Accurate and automated image segmentation of 3D optical coherence tomography data suffering from low signal-to-noise levels

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Optical coherence tomography (OCT) has proven to be a useful tool for investigating internal structures in ceramic tapes, and the technique is expected to be important for roll-to-roll manufacturing. However, because of high scattering in ceramic materials, noise and speckles deteriorate the image quality, which makes automated quantitative measurements of internal interfaces difficult. To overcome this difficulty we present in this paper an innovative image analysis approach based on volumetric OCT data. The engine in the analysis is a 3D image processing and analysis algorithm. It is dedicated to boundary segmentation and dimensional measurement in volumetric OCT images, and offers high accuracy, efficiency, robustness, subpixel resolution, and a fully automated operation. The method relies on the correlation property of a physical interface and effectively eliminates pixels caused by noise and speckles. The remaining pixels being stored are the ones confirmed to be related to the target interfaces. Segmentation of tilted and curved internal interfaces separated by $\sim 10\ \mu\text{m}$ in the Z direction is demonstrated. The algorithm also extracts full-field top-view intensity maps of the target interfaces for high-accuracy measurements in the X and Y directions. The methodology developed here may also be adopted in other similar 3D imaging and measurement technologies, e.g., ultrasound imaging, and for various materials. © 2014 Optical Society of America

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1. INTRODUCTION

Optical coherence tomography (OCT) has attracted much attention during the past two decades. Its pronounced technological progress is mainly owing to the development of optical communication technology and its unique imaging power in biomedical areas, e.g., ophthalmology and dermatology [1]. It provides 3D volumetric imaging of internal features in a way similar to ultrasound imaging and the three scanning modes, A-scan (intensity versus z depth at an x, y position), B-scan (intensity image in an x, z plane), and volumetric scan formed by a set of B-scans in Y direction in a volume. Thanks to the development of radiation sources and detectors in different wavelength regions, OCT shows renewed potential in industrial applications as well. A detailed overview of the OCT-based methods and applications in the fields of dimensional metrology, material research, non-destructive testing, art diagnostics, botany, microfluidics, data storage, and security applications is given in [2].

A potential application of OCT is quality inspection and micrometrology of embedded structures in multilayered ceramic materials [3,4]. This is highly demanded in, e.g., advanced “roll-to-roll” multimaterial-layered 3D shaping technology for manufacturing of multifunctional micro devices with complex 3D structures [5]. The end products of this technology may provide a solution to the manufacturing for the emerging markets. Components such as microfluidic devices for

medical applications or microreactions, integrated devices packaged with embedded micro-electro-mechanical systems (MEMS) and optical fibers, bioreactors, microwave devices for terahertz applications, high efficiency cooling systems (integrated heat pipes or micro heat exchangers), micro sources of energy and different types of sensors at very large scale can be manufactured by this technique. Meanwhile, the manufacturing costs will be much reduced.

High-accuracy 3D monitoring and quality inspection using OCT will improve product quality and tolerances and will also save unnecessary cost due to poor performance and shorter life cycle. It requires not only high-quality OCT hardware to do this, but equally important is an accurate, rapid, and robust data processing method of the OCT signal. It is also crucial to achieve an acceptable measurement uncertainty level by handling large amounts of data. Another significant benefit of 3D-volumetric scanning is the possibility of having a fast and accurate feedback loop for reconfigurations of materials and features at the early stage, during the research and development process of new ceramic micro devices.

However, scattering of the probing beam is the major problem in OCT inspection and measurement of embedded microstructures and defects in ceramic materials. This results in limited penetration of radiation power and formation of speckles [3,6]. Extremely low signal-to-noise ratio (SNR) in the image domain, which is approaching one [6], is therefore

a fact we have to face. Our goal of developing in-material-metrology based on OCT therefore requires a considerably improved data handling technique.

Published methods of OCT image analysis have dealt with segmentation of intraretinal layers and tissue structures, and usually rely on certain boundary models or use filtering techniques [7–11]. Besides that, to the best of our knowledge none has so far been presented for industrial applications except for our 2D “ridge detection” method [12].

