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# Combining contour detection algorithms for the automatic extraction of the preparation line from a dental 3D measurement

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## ABSTRACT

Due to the increasing demand for high-quality ceramic crowns and bridges, the CAD/CAM-based production of dental restorations has been a subject of intensive research during the last fifteen years. A prerequisite for the efficient processing of the 3D measurement of prepared teeth with a minimal amount of user interaction is the automatic determination of the preparation line, which defines the sealing margin between the restoration and the prepared tooth. Current dental CAD/CAM systems mostly require the interactive definition of the preparation line by the user, at least by means of giving a number of start points. Previous approaches to the automatic extraction of the preparation line rely on single contour detection algorithms. In contrast, we use a combination of different contour detection algorithms to find several independent potential preparation lines from a height profile of the measured data. The different algorithms (gradient-based, contour-based, and region-based) show their strengths and weaknesses in different clinical situations. A classifier consisting of three stages (range check, decision tree, support vector machine), which is trained by human experts with real-world data, finally decides which is the correct preparation line. In a test with 101 clinical preparations, a success rate of 92.0% has been achieved. Thus the combination of different contour detection algorithms yields a reliable method for the automatic extraction of the preparation line, which enables the setup of a turn-key dental CAD/CAM process chain with a minimal amount of interactive screen work.

**Keywords:** Dental CAD/CAM technology, preparation line, medical process automation, 3D data processing, contour detection, pattern recognition, classification, rapid prototyping

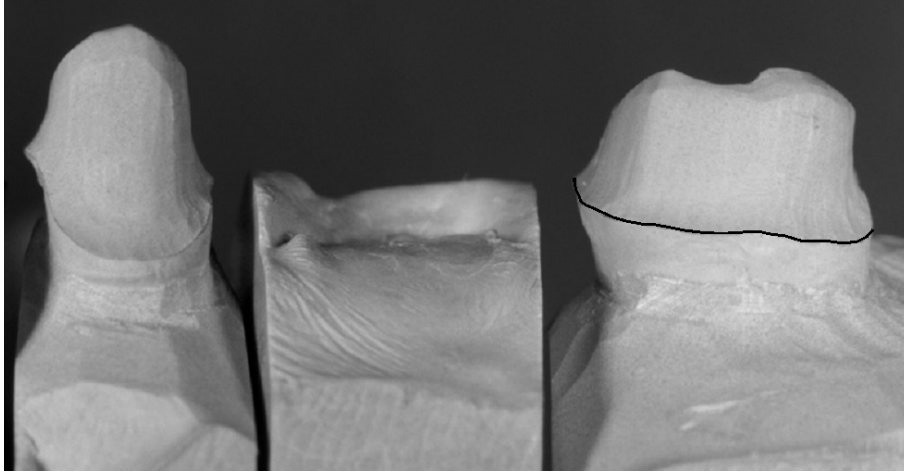
## 1. INTRODUCTION

During the last fifteen years, the use of methods from computer aided design and manufacturing (CAD/CAM) for the production of dental restorations has attracted considerable interest of both scientific and commercial nature.<sup>1,2</sup> The first motivation behind using dental CAD/CAM technology is the desire to reduce the production costs of crowns and bridges by means of automating time-consuming manufacturing processes which are conventionally performed manually. As an additional benefit, however, dental CAD/CAM technology makes it possible to use completely new restoration materials which cannot be processed by conventional techniques. In particular, high-performance ceramics like zirconium oxide can be shaped by a CAM-controlled milling machine. In clinical studies, zirconium oxide ceramics have been shown to surpass other restoration materials in strength, bio-compatibility, and esthetics.

For an efficient CAD/CAM-based production of dental restorations, it is desirable to minimize the necessary amount of user interaction. Most current dental CAD/CAM systems, however, still require a lot of interactive screen work by a specially trained person. The central steps in a dental CAD/CAM process chain are the 3D measurement of the prepared teeth, the analysis and processing of the measurement data, the design of the restoration (CAD), and the manufacturing of the denture (CAM).

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**Figure 1.** Master cast of a three-unit bridge preparation, consisting of two grinded teeth (dies) and the gap of a missing tooth in between (for demonstration purposes, the preparation line of the right die has been marked by a dark line in the figure).

