# Surface Segmentation by Variable Illumination

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**Abstract**
Surface segmentation is a method to divide a surface into areas of homogeneous properties. Meaningful surface properties, such as the reflection characteristics or the local surface orientation, are derived from series of images by estimating the parameters of a reflection model. The images of the series show the surface illuminated from variable directions. A priori knowledge about the surface geometry can be used to improve the illumination strategy. Segmentation results often correlate with surface defects and thus can be applied as preprocessing step for a subsequent detection of defects. The performance of the approach is demonstrated with test specimens and cutting tools.

**Keywords**:
Surface topography, Image analysis, Automated visual inspection

## 1 INTRODUCTION

Segmentation is an essential processing step in surface analysis and machine vision. Its purpose is to partition surface or image data into a set of meaningful and disjoint regions. Examples of such connected regions are the different faces of a polyhedron, areas showing different machining textures, or defective and intact regions. Segmentation offers at least three advantages:

- It significantly simplifies subsequent signal processing steps needed to solve a data analysis task.
- At the same time, it leads to a better understanding of the contents of the data, because it describes a region in its entirety and not only as a set of data points.
- Finally, segmentation also plays a fundamental role when comparing or associating different data sets, as is the case when a part is inspected by comparison with a reference, or when different views of an object are fused to a single representation.

There are basically two types of information that describe the relevant properties of an object under investigation: the surface topography, and the optical properties of the surface [1]. Both magnitudes are a function of the lateral coordinates $\mathbf{x} = (x, y)^\mathrm{T}$. On the one hand, the topographical data can be obtained by mechanical or optical profilometers, but the data acquisition expense is often significant, the results not always satisfactory, and they usually lack information regarding the surface reflectance [2]. On the other hand, often grey level or colour images acquired with video cameras are used to accomplish the inspection task. This technique has another drawback: Though these intensity data partly rely on the optical properties of the surface, they also depend on the applied lighting. Obviously, both alternatives complement one another. However, analyzing multiple images recorded with a variable illumination can help avoid many of the shortcomings of intensity data. Furthermore, under certain assumptions the surface topography can be derived from such data, e.g. by using photometric stereo.

The first part of this paper focuses on surface analysis methods enabling to extract features that describe both the topography and the optical properties of the surface based on intensity data. To this end, different images taken with variable illumination are simultaneously processed. In the second part, the obtained surface descriptors are applied to segment the data, and the performance of the proposed approach is demonstrated with test specimens and cutting tools.

Unlike previously published approaches (see e.g. [3]), the presented method exploits illumination patterns to efficiently estimate surface reflection parameters, and uses the extracted parameters as features for segmentation.

## 2 SURFACE ANALYSIS

### 2.1 Illumination and image acquisition

The choice of a suitable illumination is crucial to ensure a reliable analysis of structured surfaces. Compared with multidirectional illumination patterns, especially with diffuse lighting, a directional illumination performed by a distant point light source generally enables a higher contrast. Unfortunately, this advantage is often accompanied by an undesired inhomogeneous appearance of the imaged structures. Moreover, inspecting arbitrary structures with directional illumination requires a dense variation of the position $(\theta, \varphi)$ of the point light source, where $\theta$ de-

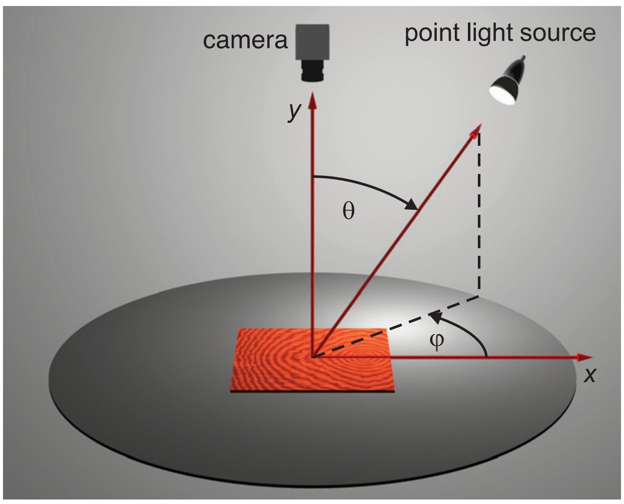


Figure 1: Distant point light source. The illumination space is defined by the azimuth $\varphi$ and the elevation angle $\theta$.