This paper is a continuation and extension of our previous work in [12]. Here, we present for the first time to our knowledge a simple but accurate and robust 3D image processing method for volumetric OCT data, dedicated to the dimensional metrology of the embedded features in ceramic materials. These features, faintly appearing in the raw OCT images, are usually presented to the human perceptual system as 3D images in a certain color format as devised by standard rendering and display methods in medical image processing [13]. The desired information we are aiming for, like the boundaries of ceramic layers and structures, may be extracted from OCT images manually by experienced operators. However, this is an extremely time-consuming process when handling large amounts of volumetric data. Also, the measurement accuracy can vary considerably from one operator to another.

We will first review the “ridge detection” for the 2D case [12] and describe in detail the “3D correlation detection” for the 3D volumetric OCT data case. The algorithm performance is finally evaluated thoroughly based on experimental OCT data.

2. EXPERIMENTAL

A. Spectral-Domain OCT

A schematic illustration of a spectral-domain OCT (SD-OCT) is shown in Fig. 1, where a broadband radiation source is used and the reference path remains fixed. At the exit of the interferometer a diffraction grating can be used for dispersing the different spectral components over a line array CCD camera by which the interferometric power is recorded. The pixel resolution of the camera determines the digitization of the continuous spectrum of the dispersed radiation, i.e., the spectral sampling interval [1]. The detection sensitivity in SD-OCT is also correlated to the number of pixels [1]. By taking the inverse Fourier transform of the measured spectrally resolved interferometric signal, the depth information is obtained as an axial distribution function (A-scan) of the local reflectivities from features and interfaces of the sample.

Fig. 1. Schematic setup of a spectral domain OCT (SD-OCT).

Table 1. Specification of the OCT System

Center wavelength	1325 nm
Spectral bandwidth (FWHM)	150 nm
Experimental A-scan rate	28 kHz
Sensitivity	106 dB
Experimental scan width	4 mm
Lateral resolution	15 μ m
Axial resolution	<8 μ m (in air)

The lateral scanning over the sample is carried out by using two galvo mirrors with rotational axes in the X and Y direction or using only one galvo mirror scanning in the X direction and moving the specimen in the Y direction. Multiple A-scans recorded at adjacent lateral positions are assembled into a B-scan, and in the same way volumetric data are obtained by recording multiple adjacent B-scans.

In this work a Thorlabs Telesto SD-OCT [14] was used for acquiring the tomographic image of the ceramic samples. The specification of the system is given in Table 1.

B. Ceramic Samples

Swerea IVF [15] provided the sintered polycrystalline alumina and zirconia ceramic materials that have densities around 99% of the theoretical density. The laser milling of microchannels in the sintered alumina ceramic sample was done at MEC, Cardiff University. The microchannels used as embedded features in this work are shown in Fig. 2. They have a designed depth of 65 μ m and widths varying from 140 to 290 μ m. These microchannels are covered by a zirconia layer and this geometry mimics a double layer stack with embedded channels [4]. Then they are positioned under the OCT probe to get volumetric data at the imaging sites, 1 and 2, as marked in Fig. 2.

3. RIDGE DETECTION ALGORITHM

The ridge detection algorithm is an automated image-processing algorithm for boundary segmentation in 2D OCT images, i.e., B-scans. It has the advantage of avoiding filtering and preset modeling, and thus introduces a simplification. The algorithm has been described in detail in [12] and its performance has been validated through measuring the thickness of ceramic layers, extracting the boundaries of embedded features with irregular shapes, and detecting geometric deformations. The accuracy and reliability of the algorithm is very high. In the following section this algorithm is briefly summarized, as it is a vital part of the 3D algorithm to be presented later.

Fig. 2. Geometric model of the ceramic sample stack for OCT imaging. The centers of the imaging sites are marked with the red frames.

