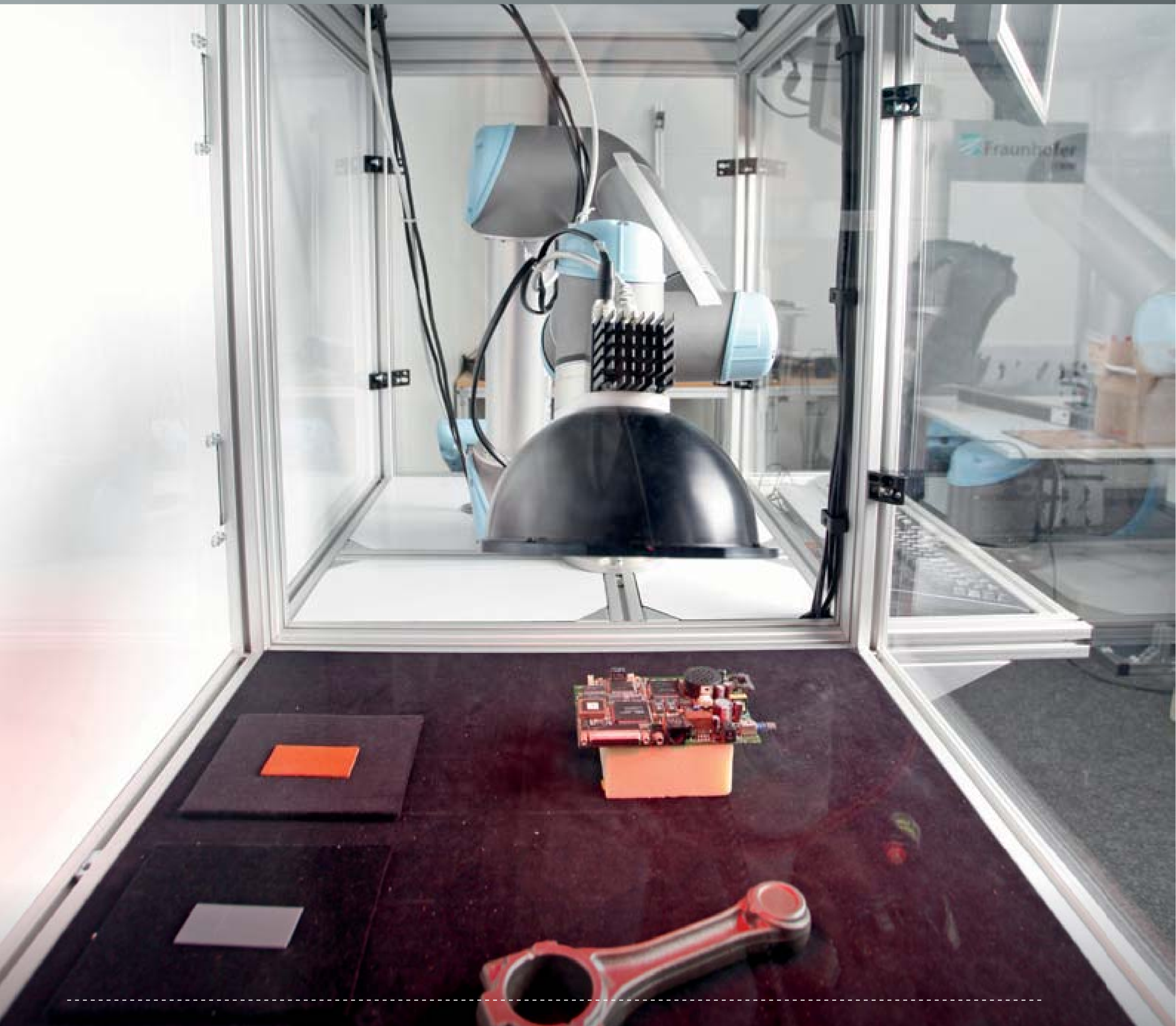
IMAGE PROCESSING



Robot-aided surface inspection of industrial components; The system on display in the department's showroom shows examples of two-dimensional and three-dimensional testing of different materials (leather, plastic, cast iron).

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HEAD OF DEPARTMENT

Image processing has become an important element of industrial production. Inspection systems have been part of production line planning in recent years, as opposed to the after-the-fact retrofitting of the past. One of the most important quality assurance measures today, is the surface inspection or the evaluation of the optical appearance of a product. The faults may be either functional or aesthetic, but an aesthetic "fault," being a subjective feeling, is especially difficult to represent as a mathematical model. One specific aim of the department is the development of mathematical models and algorithms for image analysis, primarily for industry software and use in production environments. The application range includes challenging surface inspection and the analysis of micro-structures. The micro and nano structures of modern materials are substantially determined by their macroscopic material characteristics. Analyzing the spatial geometry and relationships of the structural features of a material allows the optimization of the material characteristics by means of virtual material design. The department also develops algorithms for the characterization and stochastic modeling of such materials.

The overall goal of the Image Processing Department is to develop, in close cooperation with partners in industry and research, custom solutions in the field of image and signal processing.