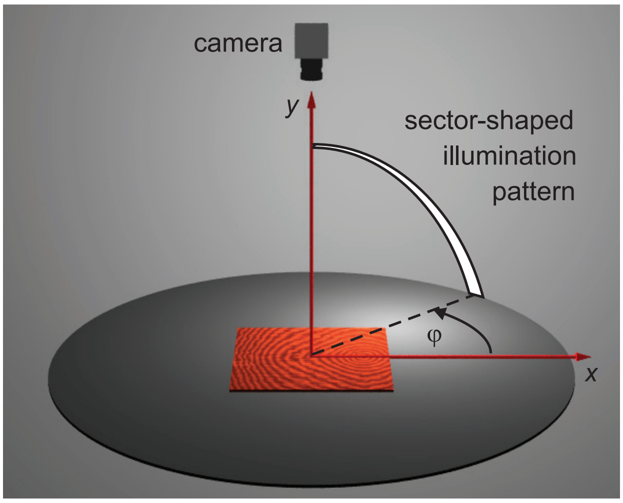


Figure 2: A sector-shaped pattern consists in a superposition of point light sources within the illustrated area.

notes the elevation angle and $\varphi$ the azimuth; see Figure 1. If, however, this effort is accepted, a notably higher amount of information on the inspected objects can be obtained as with a single image.

The feature extraction methods described in the following are based on the analysis of series of images $\{s(\mathbf{x}, \theta, \varphi)\}$ that were obtained by systematically varying the 2D position $(\theta, \varphi)$ of a point light source. Such series will be referred to as illumination series.

Beside point light sources, also variable illumination patterns can be used to generate image series. The term illumination pattern is referred to as any superposition of point light sources. A class of lighting patterns relevant in practice are the sector-shaped patterns, which are used to illuminate a surface from all elevation angles in the interval $\theta \in [0°, 90°]$ simultaneously; see Figure 2. Consequently, a sector series $\{s_S(\mathbf{x}, \varphi)\}$ is referred to as a 1D image series in which the sector-shaped illumination pattern varies only with the azimuth $\varphi$.

### 2.2 Reflection model

The local optical properties of a surface are specified by the bidirectional reflectance distribution function (BRDF) $\rho(\theta, \varphi, \theta_o, \varphi_o, \mathbf{x})$, which indicates how bright the surface at a certain location $\mathbf{x}$ appears, if it is illuminated from the $\theta, \varphi$ direction and observed from the $\theta_o, \varphi_o$ direction. The optical properties can be modelled by a superposition of different lobes, which describe the Lambertian (diffuse), forescatter, backscatter, and specular reflection; see Figure 3. By combining these models, the reflection properties of many surfaces can be approximated with sufficient accuracy [4].

For a large class of engineering materials, the diffuse and

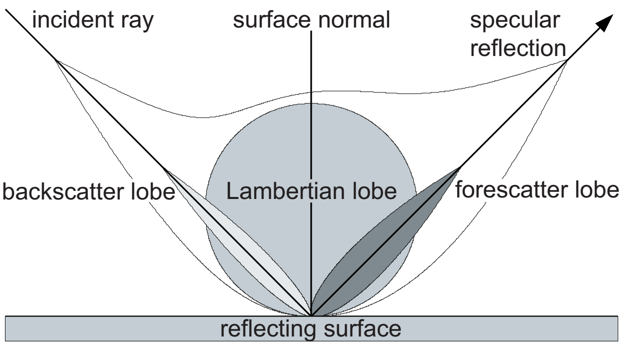


Figure 3: Incident light can be reflected in an ideal way, forescattered, diffusely reflected or backscattered.

