

ASSESSING CASTING QUALITY USING COMPUTED TOMOGRAPHY WITH ADVANCED VISUALIZATION TECHNIQUES

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Abstract

Increasing demand for high quality castings has increased the importance of computed tomography (CT) in the casting industry. With computed tomography it is possible to cover the whole sample-volume. Apparent differences in density can be detected and size and positions of these inhomogeneities can be determined in three dimensions. CT is a valuable tool because various casting defects can be detected and quantified.

This paper highlights the possibilities and limitations of computed tomography for quality control and assessment of castings from materials to finished products. Considerable improvements can be achieved using volume rendering with novel multi-dimensional transfer functions for visualising the volume data. In particular the quantification of casting defects were addressed and compared to standard metallographic procedures and common CT analysis-tools.

Introduction

The progress in CT technology and the growth in available computing capacity during the last few years has made this technology increasingly suitable for technical applications. By enabling a non-destructive 3-dimensional view into the centre of castings this technology opens up completely new options for materials research, components development and process optimization. Computed tomography can be used with various materials, such as metallic and ceramic materials, plastics, refractories, construction materials, composite materials and reinforced components. In the foundry industry, and above all amongst users of castings, there is growing interest in using CT for 3D non-destructive testing of complex component geometries. With CT it is possible to detect classical casting defects such as gas pores, shrinkage cavities, inclusions, spongy structure, etc.. Compared to radioscopic testing, CT enables the display of smaller defects in higher contrast. Moreover it provides information about the geometry and position of the detected flaws. During CT testing an X-ray source penetrates the object, while it is rotating step-wise through 360°. The penetrating X-rays are captured by a detector. From this information clustered computers reconstruct a 3D model of the specimen for different visualization and analysis tasks.

Computed Tomography of Castings

Shrinkage cavities and pores have always been important quality criteria of castings. Non-destructive determination of the overall porosity content only used to be possible by weighing

according to the Archimedes principle. This method is too inaccurate nowadays for the assessment of technologically achievable and customer-specified porosities of $<1.5\%$ [1]. Therefore evaluation of porosities is only possible by destructive methods, as described in the VDG technical standard P201 “Volume deficits of non-ferrous metal castings” [2].

Radioscopy versus CT

Through non-superposed representations in CT scanning, even very small volume deficits can be represented in high contrast. The aluminium die casting shown in Figure 1 was subjected to X-ray testing using a high-resolution micro-focus X-ray source and a 16-bit flat panel detector (Figure 1a). The visibility of volume deficits was enhanced by contrast stretching.

A CT model of this casting that was computed employing identical imaging conditions as well as using the presented radioscopic image, shows additional volume deficits. These deficits can be characterized as gas pores, (Figure 1b). Hence in the CT model more details can be identified than in a radioscopic image which is taken using identical parameters.

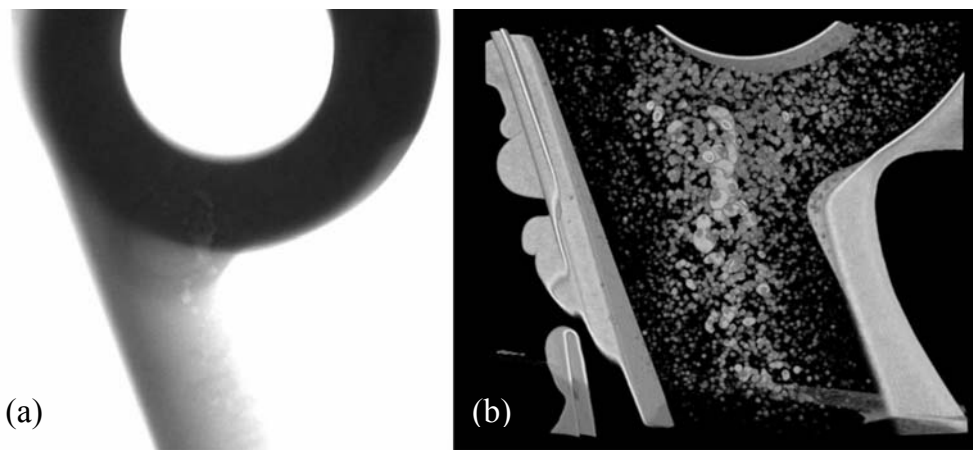


Figure 1. Aluminum die casting – (a) high-resolution radioscopic image and (b) high-resolution CT image.