MAIN TOPICS

- Quality Assurance and Optimization
- Surface and Material Characterization
- Image Understanding and Scene Analysis

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1 *Inspection system "MASC Stex 2"*

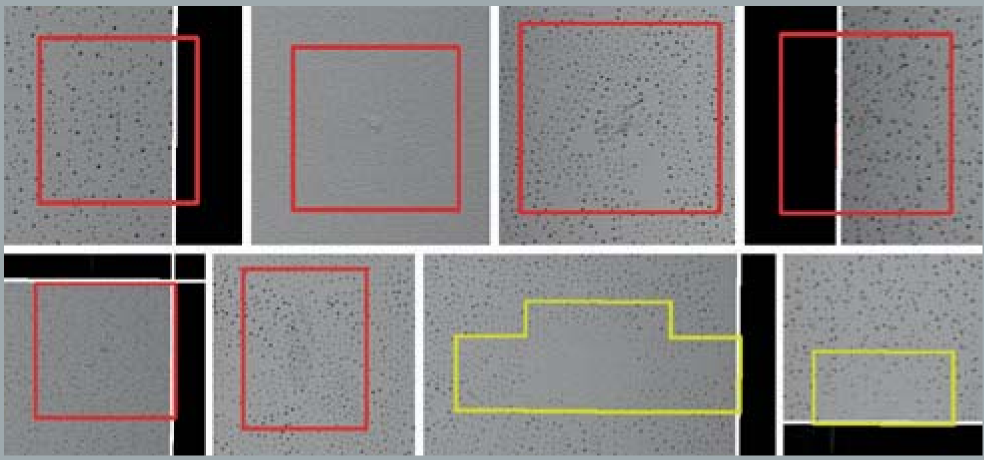
CEILING PANEL INSPECTION – MODEL-BASED LEARNING FOR SURFACE CONTROL

Industrial image processing is used for quality control in many production environments. First, every effort must be made to create optimal image acquisition conditions. The images are mathematically transformed by means of image processing algorithms in various ways to find the potential defect regions and, subsequently, to classify the product. Generally, finding such regions consists of a combination of traditional image processing methods like smoothing, segmentation, edge detection, morphological operations etc. However, the recent advances in Machine Learning, especially, in the area of Deep Learning, have intensified the wish to automate this aspect of industrial image processing and reduce the elaborate adaptation effort – the manual parameterization of large algorithmic chains. As a illustration of how the Image Processing Department is driving this automation and what limitations are encountered, we will use the surface inspection of mineral fiber panels.

The aim of the surface inspection of mineral fiber panels is to find defects in various design pattern. Typically, for many manufactured products, it is not possible to use a fully automated machine learning method for fault detection because of the infrequent occurrences of defects and because manual marking is time intense and expensive. Consequently, our approach assumes that the rejection rate is very low in good production systems. It follows that the majority of the panels produced can be classified as "good." In contrast to learning and representing all classes of fault, we learn the "good" products. This is one-class classification or, so called PU learning (positive and unlabeled data). If a new design or pattern must be learned under this method, the largest possible sample of the current production design is taken and it is assumed that this is a representative average. Using a sample of 20 to 200 panels, the one-class classifier can be trained.

At this point, it is essential to introduce prior knowledge of meaningful features – in other words: modeling of characteristics. Because of very different features in the ceiling panel illustration, we select two features to manage algorithmically and apply a binary classification learning method.

The first feature is the needling with its typical form, structure, and composition. The needling of a ceiling panel is rich in contrast and is well suited for fast segmentation. This is why we do not select pixels or generic regions as the calculation basis, but rather the segmented pinpricks. Because the pinpricks are stamped (i. e., applied mechanically), they should be geometrically similar in the "good" cases and more conspicuous in the bad/defective cases. We then calculate the appropriate features to include area, roundness, axial ratios, and average gray tone.



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2 *Examples of surface and design faults in the production of ceiling panels*

The second feature is the large-scale appearance of the panel, i. e., color application, the structural homogeneity, the existence or lack of pinpricks, the distribution, etc. In this case, local points or segmented regions are not used as the calculation basis, but the entire panel is divided into overlapping windows of a representative, but fixed size. The software calculates a feature histogram for each of these windows, which among other things, contains the gray value distribution and the ratio of pinpricks to background.

Using this training data, a one-class classifier for each of the feature classes is trained. For this purpose, a representation of the data is created by means of the so called k-Means-Cluster centers. Since different features are present in normal or good cases, an overrepresentation of the data is selected, that is, the specified number of cluster centers is intentionally too high. In the process, clusters with fewer representatives are deleted and a so called pruning takes place. While this method prevents so called over-fitting, it is noted that the random samples do not exclusively contain representatives of the normal or good parts, but they may also contain bad parts.

In the illustration, the actual classification is achieved by calculating the nearest-neighbor distance. Different distance functions are used because there are different feature types. The Euclidian distance is appropriate for geometric features of the needling, whereas for histogram distances the Mahalanobis distance is preferred. The focus of the inspection systems is set using threshold values for the described distances and can be adjusted during production. The surface and design faults that are detected in production with the method presented include discoloration, color blotches, and deviations in the pattern.