Fig. 3. Example of a cross sectional OCT B-scan of the multilayered ceramic sample. The enlarged image of the boundary is shown on the left hand side and the corresponding average A-scan is shown on the right hand side.

A. Concept

Basically, the image processing of an OCT B-scan of the ceramic sample (in Fig. 3) is a segmentation problem, but the standard methods [16] fail because the strong scattering degrades the SNR severely and the speckles appear as shown in the enlarged picture of Fig. 3. They can hardly be removed or suppressed since they can be considered as both noise and information carriers [6].

The peaks appearing in the A-scan profile in Fig. 3 are called “ridges” in our terminology. They represent interfaces where the refractive index changes and are normally associated with geometric boundaries such as surfaces of the layered ceramic stack, and they are of utmost interest for dimensional metrology. The ripples in the signal generated mainly by the small scattering particles in the ceramic materials will be treated as noise.

In an OCT image it is easy for an experienced observer to see features in the image owing to the human brain preferences for filling in lacking information. However, to teach a computer to recognize and measure these interrupted or noisy features is a real challenge. Based on the material characteristics and geometry of the features, we made a major assumption that the images of physical boundaries are longer than apparent “structures” caused by speckles and discrete small scatter centers.

The ridge detection algorithm is summarized in three steps in Fig. 4, where the labels A–C correspond to the images in Fig. 5. First, we extract local intensity maxima from the original OCT image data, and then the longer segments are extracted using the assumption of a continuous interface. A template of the extracted image is built where the ridges are marked as ones in a logical image. In the final step a subpixel resolution refinement is applied to the original OCT image based on the obtained locations of the ridges.

B. Candidate Ridge Detection

For demonstration of the method Fig. 5 shows the images that represent the steps for generating a logical template of the ridges. The input is a gray-scale OCT B-scan of the ceramic

Fig. 4. Steps of the ridge detection algorithm.

Fig. 5. Images describing the different steps in the ridge detection algorithm. (A) Input OCT image; (B) the logical connection map that contains the results after extracting the longest ridges in all directions; (C) the final logical template of ridges after the merging and cleaning process. The vertical bar in (A) represents optical distance.

layer with laser-milled microchannels, and the imaging cross section is schematically illustrated in the top left picture. The first step is to extract the local maxima in any direction from the image, and store it as a logical map in Fig. 5(B). The final logical template of ridges in Fig. 5(C) is generated after the merging and cleaning process by the assumption of a continuous interface, i.e., the surface in this case. The details of the above processes can be found in the previous publication [12].

C. Subpixel Refinement Algorithm

The template presented in Fig. 5(C) provides the locations of the candidate ridge pixels. We now use a closer neighborhood analysis around these candidate pixels in order to find where the ridge is located at subpixel resolution. The smallest neighborhood you can use is the eight pixels that surround the candidate pixel at location i, j , as shown in Fig. 6. The intensity gradients of these pixels are calculated as eight vectors originating at the centers of these eight pixels and pointing toward

Fig. 6. Eight pixel neighborhood of a ridge pixel, i, j (marked with a white square), belonging to a ridge in the X direction. The black arrows are the gradients vectors and the locations of the local maxima are marked with red dots. The red crosshair is the final subpixel location of the ridge pixel at location i, j .

Fig. 7. Result of the subpixel refinement based on the candidate pixels found in Fig. 5(C). The contrast of the image is enhanced for display reasons, where the gray scale corresponds to a dynamic range of 45 dB. The image processing is done on the original OCT data with a dynamic range of 110 dB.

the locations of the local maxima. The neighbor pixels' "opinions" of the locations of the maxima are marked with red dots that must be inside the white circle to be accepted. The red crosshair that is calculated by averaging the red dots is the subpixel location of the maximum at location i, j . The mathematical descriptions can be found in [12].

If the red crosshair is found outside the white square in Fig. 6, then we skip this location without further notice. Otherwise, the subpixel location of the maximum for the ridge pixel at location i, j will be used and a chain of pixels describing the ridge with subpixel resolution is built as shown in Fig. 7.