Automatic Pore Detection

The quality of an aluminium melt and the success of the refining process is usually evaluated using reduced pressure testing (RPT) [1]. Samples are taken before and after the refining process for solidification in air and vacuum. From the resulting differences in density the density index is calculated as a characteristic value for the melt quality. The corresponding reduced pressure test samples contain gas pores and shrinkage cavities. A CT model of such an RPT sample (Figure 2) was used to demonstrate automatic pore detection.

The software VG Studio MAX which is generally used for the analysis of technical CT data incorporates a defect analysis module for automatic volume deficit detection. This tool captures internal deficits, their individual position, size and distribution. For this type of detection various parameters must be defined, the most important being the definition of the gray values of the material and the pores. Figure 2 shows the results of pore detections evaluated with different parameter sets. The corresponding results for the determined volume porosities and the number of detected pores are given in Table I. The detected volume porosities between 2.3% and 5.2% represent such a wide bandwidth that, depending on the parameters, the test result could even lie outside specification for a casting at hand. While in evaluation variant (a) certainly not all defects have been detected, variant (c) can be assumed to have included some false positives, i.e. not true

defects. This shows that useful and reliable pore detection requires standardized procedures. As these are not yet available, the user must select individual and suitable parameters for each casting based on his experience, possibly supported by additional investigation methods.

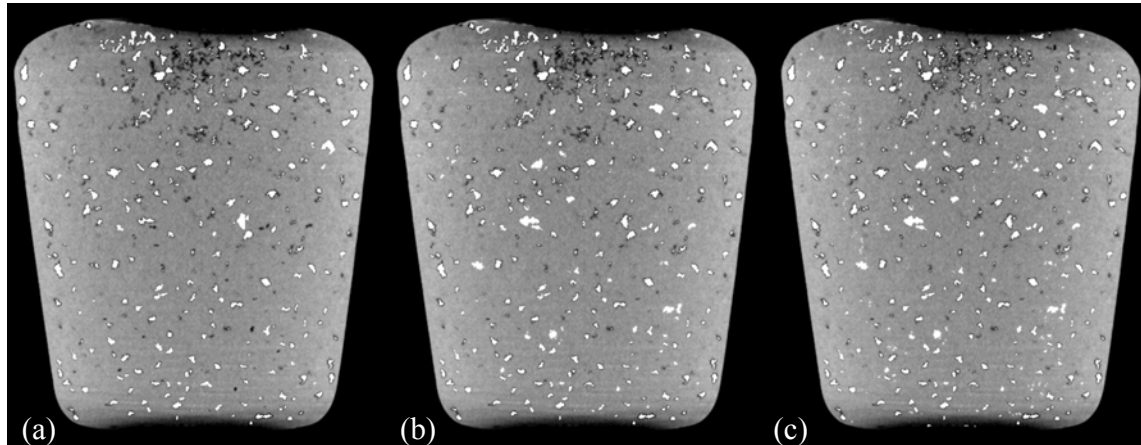


Figure 2. Comparison of pore detections with varying parameters.

Table I. Overview of the difference in volume porosity and number of pores derived from three different sets of parameters.