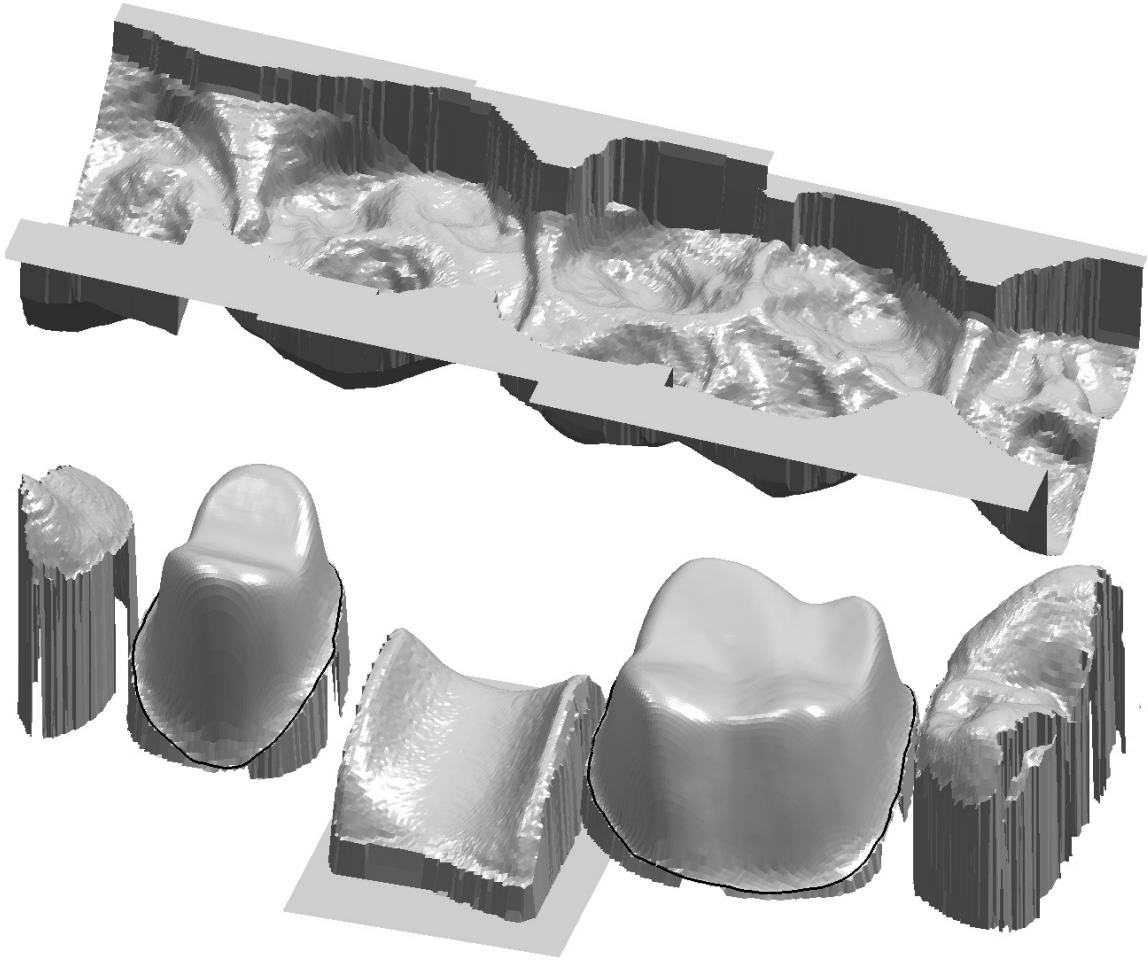
In this paper, we focus on the data analysis and processing step. Specifically, we present a method for the automatic extraction of the preparation line, which defines the sealing margin between a crown or bridge element and a prepared tooth (die, see Fig. 1). The accurate determination of the preparation line is a crucial prerequisite for the tight sealing of the restoration, which is necessary to prevent bacteria from causing secondary caries by entering the region between the die and the restoration.

The state of the art in dental CAD/CAM technology is the semi-automatically detection of the preparation line. Usually the user has to determine a set of start points interactively, which are used to extract the preparation line. In some systems a rough guess of the preparation line is provided, which has to be corrected and refined by the user. A third approach is to mark the preparation line before the scanning process by coloring the region below the preparation line. Furthermore, in some systems the automatic extraction is restricted to ideally shaped preparation lines which are rarely realized in clinical practice.

