

## Optical Seam Following for Automated Robot Sewing

Georg Biegelbauer, Mario Richtsfeld,  
Walter Wohlkinger, Markus Vincze  
Automation and Control Institute  
Vienna University of Technology  
Gusshausstr. 27-29, 1040 Vienna, Austria  
{gb, rm, ww, vm}@acin.tuwien.ac.at

Manuel Herkt  
EADS Deutschland GmbH  
Corporate Research Centre Germany  
Dept. LG-CT  
81663 Ottobrunn (Munich), Germany  
manuel.herkt@eads.net

**Abstract**—Nowadays, robust and light-weight parts used in the automobile and aeronautics industry are made of carbon fibres. To increase the mechanical toughness of the parts the carbon fibres are stitched in the preforming process using a sewing robot. However, current systems miss high flexibility and rely on manual programming of each part. The main target of this work is to develop an automatic system that autonomously sets the structure strengthening seams. Therefore, a rapid and flexible following of the carbon textile edges is required. Due to the black and reflective carbon fibres a laser-stripe sensor is necessary and the processing of the range data is a challenging task. The paper proposes a real time approach where different edge detection methodologies are combined in a voting scheme to increase the edge tracking robustness. The experimental results demonstrate the feasibility of a fully automated, sensor-guided robotic sewing process. The seam can be located to within  $0.65\text{mm}$  at a detection rate of  $99.3\%$  for individual scans.

### I. INTRODUCTION

Textiles made of carbon fibres as integral part of structures and materials become more and more important for the automobile and aeronautics industries. Infiltrating the carbon fibres with resin, robust and light-weight components can be manufactured. So far, several layer of carbon fibre mats are stitched together in the preforming process to model the parts. But gluing these carbon fibre mats stresses the parts in the final hardening step and therefore, a new technology is needed to improve the preforming process. Sewing instead of gluing serves as enhancement of the mechanical part properties in terms of impact or toughness. Since sewing heads are adopted for robotics use, this process is predestinated to be automated, where Fig.1 shows an industrial robot with a blindstitching head sewing carbon fibre mats.

Traditional teach in programming for a flexible robotic production is no longer state of the art, hence, sensors are used to guide the robot for an autonomous behavior. To reinforce the structure of the carbon fibres the seams are set along the edges of the mats. Hence, the sewing process can be fully automated using optical sensors to follow these edges, which is the aim of the project REDUX<sup>1</sup>. In this project a laser range sensor is used in front of the sewing head to guide the robot along the carbon fibre edges. The novel contribution of this project is a fully automated sensor-guided sewing robot for carbon textiles.

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Fig. 1. Industrial sewing robot with blindstitching head.

Concerning the robot guidance, the challenging task is the reliable, robust edge detection and tracking in order to set the seams correctly. Laser range sensing is the given appropriate way of measurement. The difficulties to be handled are the black and reflective carbon fibres, which cause more noise and ghost points than other materials, an edge height less than  $1\text{mm}$ , and disturbances caused by spiky filaments. Fig. 2 gives an impression - in a close up view - of the typical unfiltered profile raw data. The jump-edge to be detected is indicated with a red ellipse. A further requirement is to detect the edges at a rate of at least  $30\text{Hz}$  to enable an efficient sewing process.

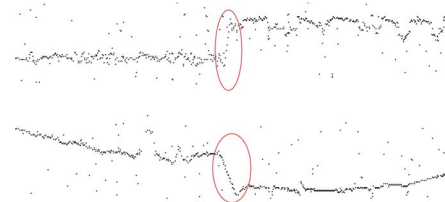


Fig. 2. Close-up view of different laser-stripe profiles including the edge.

The contribution of this paper is a reliable and robust method to detect the edge between two carbon fibre layers. First we introduce three different methods suitable to solve this task. While one is an adaptation of the model fit

technique [19], two new methods are introduced, the local weighted-voting and the accumulated gradient method. To obtain dependable results a two out of three voting scheme is applied. The experiments will show that the result is a detection rate of up to 99.3% for a localization of the edge within  $\pm 12$  pixels.

The structure of the paper is as follows: In the next section the state of the art of robotic textile sewing as well as the edge detection in 2D and 3D image processing is presented. Section II introduces a brief overview of the robotic system and its components. Section III introduces the signal preprocessing and Section IV the approach for the edge detection method is described in detail. Section V gives some experimental results concerning the detection performance and Section VI finally conclude the paper.