An important feature of the ridge detection algorithm is its ability to find the true boundary of reflection maxima with subpixel resolution. Furthermore, it can remove pixels that are not real local maxima but have been found in the candidate ridge detection. The final result is generated from the original OCT image without loss of information caused by filtering effects. A thorough evaluation of this algorithm can be found in [12].

4. 3D CORRELATION DETECTION ALGORITHM

A. Concept

A volumetric OCT image is generated from a large number of adjacent A-scans by scanning the probing beam across the sample laterally in the X and Y directions. The original A-scans contain the dimensional information in the axial Z direction, based on the principle of low-coherence interferometry. In order to fully use the information carried by the volumetric OCT image, the correlation between individual A-scans needs to be found.

The previously described ridge detection makes use of the correlation between neighboring A-scans in a cross sectional B-scan, and retrieves the ridge pixels corresponding to the physical boundaries of the sample from the noisy images. This result is then provided as the input to the 3D correlation detection algorithm. As in the case of the ridge detection we assume that an interface corresponds to the reflection peak (ridge) as demonstrated in Fig. 3. The method is then built on the following logical assumptions:

(1) A physical interface is a continuous object in a Cartesian coordinate system, and its image (appearing as an intensity ridge) is also continuous in the volumetric OCT image, unless the interface is vertical or tilted at a large angle relative to the horizontal axis (around 30° for our ceramic samples, for angles larger than that no back reflection peak or ridge appears in the image).

(2) Noise, speckles, and small scattering sites appear as discrete intensity changes and have a random distribution in the OCT image domain.

The consequences of the assumptions are as follows:

(1) The continuity of an OCT reflecting interface, e.g., a physical surface, in the image domain provides the correlation between two perpendicular cross sectional views of the volumetric OCT data, e.g., X-Z and Y-Z cross sections, in which the OCT images of the surface are independent and therefore the boundaries are extracted from these two cross sections based on different and independent sets of information. The two set of solutions, i.e., extracted boundary pixels from two perpendicular views, should have a large probability of overlapping with each other because of the continuity of a physical interface. The probability of overlapping is very high if the image of the interface has a good SNR. The probability may also decrease depending on the image quality.

(2) In contrast, the extracted pixels that correspond to noise, speckles, and small scattering particles or pores in an X-Z cross section have very small probability of overlapping with the pixels extracted in the Y-Z cross section. This is because the phases of the OCT signals are random [6] and speckles that are generated axially have no correlation in the lateral direction. The images of the small scattering sites usually contain only a few pixels, and that is not enough to form a good image in both the X-Z and the Y-Z view.

B. Method

To demonstrate this new 3D correlation detection algorithm we make use of volumetric OCT data obtained from an alumina ceramic layer with laser-milled microchannels. We pre-allocate a 3D matrix, M_0 , with 512 rows, 1024 columns, and 512 pages, and fill the matrix with the original OCT data, i.e., each voxel element is assigned a gray level. In Fig. 8 this 3D matrix is shown, which provides an overview of the volumetric data to be processed.

By applying the ridge detection algorithm described before, we can effectively extract the boundaries from each cross sectional B-scan, and get a large set of images similar to that shown in Fig. 7. This is illustrated in Fig. 9 where the B-scans are located in the X-Z planes at adjacent Y positions.

Figure 10 shows an OCT image similar to that of Fig. 7 but it corresponds to a different cross section in the volumetric OCT data, i.e., obtained at a different Y position. As can be seen, the subpixel locations of the two images (Figs. 7 and 10) differ somewhat and the faulty pixels, caused by speckles and found

Fig. 8. 3D perspective OCT image of the ceramic layer with laser-milled microchannels. The total depth of the image is 1.78 mm (optical distance). The image is rendered using the maximum intensity projection (MIP) method [13].