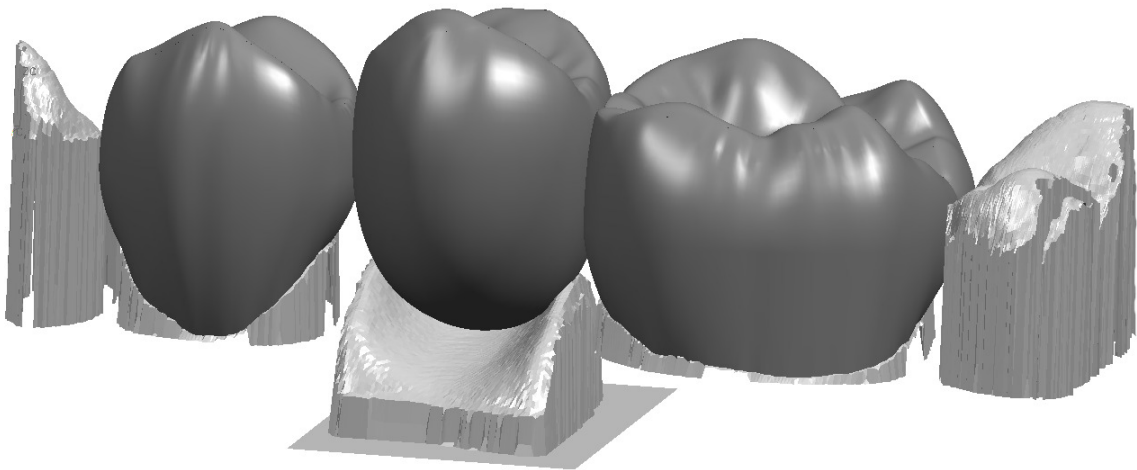
Before we proceed with the demonstration of our method for the automatic extraction of the preparation line in Sect. 2, we use the rest of this section to give a brief overview of our process chain for the fully automatic construction of dental restorations. The starting point is the master cast, a plaster model of the prepared teeth (see Fig. 1). This master cast is made by the dental technician from the impression of the prepared teeth.

The first step of any dental CAD/CAM process chain is the 3D measurement of the master cast. Several types of 3D scanners are being used in different dental CAD/CAM systems, which typically require measurements from different directions to capture the full 3D shape. As a consequence, all elements (dies, neighboring teeth, gaps of missing teeth) have to be measured on their own. Furthermore, the measurements of a single element from different directions as well as the measurements of different elements have to be registered with each other. For the design of the restoration, however, only those parts of the 3D shape are required that are visible from the direction in which the restoration will later be inserted. Within the scope of our research project, an interferometric scanner has been developed that measures only from this insert direction. As a consequence, we are able to measure several elements (dies, neighboring teeth, gaps) in a single scan without any subsequent registration.

The result of the measurement is a  $2\frac{1}{2}$ D height profile  $z(x, y)$  which contains dies, neighboring teeth, and, in case of bridge preparations, gaps of missing teeth. The further processing of this data, which includes the automatic extraction of the preparation lines, is described in detail in Sect. 2. Besides the master cast, an impression of the antagonistic teeth has to be measured by the 3D scanner to provide information required in the following design of the occlusion surface of the restoration. We end up with separate height profiles of all measured elements plus the extracted preparation lines of the dies (see Fig. 2).



**Figure 2.** Separated  $2\frac{1}{2}$ D measurement data (height profiles) of the dies, the neighboring teeth, the gap of a missing tooth, and the impression of antagonistic teeth, together with the automatically extracted preparation lines (shown as dark lines; for visualization purposes, the impression of antagonistic teeth has been elevated in the figure).



**Figure 3.** Final CAD geometry of the automatically designed bridge, together with the measurement data.

The central step of a dental CAD/CAM system is the design of the restoration geometry. In view of this, the key objective of our research project has been to develop an algorithm that automatically adapts the occlusion surface of a restoration to the surrounding tooth geometry by iterative shape modifications. Our algorithm imitates the steps of the manual design process of a dental restoration and is trained by dental technicians using concepts of machine learning. At this point, it should be obvious that the automatic design algorithm calls for the automatic extraction of the preparation line to ensure the efficiency of the whole process chain.

An example of the resulting CAD geometry, which is based on the B-spline representation of the underlying CAD system Unigraphics NX,<sup>3</sup> is shown in Fig. 3. In the final process step, these CAD data serve as the input of a CAM system, which prepares the production of the restoration by means of a milling machine or other manufacturing process.