### A. State of the Art

1) *Sewing Robotics*: In the past two decades a lot of automated sewing machines and robots have been developed mainly used for the garment industries [12], [7], whereas a robotic sewing system handling carbon fibres has been proposed only recently [6]. The reason being is that only single side stitching can be used for this material. A distinction is drawn between blindstitching [3], the one side stitching with two needles [20] and the tufting technology [18].

The standard in robotic seam tracking using laser range sensors are mainly welding applications [16], [9]. Here, the seams are geometrically well defined and comparatively easy to detect in the range data. Nevertheless, first attempts have been made following textile seams on a planar workspace using a CCD-camera [8]. However, vision systems in textile robotics are mainly used to check the quality of the seam after the sewing process where the sewing thread is clearly visible [4], [1]. Summarizing to the best knowledge of the authors, the system described in this paper is the first using a laser range sensor for fully automated carbon fibre sewing.

2) *Edge Detection*: Edge detection is a popular issue in computer vision and well investigated. In our case we have to detect a dominating jump-edge in a noisy scan line acquired with a laser range sensor. One of the oldest detector is the Roberts operator [17] calculating the magnitude of the gradient using the approximated first derivative. This operator is very fast but sensitive to noise. Smoothing the raw data with a Gaussian filter and calculating the zero-crossings of the second derivatives improves the robustness as shown with the Marr-Hildreth edge detector [14]. The most popular operator is the Canny edge detector [2], well suited for noisy jump-edges. That is a multi-scale Gaussian-smoothed approach finding the locally strongest gradient using the second derivatives and is therefore, computational time consuming.

A totally different approach that is well suited for range images is the scan line approximation [10]. The raw data points are approximated by a set of bivariate polynomial functions, where the discontinuity of the fitted functions indicate the edge position. An improved scan line approach,

better handling outliers, is proposed by Katsoulas [11] using an additional statistical merging step. Based on these techniques we propose a real time edge detection method by voting the results of different detection methodologies to achieve robust results.

## II. SYSTEM APPROACH

Fig. 3 gives an overview of the system components and their interrelations. The robot used in this study is a KUKA 125/2, 6 axis articulated robot with a maximum speed of  $2m/s$  to implement a sewing velocity of up to  $2m/min$ . The laser sensor is mounted on the stitching head directly in front of the direction of motion (Fig.1). The robot stitching programs are created by a CAD path planning tool based on the CAD model of the shape and draping of the carbon fibre mats. These programs are uploaded onto the robot controller. Since the actual draping never correspond exactly to the model, the data of the laser sensor is processed to correct on-line the trajectory of the stitching head and to enable the autonomous seam following of the robot. The sensor detects and sends the actual edge position to the robot controller, which generates the corrected path.

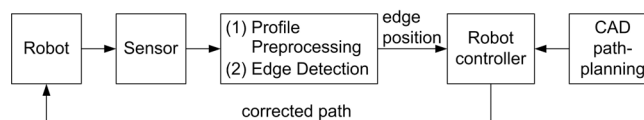


Fig. 3. Flow chart of the different components.

For the seam following task we use the laser-stripe sensor “BaseSensor” from Falldorf Sensor GmbH<sup>2</sup>. It is tuned to carbon fibres and produces a 2D profile of the mat surface. The width resolution of the sensor is  $0.054mm$  and the height resolution is  $0.11mm$  at an average measurement distance of  $109mm$ . Fig. 4 offers a closeup-view of the laser-stripe sensor and the stitching head. Processing of the laser sensor data consists of two main parts: (1) Profile Preprocessing and (2) Edge Detection.

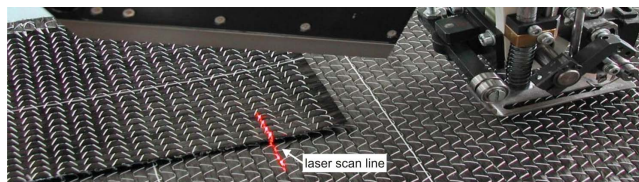


Fig. 4. Closeup-view of the laser-stripe sensor on the left and the stitching head on the right.

## III. PROFILE PREPROCESSING

The task of Profile Preprocessing is filtering the data from the sensor and normalizing it to correct for tilted and curved profiles.