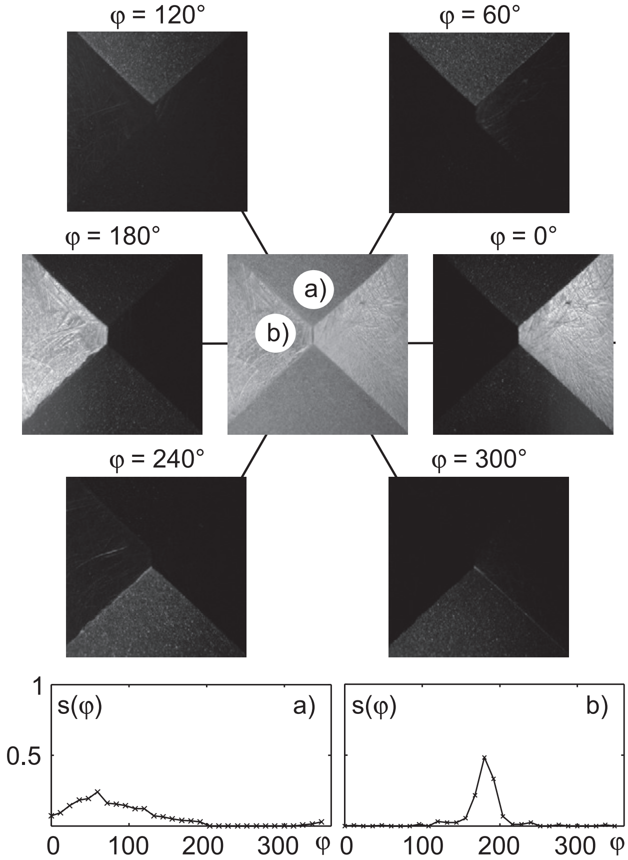


Figure 4: Six images of an illumination series of a pyramidal test object, taken with a sector-shaped illumination pattern. On the bottom, the intensity signals of the location a) and b), which feature a different orientation, are plotted. The maximum of the intensity signals is used to estimate the orientation $\phi(\mathbf{x})$.

the forescatter reflection predominate. Thus, the luminance $L$ at a fixed location $\mathbf{x}$, which can be assumed to be proportional to the intensities $s(\mathbf{x}, \theta, \varphi)$ recorded by a camera, can be modelled according to Torrance and Sparrow in one dimension by a superposition of a cosine-shaped diffuse component $\lambda_d L_d$ and a Gaussian forescatter component $\lambda_f L_f$ [5, 6]:

$$L = \lambda_d \cos(\theta - \theta_n) + \lambda_f \frac{1}{\cos(\theta_o - \theta_n)} \exp\left(-\frac{(\theta - 2\theta_n)^2}{2\sigma^2}\right). \qquad (1)$$

The factors $\lambda_d$ and $\lambda_f$ describe the strength of the respective lobes, $\theta_n$ denotes the angle between the local surface normal and the observation direction, and $\sigma$ is a measure of the width of the forescatter lobe.

### 2.3 Feature extraction

The parameters related to the reflection model (1) can be extracted as follows:

- First, the azimuthal orientation $\phi(\mathbf{x})$ is determined for each location $\mathbf{x}$ based on a sector series $\{s_S(\mathbf{x}, \varphi)\}$. Figure 4 shows such a series of a pyramidal object as well as the intensities $s_S(\mathbf{x}, \varphi)$ at two locations of the surface featuring a different azimuthal orientation. The value of $\varphi$ yielding the maximal intensity corresponds with the azimuthal orientation $\phi(\mathbf{x})$ at the corresponding location $\mathbf{x}$.
- The next step consists in analyzing a 1D illumination series recorded by varying the elevation angle $\theta$ of a point light source with the fixed illumination azimuth