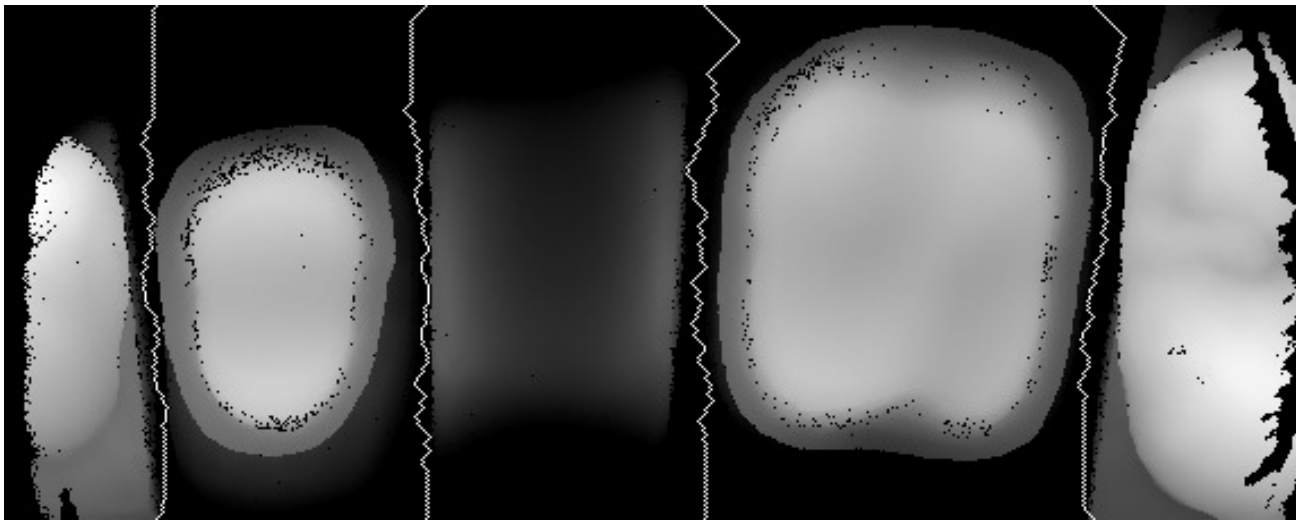
## 2. METHODS

### 2.1. Preprocessing

Our extraction of the preparation line is based on the  $2\frac{1}{2}$ D nature of the measurement data. We therefore assume that the preparation has been scanned as a  $2\frac{1}{2}$ D height profile, where the  $z$  axis is parallel to the insert direction and the  $x$  and  $y$  coordinates lie on an evenly spaced rectangular grid. In the case of full 3D measurement data, an appropriate conversion is necessary.

In all further considerations, we use the following coordinate system (see also Fig. 4): The  $z$  axis is parallel to the insert direction and points away from the jaw, the  $x$  axis is parallel to the linearized tooth arch and perpendicular to the  $z$  axis, and the  $y$  axis is perpendicular to the  $x$  and  $z$  axes such that a right-handed coordinate system is defined. In the context of image processing methods, we will refer to the coordinate pair  $(x_i, y_j)$  as the pixel  $(i, j)$  with the real-valued intensity  $z(i, j) = z(x_i, y_j)$ , where  $i \in \{1, 2, \dots, N_x\}$  and  $j \in \{1, 2, \dots, N_y\}$ .

The first step in our process chain (cf. Sect. 1) is the separation of the individual dental elements (dies, neighboring teeth, and gaps of missing teeth, see Fig. 4). For that purpose, we first determine minima of the sum of the  $z$  values along the  $y$  axis. For each minimum  $x_{\min}$ , the pixels  $(x_{\min}, 1)$  and  $(x_{\min}, N_y)$  are then used as start and end points for the determination of an optimal, i. e., minimal height, path that separates two adjacent elements. These paths are determined by means of the A\* algorithm.<sup>4</sup> The value of the cost function at the