Fig. 9. Processing X-Z cross sectional OCT images in the volumetric data using the ridge detection algorithm.

in one image, will most probably not appear in the same place in another B-scan image. If the image quality is good the noise pixels will be rarely extracted. However, if the SNR in an OCT image is very low (close to or even smaller than one [6,12]) it is a very time-consuming process to find the optimal image processing parameters for each B-scan. The remaining noise pixels may also disrupt the image segmentation and degrade the uncertainty of the dimensional measurement in the OCT data.

To circumvent this problem we developed a 3D correlation detection algorithm based on the simple idea that the ridge detection can be made on B-scans extracted as both X-Z and Y-Z planes. Fig. 11 illustrates that images can also be obtained from different Y-Z cross sections for further extraction using the ridge detection algorithm. The ridge pixels extracted from Y-Z cross sections are independent from the result of the X-Z cross sections, and thus provide new information.

The results of the ridge detection of the volumetric OCT data from X-Z and Y-Z views are stored in matrices M_{XZ} and M_{YZ} as presented in Figs. 12(A) and 12(B), respectively. Here, the image processing result from X-Z view means that we process data in the X-Z cross section and along Y. The same definition applies to the Y-Z view. Note that the ridge detection algorithm has already provided subpixel resolution of the extracted pixels in these matrices. Thus, the smallest unit to be used in the subsequent 3D correlation detection is 0.1 pixels, which is a pronounced advantage of this algorithm. M_{XZ} and M_{YZ} contain 5120 rows, 1024 columns, and 512 pages, respectively.

The difference of these two results is obvious because each ridge pixel is obtained using different information provided by its neighborhood when comparing the X-Z view and Y-Z view. The difference becomes particularly large when the channels are getting smaller. In this region the OCT image is much more noisy and blurry because the dimensions of the microstructures approach the OCT resolution limit, and some noise pixels that are not true ridge pixels corresponding to a

Fig. 10. Extracted ridge pixels of the boundaries of the microchannels. Some noise pixels are also extracted due to the non-optimized image processing parameters.

Fig. 11. Processing Y-Z cross sectional OCT images in the volumetric data for further extraction of ridge pixels.

physical interface may be extracted due to the speckles and low SNR.

The next step in the algorithm is carried out based on the assumptions that a physical interface is a continuous object in the Cartesian coordinate system and its image is also continuous in the volumetric OCT image, but a noise, speckles, and small scatterers are discrete and randomly distributed in the OCT image domain.

If we combine the ridge detection results of the X-Z and Y-Z views it is very likely that ridge pixels from the real interface will match, but it is very unlikely that uncorrelated noise pixels from speckles and small scattering sites match. The condition of the matching is overlapping of two pixels with zero tolerance at subpixel resolution (0.1 pixels). This is a very strict condition and it offers a high-accuracy segmentation of the physical interfaces present in the OCT data. This is particularly true when the interfaces are very close to each

Fig. 12. Ridge detection results of the volumetric OCT data from (A) X-Z view and (B) Y-Z view. The results are shown in 3D perspectives, where the depth range of the green box is limited to 192.1–253.3 pixels, which corresponds to the optical depth of 667.8–880.6 μm . Thus, the curvature of the surface more pronounced in this case as compared with Fig. 8.

Fig. 13. Effect of merging the ridge detection results of the X-Z and Y-Z views with an overlap criteria of 0.1 pixel. The depth range of the green box is limited to 193.2–233.9 pixels, which corresponds to an optical depth of 671.7–813.2 μm .

other. In many applications it is accurate enough to have the matching with zero tolerance at a one pixel level (1 pixel).

This correlation analysis can be done through matrix calculation. M_{XZ} and M_{YZ} contain only logical values, namely “0” and “1”, corresponding to whether a ridge pixel is found at the position (row, column, page) of an element in the matrix. These two matrices can be considered as masks for each other and their dot product is

$$M_d = M_{XZ} \cdot M_{YZ}, \quad (1)$$

where the new matrix, M_d , has the size of $5120 \times 1024 \times 512$ elements, and this operation fulfills the overlapping rule as described above.