$\varphi = \phi(\mathbf{x})$. The intensity signals $s(\mathbf{x}, \theta)$ resulting from these measurements are utilized to estimate the reflection parameters based on a least squares fit to the reflection model. The location of its maximum describes the orientation $\vartheta(\mathbf{x})$ in elevation direction. Meaningful parameters of the model include the width $\sigma(\mathbf{x})$ of the forescatter lobe, the local surface normal

$$\mathbf{n}(\mathbf{x}) = (\cos\phi(\mathbf{x})\sin\vartheta(\mathbf{x}), \sin\phi(\mathbf{x})\sin\vartheta(\mathbf{x})\cos\vartheta(\mathbf{x}))^{\mathrm{T}}, \quad (2)$$

and the strength $\lambda_i(\mathbf{x})$ of the different lobes.

In the following, these parameters will be used as features for surface segmentation.

## 3 SEGMENTATION

### 3.1 State of the art

Segmentation methods are often categorized into region-oriented and edge-oriented approaches. Whereas the first ones are based on merging regions by evaluating some kind of homogeneity criterion, the latter ones rely on detecting the contours between homogeneous areas. Despite segmentation is being widely treated in the literature, its application to series of images recorded with a varying illumination still remains a topic under investigation. This paper focuses on region-oriented methods. The obtained results will be compared with an edge-detection based approach proposed in [7]. The performance of both methods will be demonstrated by examining the surface of two different cutting inserts: a new part, and a worn one showing abrasion at the top of it; see Figure 5.

### 3.2 Region-based segmentation

Based on the surface normal $\mathbf{n}(\mathbf{x})$ computed according to (2), the partial derivatives with respect to $x$ and $y$, $p(\mathbf{x})$ and $q(\mathbf{x})$, are calculated. It is straightforward to use these image signals as features to perform the segmentation. To this end, a region-growing algorithm is applied to determine connected segments in the feature images [8]. To suppress noise, a smoothing of the feature images is performed prior to the segmentation.

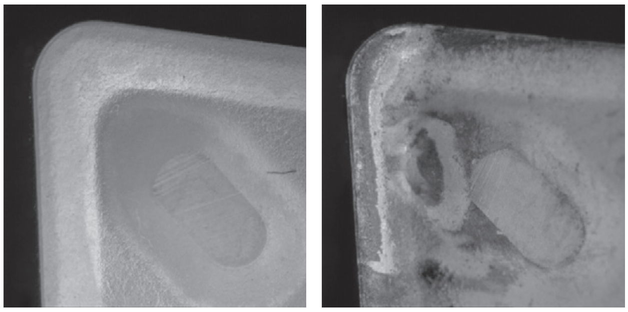

Figure 5: Test surfaces recorded with diffuse illumination: (left) new cutting insert; (right) worn cutting insert.

Figure 6 shows a pseudo-coloured representation of the derivatives $p(\mathbf{x})$ and $q(\mathbf{x})$ for both the new and the worn cutting insert. The worn area can clearly be distinguished in the second feature image $q(\mathbf{x})$. Figure 7 shows the segmentation results. The rightmost image features two regions that correspond with the worn areas visible in the feature image $q(\mathbf{x})$.

In this case, a subset of the parameters of the reflection model was sufficient to achieve a satisfactory segmentation. Further features of interest of the surface could be detected additionally by exploiting the remaining surface model parameters [3].

Figure 8 shows a segmentation result based on the model parameters $\lambda_d(\mathbf{x})$, $\lambda_f(\mathbf{x})$ and $\sigma(\mathbf{x})$. It was obtained by thresholding the three parameter signals, and then combining them by a logical conjunction. The right image of Figure 8 compares the segmentation result with a manual selection of the worn area. This result was achieved using a different raw dataset than for Figures 6 and 7. For this reason, the cutting inserts are depicted with both a different rotation angle and a different magnification.