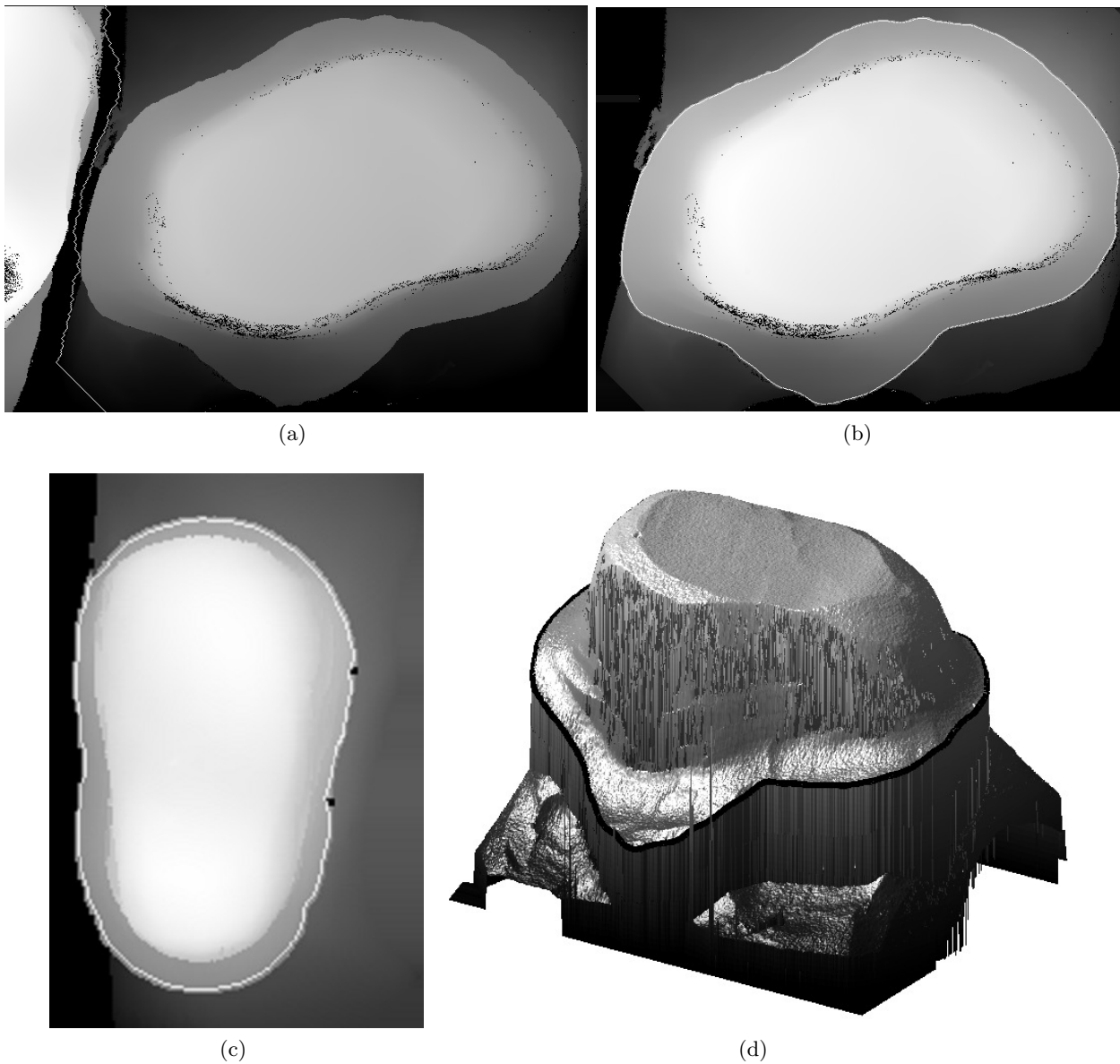


**Figure 4.** Grayscale representation of the common  $2\frac{1}{2}$ D measurement of the dies, the neighboring teeth, and the gap of a missing tooth (brighter pixels represent larger  $z$  values). The A\* paths separating the individual image elements are shown as white lines. Coordinate system: the  $x$  and  $y$  axes run parallel to the horizontal and vertical image axes, respectively, the  $z$  axis points out of the image plane, and the origin lies at the lower left corner of the image (right-handed coordinates).

path pixel  $(i, j)$  is proportional to  $z(i-1, j) + 2z(i, j) + z(i+1, j)$ , where the horizontal averaging increases the robustness of the algorithm.