The laser-stripe sensor delivers unfiltered point clouds that exhibit a non-linear relationship between the pixel position

<sup>2</sup><http://www.falldorfsensor.de/>

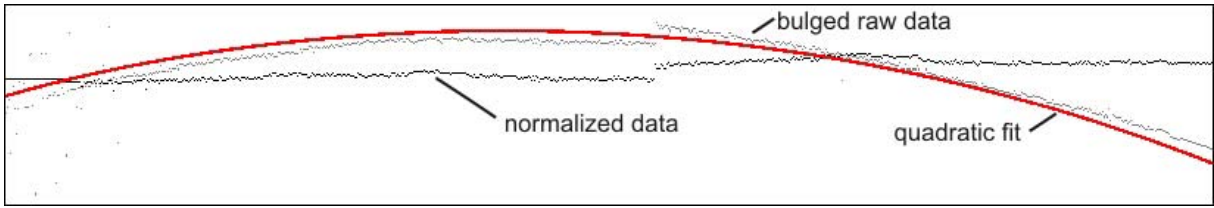


Fig. 5. Normalization of the laser-stripe profile in the preprocessing step.

in the camera frame and the real world distance. The height profile is transformed from camera coordinates to real world coordinates, which is solved by a bilinear transformation using a look-up table.

To eliminate the worst outliers and noise, the laser data of one profile is filtered sequentially by a geometrical filter and a closing filter.

The second task of normalization is to handle the different profiles shown in Fig. 6. In practice, demonstrated by manufacturing examples (shown in Section V), it is required to align the data to obtain a flat profile. This is necessary to apply global edge detection methods. *Global methods* for edge detection are working with the complete set of raw data points of one laser-stripe profile. Instead *local methods* only take a small number of pixels of the profile. Thus the algorithms for global methods are not able to find the edge of convex/concave or tilted edges, [13].

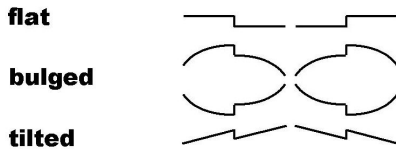


Fig. 6. Types of different edges and no edge types.

To normalize the different profiles a quadratic least-squares fit is used (Fig. 5). This least-square distance function adapts the curve to the profile data by finding minimal distance to all data points. This curve fitting preserves the edge and a normalized data profile is generated. The drawback of the data manipulation is that the original information about the height related to distance of sensor and the fibre mat is lost. To avoid this, the original unchanged data is saved in the system together with the new plane data profile. As a direct result of normalizing the data, filling the holes, caused from the previously filtering step, can be done through connecting boundary points with horizontal lines without causing artificial edges.

#### IV. EDGE DETECTION

This section describes how to detect the edge between carbon fibre mats in the normalized profiles. Of utmost importance is to obtain reliable detections over the range of different profiles in real-time. The idea to increase the true positive rate of detection is to use a voting over three complementary individual edge detection methods, an approach taken when building dependable systems such as for aviation.

Specifically, an edge is classified as detected correctly if at least two out of three methods find the edge within a certain tolerance. The complementary methods implemented are:

- **Model-Fitting:** global least-squares fitting of an edge model. This is adapted from [19].
- **Local Weighted-Voting:** the neighborhood of pre-selected edge candidates gives their vote weighted with the edge height. Voting is an established and robust method [15], which is introduced in edge detection.
- **Gradient-Accumulation:** sums up the gradient magnitude calculated with an increasingly kernel size. It is inspired by the Roberts operator [17] and mixes the global and local approach.

The following sub sections present the proposed edge detection methods in detail. The methods are based on laser-stripe profiles with a length of 1024 pixel.

##### A. Model-Fitting

In model based recognition the target object shape is represented by its geometry. E.g., a template represents an object as a rigid curve or an image. The advantage of model fitting is that the model encodes the object shape thus allowing predictions of image data. Coincidental features have less chance of being falsely recognized. To find the optimal template location a metric or a similarity measure is necessary that reflects, how well the image data match the template [19].