Part of the matrix, M_d , is visualized in Fig. 13. Almost all remaining ridge pixels correspond to the desired surfaces, and the noise pixels are effectively removed. These pixels are now used for further processing for the dimensional measurements of the microchannels.

C. Segmentation

By effectively reducing noise and using subpixel resolution it is now much easier to segment the top and bottom surfaces of the microchannels. A simple and straightforward method is to separate peaks in the histogram of the Z coordinates of the elements in M_d . A typical example can be found later in the evaluation section.

The segmented pixels are stored in two 3D matrices, M_{d1} and M_{d2} , with the same size as M_d . They correspond to the top and bottom surfaces, respectively, and are fitted to proper polynomial functions by a least squares optimization. In Fig. 14 a fourth-order polynomial function has been fitted to the top surface data (A) and the bottom channel data (B) of the ceramic layer.

An obvious advantage of this method is that we can easily extract the tilt and curvature of the surfaces. As will be discussed in the next section, the observed curvature is not attributed to the ceramic surface itself which is very flat, as measured with our scanning white light interferometer (SWLI) [17], but rather an effect of the OCT scanning optics. Consequently, the wavefront error and the tilting angles can be quantitatively determined and easily compensated for to improve the measurement accuracy.

Fig. 14. Segmentation of the (A) top and (B) bottom surfaces of the ceramic layer based on the result shown in Fig. 13. The polynomial fitting of the surfaces are plotted by false colors and the extracted ridge pixels are presented as small gray dots. The unit of the axes is in pixels.

The best-fit surface functions also provide the Z positions of the segmented surfaces as functions of X and Y coordinates. Now we create two new matrices, M_{s1} and M_{s2} , with the same size as M_d and with logical values, “0” and “1”, where the index of each element (row, column, page) corresponds to the (Z, X, Y) coordinates of the surfaces over a full field of view (FOV), i.e., 1024×512 pixels.

Since M_{s1} and M_{s2} contain 5120 rows corresponding to the subpixel resolution Z coordinates, the original volumetric OCT data, M_0 , that has only 512 rows needs to be extended to match the larger matrices for further calculation. This can be done by rescaling M_0 to a matrix, M_{0L} , with 5120 rows, 1024 columns, and 512 pages, which is done by resampling each A-scan to 5120 pixels in the Z direction, where a cubic interpolation [18] is used.

Then M_{s1} and M_{s2} serve as logical masks and they are used for retrieving the corresponding surface pixels from the extended volumetric OCT data, M_{0L} ,

$$M_{01} = M_{s1} \cdot M_{0L}, \quad (2)$$

$$M_{02} = M_{s2} \cdot M_{0L}. \quad (3)$$

M_{s1} and M_{s2} contain accurate positions of the surfaces. Hence, in M_{01} and M_{02} we obtain the original interferometric signal levels on each pixel of the surfaces. As shown in Fig. 15, the top-view intensity images generated from M_{01} and M_{02} over a full FOV are similar to optical microscope images of the sample surfaces.

After this processing the channel widths can now be measured with high accuracy from these enhanced images. The standard Canny detection method combined with our subpixel refinement algorithm can be used for further edge detection and measurement as demonstrated in Fig. 16.

Up until now we have demonstrated the 3D correlation detection method for measuring the depth and width of the

Fig. 15. Top-view gray-scale images of the (A) top and (B) bottom surfaces of the ceramic layer derived from the 3D correlation algorithm. The gray levels cover a 110 dB dynamic range. The brighter pixels in both images correspond to the surfaces, while the dark gray pixels in the upper image correspond to the air and the dark gray pixels in the lower image originate from the backscattering signal within the ceramic material. The image size is 1024×512 pixels for $4 \text{ mm} \times 4 \text{ mm}$ (the obtained image is twice as wide as the sample actually is).

microchannels in the volumetric OCT data. We used a simple volumetric OCT image to demonstrate the technique. However, it is capable of handling much more complicated OCT images, as will be shown in the next section. The entire image processing procedure, including the ridge detection and 3D correlation detection algorithms, can be fully automated. The performance is evaluated and presented in the next section.