## 2.2. Contour detection

Due to the  $2\frac{1}{2}$ D nature of the measurement data, the extraction of the preparation boundary reduces to a contour detection problem, which can be tackled by means of image processing methods. In the course of producing the master cast, the dental technician removes plaster material below the preparation line, as can be seen in Fig. 1. The preparation line is thus characterized by a discontinuity of the  $z$  coordinate of the height profile (see Fig. 5).



**Figure 5.** (a) Grayscale representation of the common  $2\frac{1}{2}$ D measurement of a single die with one neighboring tooth, together with the separation path (cf. Fig. 4). (b,c) Grayscale representations of separated dies, together with the automatically extracted preparation lines (shown as white lines). (d) 3D representation of a die and its preparation line (shown as a dark line).

Henceforth, the local gradient of the height profile is determined by applying Sobel filters in  $x$  and  $y$  direction and transforming the resulting  $x$  and  $y$  coordinates of the gradient vector to magnitude and direction values. From the gradient and height profile representations of the die, potential start pixels on the preparation line are extracted. A priori knowledge about the possible extension of the die and the preparation line enables the automatic extraction of these start pixels. Besides, the center pixel of the die is determined as the center of a 2D section parallel to the  $(x, y)$  plane at a given distance from the die top.

After these preliminary operations, the contour detection algorithms described below are applied one after another to obtain several different closed contours. The validity of each potential preparation line is then determined by a classifier which is described in Sect. 2.3 below.

**Contour following 1.** First, a contour following algorithm is applied to find a closed contour.<sup>5</sup> Beginning at one of the start pixels that have been extracted in advance, the next contour pixel is iteratively determined by the largest value of the gradient magnitude of the three neighboring pixels around the normal direction of the local gradient vector. The algorithm stops when the start pixel is reached again.

**Contour following 2.** As a variant, a second contour following algorithm is applied that makes use of the fact that the 2D projection of the preparation line onto the  $(x, y)$  plane often has a roughly elliptic shape. Instead of the normal direction of the local gradient vector, the normal direction of the local radius vector is used to determine the next contour pixel. The local radius vector is defined by the center pixel of the die and the current contour pixel.

**Active contour.** An active contour (snake) approach is used which is based on a closed spline contour.<sup>6</sup> The initial contour is determined by the start pixels that have been extracted in advance. The contour energy, which is influenced by the curvature of the contour and the local gradient magnitude at the contour pixels, is minimized by means of a simulated annealing algorithm.

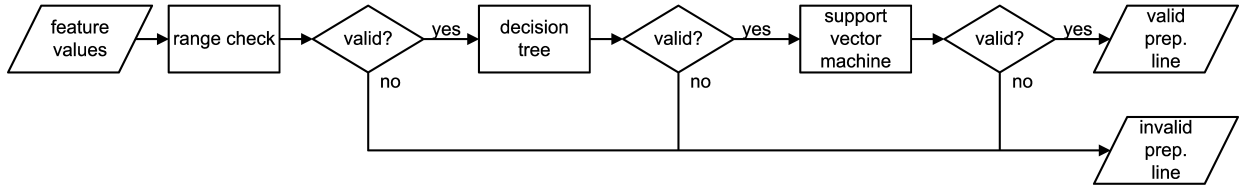
**A\* algorithm.** The A\* algorithm, already mentioned in the context of preprocessing in Sect. 2.1 above, is also applied to detect a closed contour.<sup>4</sup> Here, the start and end points are given by two start pixels on the contour that lie on roughly opposite sides of the center pixel. Two contours are detected between these start pixels, which are combined to form a closed contour. The cost function is proportional to the local gradient magnitude.

**Region growing.** Finally, a region growing algorithm is applied.<sup>5</sup> In contrast to the other algorithms, no start pixel on the contour is needed. Starting from the center pixel of the die as the seed pixel of the region, neighboring pixels are iteratively added to the region as long as the  $z$  value difference between a region boundary pixel and its neighbor pixel is less than a threshold  $z_{th}$ .