### 3.3 Edge-based segmentation

Unlike region-oriented segmentation methods, edge-ba-

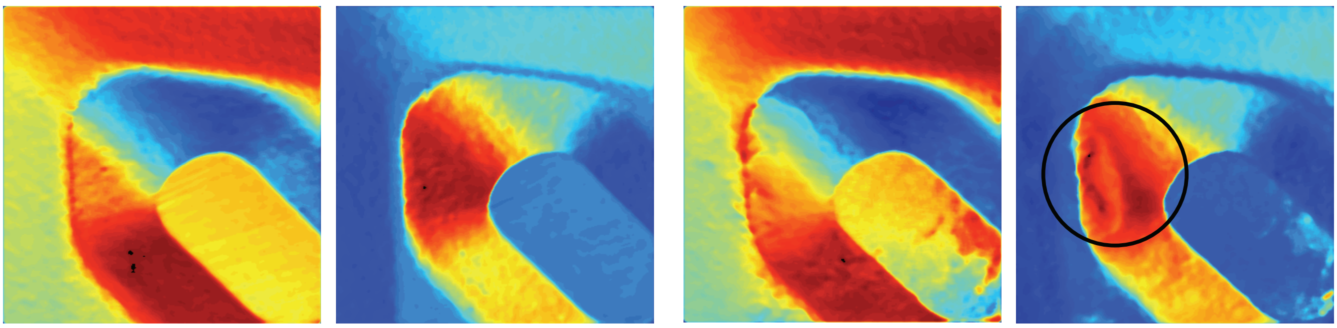

Figure 6: Pseudo-coloured representation of the derivatives $p(\mathbf{x})$ and $q(\mathbf{x})$ of the surface normal: (left) new cutting insert; (right) worn cutting insert. The worn area is clearly visible in area of the rightmost image as marked by a circle.

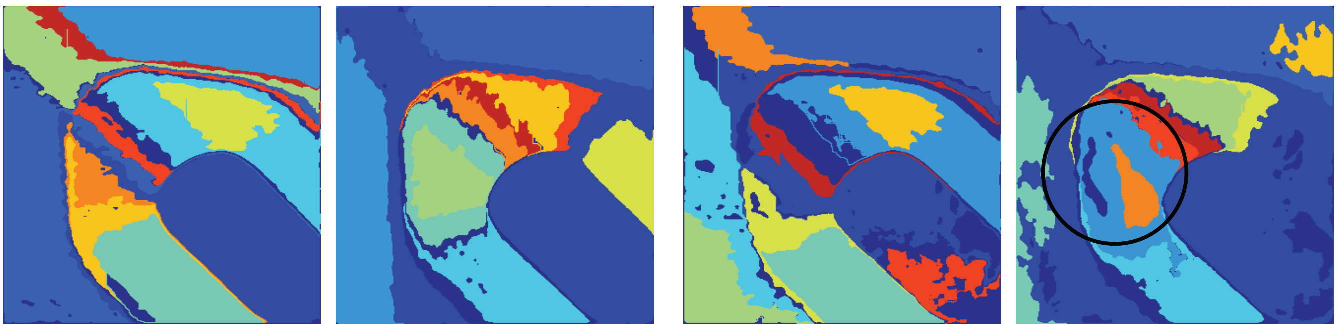

Figure 7: Results of the region-based segmentation of the feature images $p(\mathbf{x})$ and $q(\mathbf{x})$: (left) new cutting insert; (right) worn cutting insert. In the rightmost image, the worn regions were correctly discerned from the intact background.