	Figure 1 (a)	Figure 1 (b)	Figure 1 (c)
Volume porosity	2.3 %	4.8 %	5.2 %
Number of pores	6,191	8,029	20,032

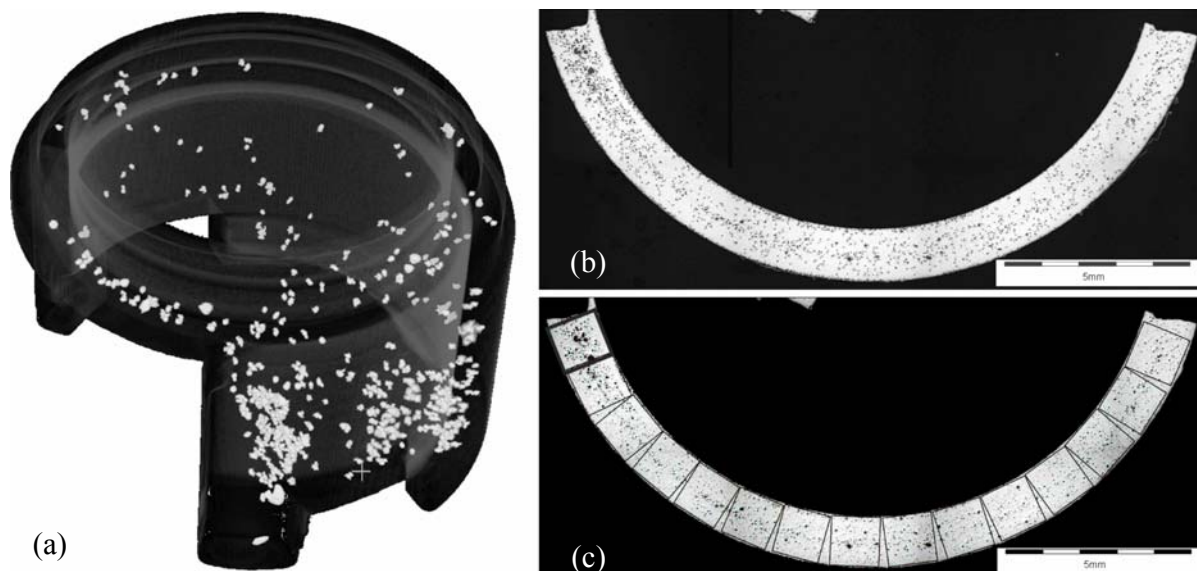


Figure 3. Porosity evaluation of a thin walled zinc casting by means of CT (a), metallographic examination of the whole microsection (b) and according to VDG technical standard P201 (c).

Evaluation of Porosity

Not only the detection but also the evaluation of size, position and distribution of pores is of great importance for each individual component. A thin-walled zinc die casting was used for the following porosity evaluations (**Figure 3**): volume porosity was determined by CT (0.25 %),

surface porosity was determined for the whole microsection (0.9 %) and the latter also according to the VDG technical standard P201 (9 %).

It can be generally stated that there are significant differences in the porosities determined by different methods. Therefore it is particularly important to define appropriate thresholds for each method. It is recommendable not only to evaluate pore accumulations in critical areas, for example by means of the described VDG P201 method for surface porosity assessments, but also for the assessment of the volume porosity.

Differentiation between Pores and Shrinkage Cavities

Pores and shrinkage cavities are interacting volume deficits driven by superaturated gas and negativ metallostatic pressure respectively. Therefore it is important for the foundryman to know which type of deficit is located in which area of the casting. Remedial action has to be taken depending on the type and position of the defect. In principle the two defects differ in terms of morphology. However, due to the complexity in morphology there is still no commercial software tool available on the market capable of automatically differentiating between the two.

The differentiation between pore and shrinkage hole can only be performed semi-automatically by the user. The setting of suitable imaging parameters requires well-grounded know-how of the casting technology and experience in visualizing of tomographic images.

Spongy Structure

Another frequent and therefore important defect to be detected is spongy structure. Spongy structure can be interpreted as an accumulation of pores. The resolvability of individual pores is limited because of the extremely fine structure of the pores. Nevertheless spongy structures are detectable in CT because they result in a local reduction of density.