For an explicit description, the raw data points of a profile scan are defined as  $f(i)$  and the model-function of an upward jump-edge (compare the right column of Fig. 6). The height of the maximum and minimum pixel is given by

$$h(i, j) = \begin{cases} \min(f(i)), & i < j \\ \max(f(i)), & i \geq j \end{cases} \quad (1)$$

where  $j$  is the position of the edge. The concept of least-squares fitting is to find the global minimum of the squared distances from the model to the raw data points. Thus, the least-squares sum of a desired edge position is

$$S(j) = \sum_{i=1}^m d(i, j)^2 \quad (2)$$

where  $m$  is the length of the profile line and  $d(i, j)$  the distance function:

$$d(i, j) = f(i) - h(i, j) \quad (3)$$

Finding then the best fit, all pixel positions in the profile scan are evaluated and the one with the smallest sum wins:

$$\min(S(j)) \quad (4)$$

Note, due to computational efficiency a pre-selection of possible edge candidates is previously passed. The median value of all different heights of the data points in the profile scan is calculated and each time the gradient of  $f(i)$  crosses the normalized median line, these points are potential candidates for a probable edge position. This speeds up the computation approximately by the factor of 100.

### B. Local Weighted-Voting

The proposed approach works as a local method using weighted-voting of every pixel in a neighborhood of the considered edge using a kernel size of usually  $n = 75$ . At the beginning a pre-selection of potential edge candidate points is made calculating the absolute difference of neighboring pixels. The first thirty most significant edge candidate points are used for further processing. Considering a right oriented edge, the edge height – respectively the weighting factor – of each edge candidate is calculated with

$$w(j) = |\max(f(j+k)) - \min(f(j-k))|, 1 \leq k \leq 3. \quad (5)$$

To further improve robustness we exploit the following constraint. As already mentioned, spiky carbon filaments cause short but large jump-edges. To handle these unwanted edges the local average is calculated with

$$a(j) = \frac{1}{2n+1} \sum_{i=j-n}^{j+n} f(i) \quad (6)$$

and all points which cross the average get no weight for the voting process. Hence, the voting function is written as

$$v(i, j) = \begin{cases} j-i, & (i < j) \wedge (f(i) < a(j)) \\ i-j, & (i > j) \wedge (f(i) > a(j)) \\ 0, & (i > j) \wedge (f(i) < a(j)) \\ 0, & (i < j) \wedge (f(i) > a(j)) \end{cases} \quad (7)$$

with a voting factor  $i-n$ , respectively  $i+n$ , rating pixel stronger that are far away to the edge pixel. The weighted voting sum is finally given by

$$S(j) = w(j) \sum_{i=-n}^n |v(i, j)| \quad (8)$$

and the edge with the maximum sum considering only the pre-selected edge candidates wins:

$$\max(S(j)) \quad (9)$$

Note, that sometimes several fibres can be disconnected from the edge and then two new additional jump-edges are build. With this simple local method, the hit probability to detect the correct edge is higher compared to the model fitting method.

### C. Gradient-Accumulation

Generally, the position of a jump-edge is characterized through the maximum peak of the first derivative. Inspired by the Roberts edge detector [17] the scan line can be expressed as continuous height function  $f(x)$ . Hence, the magnitude of the gradient is given by

$$g(x) = \sqrt{\left(\frac{\partial f(x)}{\partial x}\right)^2}. \quad (10)$$

Because of the pixel quantization of the profile scan, the gradient has to be calculated on discrete values and can therefore be approximated with

$$g(i) = |f(i-n) - f(i+n)|, \quad (11)$$

where  $n$  is the kernel size for the approximation, usually  $n = 1$ . Applying the gradient filter of Eq. (11) on the noisy profile raw data  $f(i)$ , this will result as well end up in a noisy gradient function  $g(i)$ . Due to the small edge height compared to the noise, no significant gradient peak, indicating the edge position, can be detected. So with the classical approach, outliers and artifacts causes larger peaks then the edge itself and detection will fail. Increasing the kernel size  $n$  does not change this fact. Hence we propose a new summation function.

Considering the fact that we are searching for a global jump-edge shape, corrupted with noise, a multi-scale gradient calculation will suppress the noise of the local outliers and artifacts in the range data. Summing up the gradient functions for each pixel position with different kernel sizes, the correct edge is determined. The modified function  $G(i)$  calculates the accumulated gradients using increasingly kernel sizes:

$$G(i) = \sum_{k=1}^n |f(i-k) - f(i+k)| \quad (12)$$

with  $\{i \in \mathbb{N} \mid n < i < (m-n)\}$

where  $m$  is the profile length. Using a kernel size of 10% of every scan line has been found to be optimal with respect to calculation time and performance based on testing several thousand profiles. Finally, the maximum of  $G(i)$  localizes the position of the edge.