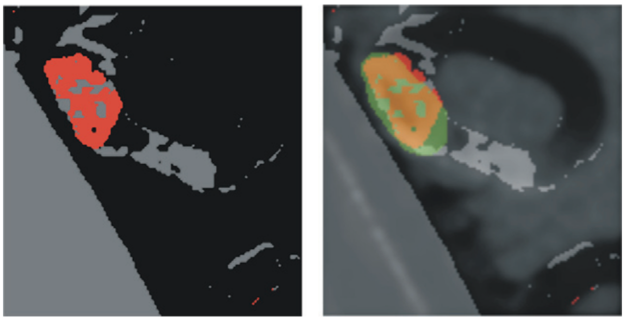

Figure 8: Result of the region-based segmentation of the defective cutting insert based on the parameters of the reflection model: (left) segmentation result; (right) overlay of an original image, a selection of the defective area by an expert (green), and the segmentation result (red).

sed approaches do not yield a set of disjoint regions but an image containing only contours. Edge-detection methods are based on amplifying local intensity differences. They do not only detect ‘true’ edges, which are due to changes of either the surface topography or the optical properties of the surface, but they also identify ‘false’ ones, which are caused by shadows and undesired reflections.

Much better results can be obtained by the method proposed by Pfeifer and Wiegers [7], which is based on filtering the images of an illumination series by a conventional edge detector and then checking for plausibility of the detected contour points. Thereby, ‘moving’ edges turned out to be more likely false ones, whereas ‘true’ edges remained stable over several images of the series.

Figure 9 shows the results of the edge-based segmentation that are obtained by the approach suggested in [7]. Although this method yields fair results and it also enables to distinguish the new tool from the worn one, the algorithm cannot discern between edges caused by changes of the optical properties of the surface and relief edges. Furthermore, as is the case with many edge detection methods, the resulting contours are generally not closed.

### 3.4 Discussion

The segmentation approaches presented in this section utilize significantly more information than conventional methods relying on the processing of a single image. Consequently, they are able to distinguish a larger number of surface characteristics. However, as is the case with most standard segmentation approaches, the edge-based method according to [7] still performs an analysis of intensity changes. In contrast to this, the region-based methodology allows to exploit multiple clearly interpretable surface features, thus enabling a discrimination of additional nuances. For this reason, a more reliable segmentation of surfaces with arbitrary characteristics can be achieved.

## 4 SUMMARY

In this paper, illumination-based methods to perform a robust segmentation of structured surfaces have been addressed. To this end, a reflection model describing the image formation has been utilized. Following, meaningful surface features, such as the reflection characteristics and the local surface orientation, have been extracted from series of images by determining the parameters of the model. The different images of the series were obtained by varying the position of the light source systematically.

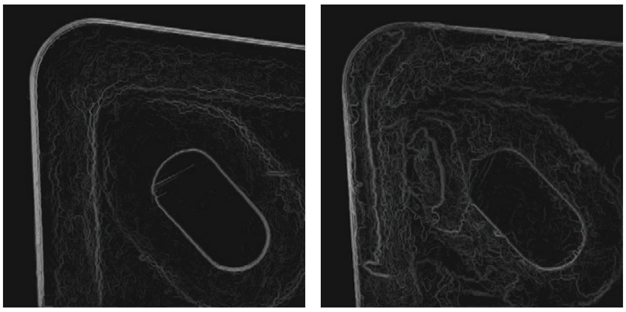

Figure 9: Results of the edge-based segmentation of the illumination series of the test surfaces according to [7]: (left) new cutting insert; (right) defective cutting insert.

To perform the segmentation, two different classes of methods have been discussed. Region-oriented approaches are based on merging regions by evaluating some kind of homogeneity criterion and allow a simultaneous consideration of multiple features. Edge-based approaches rely on detecting the contours between homogeneous areas and are typically sensitive to intensity changes. The performance and the potential of both approaches have been demonstrated with images of two different cutting tools.

The results demonstrate that illumination-based segmentation is a very promising approach. Particularly, thanks to the simultaneous analysis of multiple lighting situations, a more robust and precise segmentation of the areas of interest can be attained. The increased expense regarding the acquisition of the image data is more than compensated thanks to a simplified signal processing.

## 5 ACKNOWLEDGMENTS

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