Processing and Visualization of CT-Data

Today the most widely used approach for the visualization of volume-data is “Direct Volume Rendering” (DVR) which uses the whole volume for image generation [3]. A quadruple of (r, g, b, α) is assigned to each position in the volume, where α corresponds to the opacity and r, g, b give the color of one voxel. One-dimensional transfer functions where color and opacity are assigned on the basis of the local density value (gray value) are the most widely used transfer functions. They are basically 1D tables. With this approach all positions in a volume with the same density are represented in the same way and material boundaries such as pores or shrinkage porosity cannot be addressed directly.

This leads to the standard approach of feature detection which is usually performed via some type of segmentation, which most commonly builds on region-growing and filtering operations such as morphological operators. Segmentation results in one or several static segmentation masks, which can be visualized as part of the 3D volume and also form the basis of quantification. The segmentation cannot be modified without re-computation. This decouples the detection of features from visualization and prevents working in a fully interactive manner. Most of all, it hampers interactive exploration of the volume without knowing what features are contained in the volume beforehand. Whenever the segmentation results for specified parameters are not satisfactory, the user has to modify the parameters and the entire segmentation has to be

computed all over again. This is often time-consuming and tedious. Unlike this standard approach we propose a visualization-driven method for feature detection allowing features in the volume to be explored interactively without re-computing the segmentation.

Density/Gradient Magnitude Transfer Function

The most straightforward approach for a two-dimensional transfer function uses the gradient magnitude as the second dimension besides the density [4]. This type of transfer function is useful to visualize material boundaries, as the gradient magnitude is nearly zero in homogenous areas (due to intrinsic noise), whereas it reaches a maximum at the edges between two materials (e.g. metal and air). Different features of the volume can be displayed by interactively selecting the corresponding ranges of the gradient magnitude over density. This transfer function offers a quick interactive way to analyse the size and distribution of different kinds of defects in a casting [5].

Feature Size Transfer Function

This novel type of two-dimensional transfer function is defined by density and feature size [6]. In a preprocessing step, each voxel of a volume is assigned to a homogenous region (feature) to which it may belong via region-growing. In the visualization step the features can be distinguished and interactively selected according to their density and size. As this kind of transfer function is designed for the exploration of different discontinuities a separate transfer function, for instance a simple one-dimensional transfer function, has to be used to visualize the the whole object. In this way the features can be shown in the context of the test volume.

Although exploration of the sample is conceptually the most important part of our concept, the basis for interactivity during exploration is a complex pre-computation stage. However, no user input is required for this stage and thus it is, although technically complex and important, decoupled from the exploration itself. The main goal for pre-computing additional information is to enable exploration of different classes of features with different parameters in such a way that, e.g. the main parameter used to control region-growing (e.g. maximum variance) can be changed interactively after the region-growing process. In order to allow this, we perform region-growing in multiple passes and track the progress of each voxel.

Two different region-growing approaches, which are outlined below, were used for the exploration and analysis of castings. One method uses a variant of seeded region-growing [7] which is also able to include a region's boundary. In this way the feature is grown by adding a voxel to the region when the difference of its density with respect to the average density of the whole region is below a given threshold ε : $|v - v_r| < \varepsilon$, where v is a voxel's density, and v_r is the current region's average density. After a new voxel is added, v_r is updated accordingly. In a second step feature boundaries are added to the features after checking a gradient magnitude criterion.

The other method was suggested by Huang et al. [8]. They use a combination of region-growing based on density variance and gradient magnitude variance. They determine the variances f for the fixed neighborhood of a seed voxel. The main parameter is a scale factor $k > 0$:

$$f_{ca} = \frac{|v - v_s|}{k\sigma_v} \quad (1)$$

$$f_{cb} = \frac{|v' - v'_s|}{k\sigma_{v'}} \quad (2)$$

$$f_{cc}(p) = p f_{ca} + (1-p) f_{cb} \quad (3)$$

where v is a voxel's density value, v_s the density of the seed, v' a voxel's gradient magnitude value, v'_s the gradient magnitude of the seed, and σ_v and σ_g the corresponding variances in the seed neighborhood, respectively. The factor p can be set to a constant value but is set by default to $p = \sigma_{v'}(\sigma_{v'} + \sigma_v)^{-1}$.