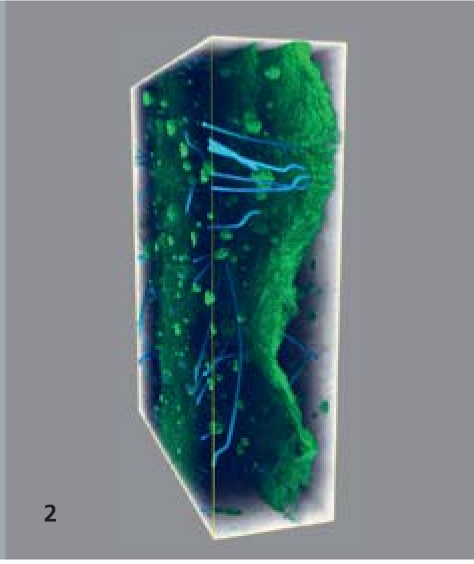


IMAGE ANALYSIS OF STEEL FIBERS IN CONCRETE

1 *The crack extracted from a conrete sample after testing (three-point bending test)*

2 *Volume rendering of a reconstructed tomography image*

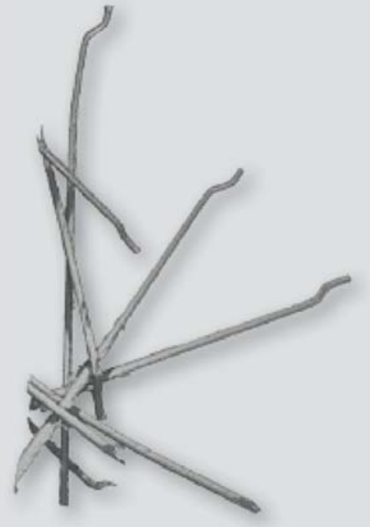
Steel fiber reinforced concrete is a composite material made of concrete and steel fibers, which are mixed in the liquid state. The features of the hardened material vary depending on the shape and dosing of the fibers. Some absorb forces better and some have a stabilizing effect on possible fractures in the event of cracking. Mathematicians from the Image Processing department are working in close cooperation with civil engineers at TU Kaiserslautern to better understand the effects of the admixture of steel fibers. Of major interest are how concrete behaves after a crack has formed and what role the addition of fibers plays. In simple terms, the fibers crack-crossing determine the post-cracking behavior of steel fiber reinforced concrete. Consequently, it is necessary to look at both the crack and the fibers for a proper analysis.

Previous methods for analyzing fiber orientation and quantity require the cracked area of the sample to be broken open or sawed, making an undisturbed analysis of the fibers impossible. However, analysis of the material using 3D imaging by computed tomography (CT scans) allows to inspect the cracked area. At the same time, this prevents biasing of results due to pulling out fibers when breaking the sample.

A special challenge in evaluating 3D images of steel fiber reinforced concrete is caused by the size of the analysis sample. The sample size is limited by the size restrictions of modern µCT technology and, in some cases, does not support a clear separation of fibers that are in contact with one another. Since individual fibers are required for the analysis, Fraunhofer ITWM has responded by developing an algorithm that separates aggregated fibers, so called fiber clusters, into individual objects. This allows the filtering of the crack-crossing fibers that are involved in the transmission of force, which in turn enables the subsequent determination of parameters such as fiber length, orientation, and bond length along the crack.

The algorithm for detecting and separating fiber clusters was developed with ToolIP (Tool for Image Processing), a software for creating image processing and analysis solutions. First, to locate all aggregations, the following method is performed: The distance between the two most distant points in every object is computed in the 3D image, whereby distances are measured only within the objects. The algorithm is based on a simplified model that assumes single fibers to have a cylindrical shape, whose length is the measured distance.

The model yields an estimated volume that is then compared to the measured volume of the object in the image. In the case of a fiber cluster, the volume is significantly larger than the one determined on the basis of the cylinder model. On the other hand, if the volumes are nearly



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the same, the algorithm classifies the object as a single fiber. If the 3D image being inspected is very noisy, a manual analysis of the borderline cases is necessary.

The separation of the aggregated fibers is then accomplished as follows: First, the algorithm reduces the surface noise by highlighting the fibers. For this purpose a decision is made for each surface location as to whether it is shaped cylinder-like. If yes, it is amplified and if not, it is attenuated. Finally, the algorithm estimates the location of the axis of the fiber by looking for points that are furthest away from the fiber surface. Along the thus located axes, the algorithm joins fiber segments by assigning the remaining points to the closest axis. Due to noise, sometimes over-segmentation (fibers consisting of several pieces) can occur and some pieces may even be missing. To close any resulting gaps, the algorithm enlarges all pieces found within the fiber's surface area. Using an interactive tool, the user assigns the few remaining segments to different individual fibers.

The method described above supports the analysis of steel fiber reinforced concrete by automating parts of the evaluation of this material. The engineer is not required to have expert knowledge of image processing.

3 *Example of a fiber cluster: Multiple single fibers in contact in an arbitrary spatial alignment.*

4 *Example of a segmented fiber cluster: Single fibers are recognized as different objects enabling their individual evaluation.*