5. EVALUATION OF THE ALGORITHM

The methodology for evaluating our image processing algorithm has been introduced in [12], where a thorough evaluation of the ridge detection algorithm was given. In this paper we limit the evaluation to the 3D image processing algorithm qualitatively and quantitatively based on the same methodology. We will only show the most challenging examples in this paper, although the algorithm has been

Fig. 16. Canny detection combined with the subpixel refinement algorithm for edge detection and subsequent measurement of the widths of the channels using the upper image of Fig. 15. The small red crosses present the result of the edge detection.

Fig. 17. Top-view gray-scale OCT image of the extracted top surface of the USAF 1951 resolution test target.

proved by handling many measured OCT data with different ceramic samples.

A. Evaluation Based on Test Standard

A chrome-on-glass USAF 1951 resolution test target [19] is used for evaluating the 3D correlation algorithm by comparing nominal and measured line widths of the standard test chart. The volumetric OCT data is obtained for the test chart using the same OCT setup. Following the same steps as described in the previous section we extract the top surface of the test chart from the volumetric data. The top-view intensity image is shown in Fig. 17.

From this image the test bars of group 2 and elements 1–6 can be clearly seen and their line widths can be measured using the Canny edge detection method combined with our subpixel refinement algorithm. The measurement result, after compensation of the wavefront aberration (see below) and the tilting angles, agrees with the nominal values as listed in Table 2. The uncertainty of the result is calculated based on the central limit theorem [20] of a large number of measurements along the test pattern.

The measurement uncertainty of element 2 is relatively larger due to the uneven intensity near the upper part of Fig. 17 (which is caused by a slight tilting of the sample to avoid the strong specular reflection by the top surface). This indicates that there is an effect of the uneven intensity distribution on measurement uncertainty. However, it is beyond the scope of this paper to further elaborate on that.

The glass substrate is sufficiently flat. Thus, the detected surface distortion is mainly due to a wavefront aberration (defocus and astigmatism) [21] caused by the two galvo mirrors scanning the beam in the X and Y directions. The wavefront

Table 2. Line Widths in the USAF 1951 Resolution Test Target

Element ^a	Nominal Value (μm)	OCT Measured Value (μm)
1	125.00	124.7 ± 0.4
2	111.36	106.4 ± 1.7
3	99.21	97.2 ± 1.3
4	88.34	87.7 ± 0.7
5	78.74	77.8 ± 0.4
6	70.13	69.1 ± 0.3

^aElements in group 2

Fig. 18. Plot of the least square fit wavefront of an OCT system using a pair of galvo mirrors for the lateral scanning. The FOV is $4\text{ mm} \times 4\text{ mm}$ and the colorbar corresponds to height values in micrometers. The peak-to-valley (P-V) value of the deviation is around $20\text{ }\mu\text{m}$.

Fig. 19. 3D perspective OCT image of the two-layer ceramic stack (render mode is MIP). The channel layer is embedded beneath a $375\text{ }\mu\text{m}$ thick zirconia layer. The image contains $1024 \times 512 \times 512$ pixels that correspond to $4\text{ mm} \times 4\text{ mm} \times 1.78\text{ mm}$ in X, Y and Z directions, respectively, where the Z axis represents optical distance.

aberration can be detected by our algorithm as demonstrated in Fig. 18, and therefore it can be compensated for numerically.

In summary, the result verifies the accuracy of our image processing algorithm. Now we evaluate the algorithm using the OCT image of embedded microchannels in ceramic materials.

B. Evaluation Based on Volumetric OCT Images

The test volumetric OCT data of a two-layer ceramic stack is visualized in Fig. 19, which is based on the geometric model shown in Fig. 2.

We show a cross sectional B-scan in an X-Z plane from the volumetric data in Fig. 20. Within the region of interest (ROI) the rear boundary of the zirconia top layer is very close to the top surface of the alumina layer containing the channels. The distance between them approaches the axial resolution limit

Fig. 20. Cross sectional OCT image of the microchannels with a $375\text{ }\mu\text{m}$ thick zirconia top layer. The contrast of the image is enhanced for display reasons, where the gray scale represents a 45 dB dynamic range. The vertical bar presents optical distance.