The main difference between the two region-growing methods is, that the first one uses the whole feature area for the calculation of the average density, while the second method uses the average density of a given seed region. It can be shown that the first method is preferable for larger features, while the second method is best used with fine distributed features.

Multi-dimensional Transfer Functions for Casting Applications

As a reference to determine the effectiveness of the multi-dimensional transfer functions a reduced pressure test (RPT) sample with a high gas content was chosen. The gas in the melt forms pores as the metal solidifies. Furthermore, the shrinkage of the Al-Si alloy during solidification causes shrinkage cavities to be formed in the center of the upper regions of the sample. Therefore, this sample is an ideal test piece for the evaluation of feature detection, as it is virtually full of different pore sizes and shrinkage cavities.

The CT-dataset was subjected to analysis using gradient magnitude transfer functions to demonstrate the feasibility of simple differentiation between pores and shrinkage cavities with this method. One result of this analysis is given in **Figure 4**. The boundaries of the RPT Sample, the pores and the shrinkage cavities should be depicted, although these three feature classes have comparable densities. As a consequence, the transfer function was defined by selecting the appropriate gradient magnitude regions for each feature class. In **Figure 4** pores are depicted in light gray; shrinkage cavities are shown in dark gray. While pores of different sizes can be found all over the volume of the RPT Sample, shrinkage cavities are concentrated mainly around the center of the sample. With this concept differentiation between pores and shrinkage cavities was easily accomplished. Thus in general, the gradient magnitude transfer functions offer a simple way to purposively visualize and evaluate different features of the dataset.

The dataset of the RPT sample was also analyzed with feature size transfer functions (**Figure 4**). The results were then compared to results obtained using standard CT-software tools as well as to metallographic examination. Since metallographic evaluation is the standard procedure today for the evaluation of the porosity of castings, it was used as a reference for the CT based measurements. Two different software tools were utilized: VG Studio MAX as the most widely distributed software tool for handling industrial CT-data, and the software package using the novel multi-dimensional transfer functions.

The pores within the RPT sample were subdivided into five classes according to their volumes, disregarding shrinkage cavities. This classification was performed via selecting the appropriate feature sizes in the transfer function (**Figure 4**). The result of this classification can subsequently be quantified.

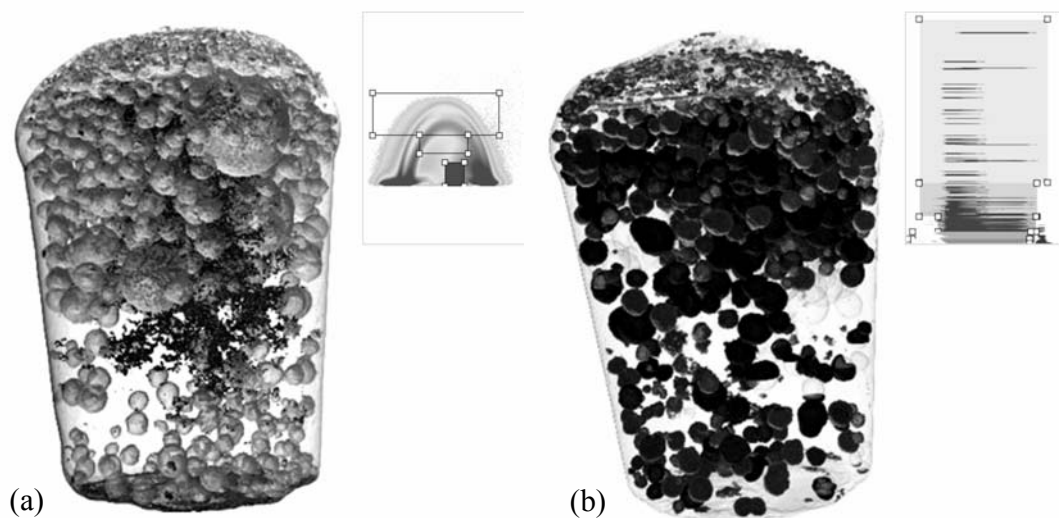


Figure 4. CT visualization of a reduced pressure test sample by using gradient magnitude (a) and feature size (b) transfer function. The applied transfer functions are given on the upper right hand side of each image.