### 2.3. Classification

A classifier is used to decide between correct and incorrect preparation lines. Accordingly, for each potential preparation line a set of  $N_{ft}$  feature values,  $\{x_1, x_2, \dots, x_{N_{ft}}\}$ , is evaluated to classify it into one of the two categories “valid” and “invalid”. In detail, the values of the following features are calculated:

- extension of the preparation line in  $x$ ,  $y$ , and  $z$  direction;
- aspect ratio between extensions in  $x$  and  $y$  directions;
- minimal and maximal  $z$  difference between preparation line and die top;
- length of the preparation line in 2D (projection onto the  $(x, y)$  plane) and 3D, ratio between the length and the circumference of an approximated elliptic preparation line;
- average and maximal absolute derivative of the  $z$  coordinate of the preparation line;



**Figure 6.** Flowchart of the classifier working at three stages: range check, decision tree, support vector machine.

- average and maximal distance in the  $(x, y)$  plane between the preparation line and the closest edge;
- minimal distance in the  $(x, y)$  plane between two points on the preparation line which are separated by a given distance along the contour.

The classifier itself works at three subsequent stages. Those potential preparation lines that are classified as invalid at a certain stage do not enter the following stage (see Fig. 6).

**Range check.** At the first stage, a simple range check is performed, i. e., each feature value  $x_i$  is checked against a range  $[x_{i,\min}, x_{i,\max}]$  of correct values. The range boundaries  $x_{i,\min}$  and  $x_{i,\max}$  are determined from a training data set consisting of both correct and incorrect preparation lines, with additional knowledge input from human experts, i. e., dental technicians and dentists.

**Decision tree.** At the second stage, a decision tree classifies the remaining potential preparation lines as valid and invalid.<sup>7</sup> The decision tree is constructed from a training data set with the aid of the C4.5 algorithm.<sup>8,9</sup>

**Support Vector Machine.** At the third stage, those potential preparation lines that are still remaining are classified by a support vector machine (SVM).<sup>7</sup> First, the values of  $M$  highly distinctive features are selected to form a new set of normalized feature values,  $\{\tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_M\}$ , where

$$\tilde{x}_j = \frac{x_{i_j}}{x_{i_j,\max} - x_{i_j,\min}}.$$

From these values, an extended feature vector  $\vec{y}$  is constructed by including all polynomials of  $\tilde{x}_j$  up to second degree,

$$\vec{y} = (1, \tilde{x}_1, \tilde{x}_2, \dots, \tilde{x}_M, \tilde{x}_1^2, \tilde{x}_1\tilde{x}_2, \dots, \tilde{x}_1\tilde{x}_M, \tilde{x}_2^2, \tilde{x}_2\tilde{x}_3, \dots, \tilde{x}_M^2).$$

A linear discriminant vector  $\vec{a}$  is then determined from a training data set by means of an optimum margin perceptron algorithm.<sup>7,10</sup> Finally, a potential preparation line is classified as valid if the inner product  $\langle \vec{a}, \vec{y} \rangle > 0$ .

## 2.4. Comparing incorrect preparation lines

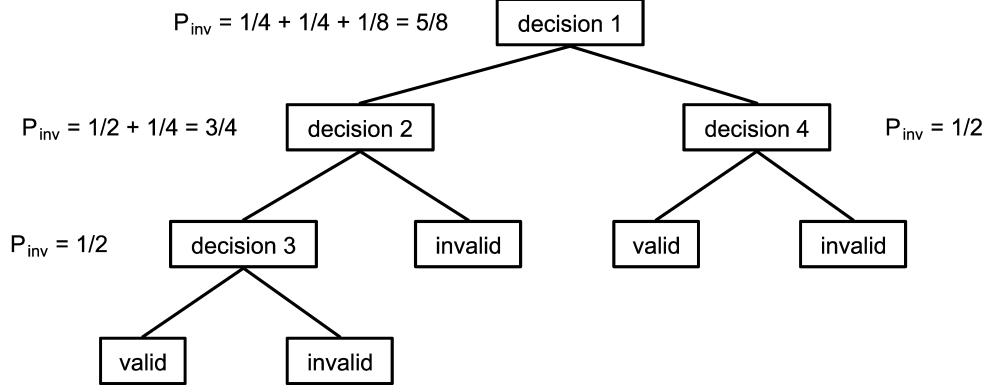
In the case that none of the extracted potential preparation lines has been classified as correct, it is desirable to present the “closest” of all incorrect preparation lines to the user, in order that he or she can decide by visual inspection if it is a correct preparation line or, if not, modify it interactively. We determine this closest preparation line by comparing the different extracted potential preparation lines at the three stages of the classifier, starting from the last stage.