Fig. 21. Optimized histogram for fine segmentation using a 0.1 pixel resolution of the original OCT z pixels. Two peaks are found after removing the form. They represent the lower surface of the top layer and the top surface of the channel. One z pixel in the right hand histogram corresponds to $0.348\text{ }\mu\text{m}$.

of the OCT system or even beyond the limit at some positions. It is therefore a real challenge for an automated computer algorithm to resolve and segment these boundaries with high accuracy.

The ROI is processed and the faulty pixels due to noise and speckles are effectively removed. The channel bottom can be easily segmented from the histogram of Z coordinates. An additional fine segmentation is required for segmenting the rear surface of the top layer and the top surface of the channel layer. It optimizes the histogram by removing the tilting and form of the interfaces and using subpixel resolution.

Fig. 22. Segmentation of the surfaces of the ceramic stack from the OCT data in Fig. 19. Three extracted surfaces are shown: (A) the bottom surface of the zirconia top layer, and (B) the top and (C) bottom surfaces of the channel structure. The polynomial fittings of the surfaces are plotted by false colors and the extracted ridge pixels are presented as small gray dots. The unit of the axes is in pixels.

Fig. 23. Comparison of top-view OCT images of the top and bottom surfaces of the microchannels that are extracted by (A) the 3D image processing algorithm and (B) the manual selection of cross sectional image using conventional software, e.g., Amira [22].

The effect is shown in Fig. 21. Two peaks corresponding to the closely positioned interfaces can be now easily found.

The three segmented surfaces (similar to Fig. 14) are shown in Fig. 22. Despite some lack of pixels, there are still a large number of pixels being extracted and they provide sufficient information for extracting the surfaces with high accuracy.

The measurement results of the depths of the microchannels by OCT are compared with the same sample but measured using the well-calibrated SWLI. The average depth of the microchannels is measured as $67.1 \pm 0.02 \mu\text{m}$ by the SWLI, which agrees with the OCT-measured values, $66.2 \pm 0.1 \mu\text{m}$ and $66.6 \pm 0.1 \mu\text{m}$, from data in Figs. 8 and 19, respectively.

The evaluation is also made by comparing the microchannel surfaces that are extracted by the 3D correlation algorithm and by manually segmenting the target planes using traditional image processing software [22]. As shown in Fig. 23 the advantage of the image processing algorithm can be seen immediately, which is more accurate, robust, and efficient.

6. CONCLUSION

In this paper we have presented an accurate, robust, and automated 3D image processing method. The purpose is to handle large amounts of data generated by online inspection using OCT in the future for roll-to-roll multilayered 3D manufacturing of ceramic microcomponents. It is also extremely important for high-accuracy and high-precision dimensional metrology that this method does not use any filtering technique, and therefore largely preserved the information carried by the original OCT data. The evaluation of the algorithm is

demonstrated on a test standard and on real multilayered ceramic samples. The numerical compensation of the wavefront aberration detected by our algorithm, ensures a more accurate measurement. When the dimensions of the physical features approach the OCT resolution limit (a few micrometers), the images of the features mix with speckles and can hardly be distinguished even by human eyes. In that case, the quality of the automated detection by our algorithm may be reduced. By using a PC with Intel Core2 Quad CPU Q9400 @2.66 GHz with 8 GB RAM, the processing time for a volumetric OCT data ($512 \text{ pixels} \times 512 \text{ pixels} \times 200 \text{ pixels}$) is around 5 min. Optimization of the MATLAB code may improve this efficiency significantly.

The method and concept developed here may also be applied in other similar 3D imaging and measurement technologies, e.g., ultrasonic imaging, and for various industrial applications. It is a powerful tool that provides quantitative evaluation and processing of the obtained volumetric imaging data.

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