For the comparison to metallographic examination a number of axial slices from the volume were selected and the sizes of the pores within these slices were evaluated by metallographic examination. These results were then compared with the results from the standard software tool to verify that reasonable values were achieved with the dataset used. **Figure 5 Fehler! Verweisquelle konnte nicht gefunden werden.** depicts one of the evaluated slices. The left part of **Figure 5** shows the CT data as analyzed with the software package; the right part pictures the result from metallographic examination. In both images the same pore is selected to show the congruence of the two results.

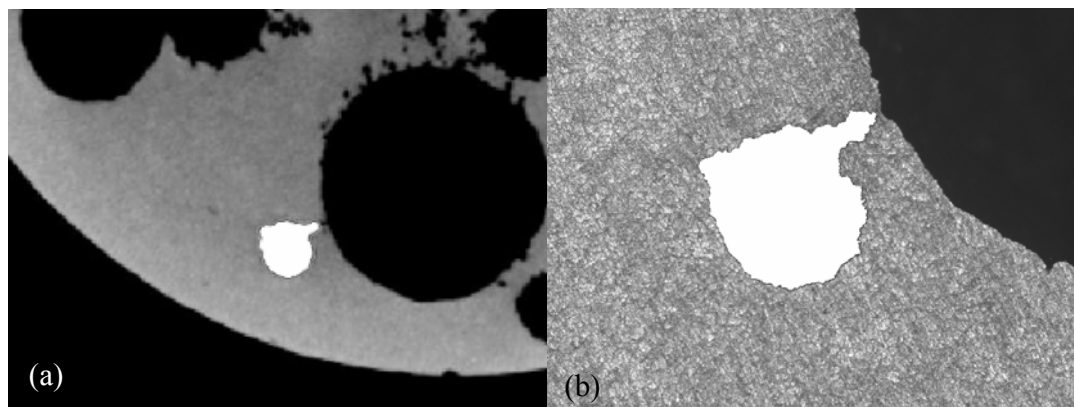


Figure 5. Comparison of a specific pore in CT representation (a) and metallographic examination (b).

Further analysis reveals that the pore sizes derived from the two methods have a mean deviation of 4.6 %, giving higher pore volumes for the CT-dataset. The deviation of the individual slices analyzed varied between -3 to 9 % depending on the morphology of the pore in that slice. From these results it can be concluded that metallography and CT data deliver comparable results where CT data slightly overestimates the size of the pores.

The next step was the evaluation of the pore volume with the appropriate transfer function and the comparison with the volume derived from the standard software. One specific feature from the volume was chosen and its size was evaluated by using both, the standard software and with the novel transfer function. Evaluation with the transfer function gives a pore volume of 8.189 mm³. This corresponds well with the volume obtained from the standard CT software, which is 8.222 mm³. It can be seen that the results are in reasonable agreement for the evaluation of pore sizes. Further comparisons for different pore morphologies and different pore sizes have to be conducted.

Conclusions

With the technique of multi-dimensional transfer functions a novel concept for the examination and evaluation of casting quality was presented. After discussing possibilities and limitations of CT as a tool for investigating different casting defects, the feasibility of the new method was exemplified for the porosity in a reduced pressure test (RPT) sample. Gradient magnitude transfer functions allow a reliable differentiation between pores and shrinkage cavities. Furthermore the novel feature size transfer functions allow the interactive classification of different pore sizes. Comparisons of the metallographic examination, standard CT-software tools and the new software concept correspond well for the given dataset from the RPT sample. As a consequence, it was shown that multi-dimensional transfer-functions represent a valuable new method for the analysis of CT data in assessing the quality of castings. This offers a unique visualization driven approach for the casting expert.

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