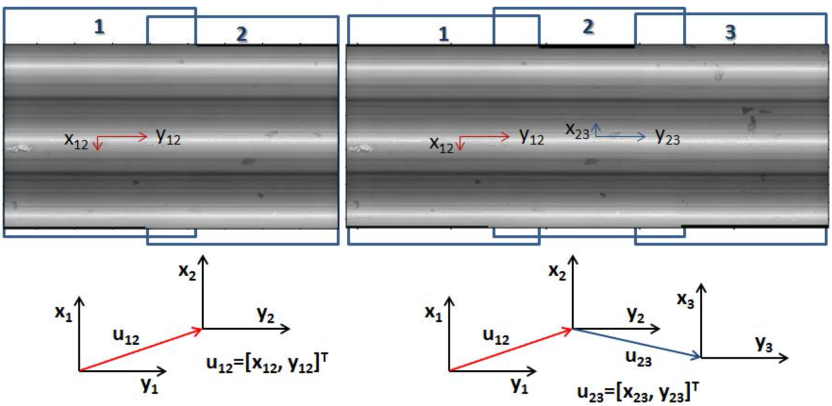

Fig. 6. Fig. 6. A data fusion a) for two sets; b) for three sets.

5. Results and discussion

By carrying out the above-described procedure, the measurement data were collected for three locations of the workpiece. These measured datasets after the pre-processing are presented in Fig. 7 and Fig. 8 (1, 2, 3). These figures also present the data after the registration process and fusion (after the stitching process).

When analysing the correctness of stitching, due to the lack of a reference dataset it is not entirely clear whether the procedure was accurate and the data after stitching correspond to the actual measurement points. In Fig. 7 the machined surface profile after the stitching procedure

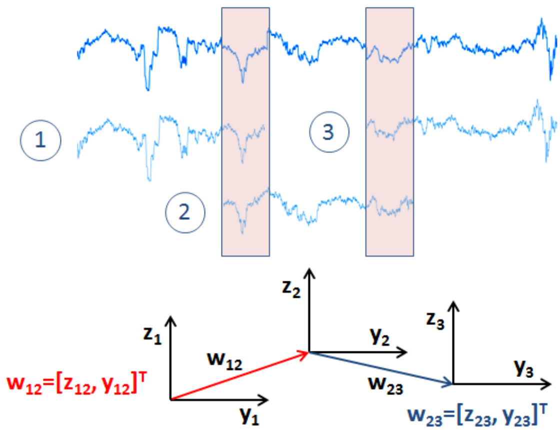

Fig. 7. A machined surface profile after the stitching process.

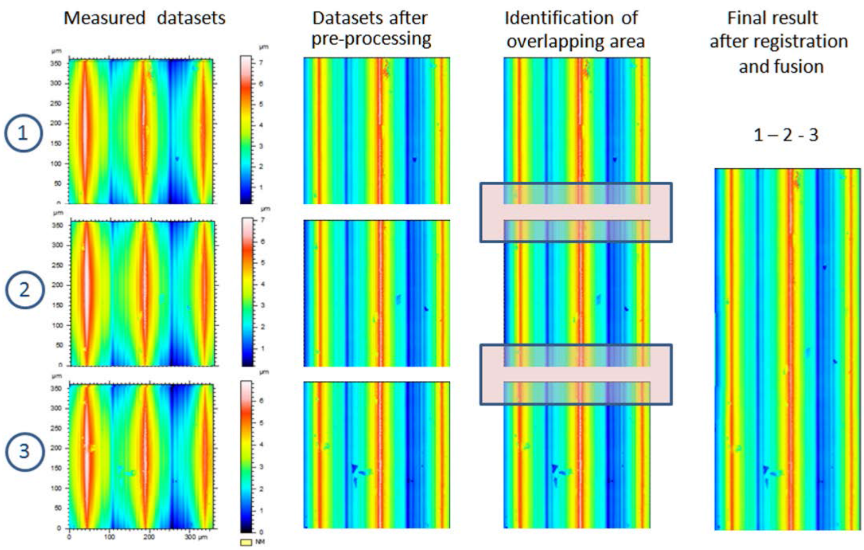

Fig. 8. A machined surface after registration and fusion of datasets 1–2–3.

is shown. The raw datasets were filtered, the cylindrical form was removed, and the fusion was performed to obtain the resultant profile. The appearance of data is very similar to that of the input profiles. It additionally confirms correctness of the stitching procedure.

A machined surface after registration and fusion of datasets 1–2–3 is presented in Figure 8. The final surface data are fused in such a way that stitched areas are not visible. For the purpose of determining the correctness of the stitching procedure, the parameters of each of the measured surfaces were compared with the parameters of the surface data after the stitching process. The parameter values have been determined in accordance to the ISO 25178 standard [11, 21].

The parameters that have not changed their values beyond the scope of the measurement error (5%) are: *Sa, Sq*, texture direction *Std*, parameters of material volume (*Vm, Vmp, Vmc, Vvc*) and others presented in Table 1. This group of parameters relates to the mean characteristics. The parameters calculated for the same number of points change in the range of the measurement error – stitching does not change the values of these parameters.

Table 1. Changes of the ISO 25178 standard parameters for fused datasets.

Parameter change	Parameters calculated according to ISO 25178 standard
< 5%	*Sq, Sa, Sku, Smc, Sal, Str, Std, Vm(p), Vv(p), Vmp, Vmc, Vvc, Spc, S5p, Sk, Svk, Smr2, Spq, Svq, Smq, Sxp, Sdq, Sdr, Vvv, Sdv, Spk*
> 5%	*Sp, Sz, Spd, Sda, Sha, Shv, Ssk, Sv*

A slightly different situation is when the extreme characteristics of the surface are calculated. Their internal variability is greater and also changes of the number of measuring points and of the measurement area can influence their values. The parameters that have changed when stitching was applied are *Sp, Sz* and others (Table 1). The changes slightly exceed 5% and due to the averaging nature of the data fusion in the overlapping area, the changes are negative. In the presented research, for example:

- *Sp* parameter (ISO 25178) – maximum peak height: the height difference between the highest peak and the mean plane: 3.85 μm (without stitching), 3.59 μm (with stitching) (−6.7%).
- *Sz* parameter (ISO 25178) – maximum height: the height difference between the highest eak and the deepest valley: 6.47 μm (without stitching), 6.02 μm (with stitching) (−6.9%).

6. Conclusions

Modern engineering is based on measurements performed for free-form surfaces. To obtain measurements suitable for analysis the macro- and micro-scale characteristics must be evaluated with the area adjusted to their scale. This requires the application of stitching to many high-resolution areas. These partial data either can have the same structure or can be of different nature and scale. Because of these different conditions of data fusion, many different data fusion methods were developed. For measuring the full 3D geometry of a workpiece multiple local measurements need to be performed and their results fused. Spatial merging of the measured datasets to position them after the registration process is recognized as data stitching.

Some existing data stitching methods can be found in many surface texture measurement instruments. However, stitching of spatial data is mainly performed for well-overlapping data. A problem appears when the texture datasets are parts of free-form surfaces. For the free–form surfaces the stitching process is based on pre-processing, registration and fusion.

In order to analyse the effect of stitching on the surface roughness parameters, their values were measured for three datasets, which were then compared with the surface parameter values obtained after the stitching process. The experiment was repeated three times. Changes of a dozen or so surface roughness parameters were analysed and are presented in Table 1. The results of tests unambiguously indicate that stitching has no effect on average values of such parameters as *Sa* or *Sq*. In the case of extreme values of parameters, increasing the number of points contributes to a greater variability of stitching.

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