**Support Vector Machine.** First, those potential preparation lines are compared that entered the SVM stage of the classifier. The comparison is based on the distance of the extended feature vector  $\vec{y}$  from the discriminant plane given by the vector  $\vec{a}$ . Henceforth, the error of a potential preparation line is defined as

$$e_{sv} = -\langle \vec{a}, \vec{y} \rangle.$$

The potential preparation line which possesses the smallest value of  $e_{sv}$  is regarded as the closest preparation line.





**Figure 7.** Example of a decision tree, together with the values of the probability  $P_{\text{inv}}$  to end up with an invalid preparation line from a particular decision node, assuming that each of the two results of an individual decision occurs with probability  $P = \frac{1}{2}$ .

**Decision tree.** If there are no potential preparation lines that entered the SVM stage, the comparison is continued at the decision tree stage. Here the comparison is based on the probability to end up with an incorrect preparation line from that decision node of the tree that precedes the particular category leaf which classified the potential preparation line as invalid (see Fig. 7 and caption). The error of a potential preparation line is defined as the sum over the invalid category leaves below the preceding decision node,

$$e_{\text{dt}} = \sum_{\text{invalid leaves}} 2^{-(d_{\text{lf}} - d_{\text{nd}})},$$

where  $d_{\text{lf}}$  and  $d_{\text{nd}}$  are the tree depths of the category leaf and the decision node, respectively. Again, the potential preparation line which possesses the smallest value of  $e_{\text{dt}}$  is regarded as the closest preparation line.

**Range check.** If there are no potential preparation lines that entered the decision tree stage, the comparison is continued at the range check stage. We first calculate the relative distances  $\Delta x_i$  of all  $N_{\text{ft}}$  feature values from the correct ranges  $[x_{i,\text{min}}, x_{i,\text{max}}]$ ,

$$\Delta x_i = \frac{[(x_{i,\text{min}} - x_i) \Theta(x_{i,\text{min}} - x_i) + (x_i - x_{i,\text{max}}) \Theta(x_i - x_{i,\text{max}})]}{x_{i,\text{max}} - x_{i,\text{min}}},$$

where  $\Theta(x)$  is the Heaviside function,

$$\Theta(x) = \begin{cases} 0 & \text{if } x < 0, \\ 1 & \text{if } x \geq 0. \end{cases}$$

The error of the preparation line is then defined as the sum of the squared feature distances,

$$e_{\text{rc}} = \sum_{i=1}^{N_{\text{ft}}} (\Delta x_i)^2.$$

As before, the potential preparation line which possesses the smallest value of  $e_{\text{rc}}$  is regarded as the closest preparation line.

### 3. RESULTS

For the training of the classifier, a data set consisting of 273 potential preparation lines has been used. These potential preparation lines have been extracted from the measurement data of 47 different dies, using the algorithms described in Sect. 2.2. After visual inspection and classification of the potential preparation lines by dentists and dental technicians, the classifier is trained by the learning algorithms described in Sect. 2.3.

In a subsequent test with clinical crown and bridge preparations containing 101 different dies, we were able to extract 93 correct preparation lines using our method, which is equivalent to a success rate of 92.0%. This success rate is achieved for measurements performed with our own  $2\frac{1}{2}$ D scanner, as described in Sect. 1. In addition, 15 restorations that were designed by our dental CAD/CAM process chain (cf. Sect. 1) have been produced using different materials and manufacturing processes. These restorations, which are based on measurement data from different 3D scanners, confirm the accuracy of the extracted preparation lines by tightly fitting the master casts.

#### 4. CONCLUSION AND DISCUSSION

In conclusion, we have shown a method for the automatic extraction of the preparation line from a measured  $2\frac{1}{2}$ D height profile of a dental preparation. The combination of different contour detection algorithms and a subsequent classification form the basis of a reliable automatic extraction of the preparation line without user interaction, also in clinical cases of unusually shaped, non-smooth preparation lines. The automatic extraction of the preparation line is a prerequisite for the efficient, automatic CAD/CAM-based production of high-quality dental restorations.

Although we started from the automatic treatment of side teeth, the extension of our method for the extraction of the preparation line towards front teeth turned out to be straightforward: Only the classifiers had to be adapted to front teeth. At the moment, our method is limited to the extraction of preparation lines of crown and bridge preparations. As a generalization of these, preparations of partial crowns are planned to be included in the preparation line extraction method. A further extension is given by inlay preparations which, however, require substantial modifications of the contour detection and classification algorithms due to the different properties of inlay preparation lines.

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