### D. Edge-Voting and Prediction

The above three edge detection methods are executed independently on each profile. The idea is to use two out of three voting to obtain a dependable result as it is common in aviation technology. The edge of one profile is considered detected successfully if at least two of three methods locate the edge within a certain tolerance. The evaluation below will show that, due to the noisy raw data, the edge detection based on a single profile is still not satisfactory. To further reduce the true negative rate, several profiles are considered depending on the robot velocity.

The robot controller needs every 100ms the actual edge position for correcting the path trajectory. The sampling rate of the laser range sensor varies from 30Hz to 100Hz depending on the reflectivity properties of the carbon fibre mats.

Therefore, three to ten profiles are available to determine the correct edge position. Assuming linear fibre mat edges in between two sampling instances ( $100ms$ ), all detected edge positions – inclusive the last transmitted edge position – are used for edge prediction. The final edge point is calculated using a RANSAC-based line fit [5]. This further increases robustness of edge detection as the next section will show.

## V. EXPERIMENTAL RESULTS

30 different seam examples and about 20,000 thousand profiles have been used to evaluate the above methods. All tests were performed on AMD Athlon 64X2 Dual Core 4800+ processor with 2GB RAM. First the edge detection behavior is shown on two examples of difficult cases, that is, a double edge and a tilted edge profile. Then the performance of the methods is evaluated concerning the computational effort and the true positive rate of detection.

### A. Double-Edges

When draping the fibre mats the fibre layers in some cases shift and the resulting edge looks like a double edge (Fig. 7). The Figure shows that the model-fitting method detects the correct edge (vertical line), because the sum of the distances is minimal in this position. The local weighted-voting method detects the same edge, because the voting factors increase the probability to detect the correct edge. The gradient-accumulation method detects also the correct edge by looking after the maximum in the sum of the first derivatives (see the course of the summed up gradient).

### B. Slant-Edges

Another problematic case is shown in Fig. 8, which plots a tilted laser-stripe profile with a slant edge after normalization. The interesting point in this case is that every method detects the correct edge, but at different positions in the area of the slant edge. This naturally occurs because the three methods implement three different criteria of edge detection.

In the edge-voting process at least two edge detection results in one profile must be located within a tolerance of up to 12 pixel to be considered for the edge prediction calculation. In contrast to the example of the double-edge, where all three methods detect the same edge position, in this case, only the model-fitting and the gradient-accumulation results agree and are used for the RANSAC-based edge prediction. Note, that Figs. 7 and 8 only show a single profile result, whereas the detected edges used for the edge voting are indicated with a thick vertical line.

### C. Duration and True Positive Rate of Detection

To obtain the result in real time all methods inclusive pre-processing must be sufficiently fast. For robotic sewing real time is dependent on the frequency of the sensor, which in turn depends on the sewing speed of the robot. All tests have been made under the same conditions, that is, the same fibre mat type, 1,100 laser-stripe profiles for a statistical analysis and an exposure time of  $12ms$ . Tab. I shows the results. When using all methods the worst enables operation

at  $250Hz$  and confirms the suitability of the method to obtain real-time operation. Adding the exposure time of obtaining a profile, an effective scan rate of  $62s^{-1}$  was achieved for these experiments.

TABLE I  
DURATION OF EVERY METHOD.

Methods	Min	Average	Max
Profile Preprocessing	0.638ms	0.679ms	1.314ms
Model-Fitting	0.129ms	0.132ms	0.397ms
Local Weighted-Voting	0.208ms	0.249ms	0.502ms
Gradient-Accumulation	0.375ms	0.384ms	1.744ms
Sum including edge-voting	1.445ms	1.445ms	3.957ms

Finally, the true positive rate of detection given a certain tolerance has been evaluated for the three edge detection methods and the combined edge-voting method. Evaluation is based on 2,000 semi-automatic hand labeled profiles from different mats such as exemplified in Fig. 2. A true positive detection is defined as a detection result within a certain pixel tolerance of the labeled edge. Tab. II shows the results which were achieved under the same conditions as before. Note that a tolerance of 12 pixels corresponds to  $0.65mm$ , which is totally sufficient for the sewing task. Also note that the slant edge in Fig. 8 extends over about  $2mm$  and the seam deviation can be several centimeters. When using the edge-voting method, only three times the robot controller could not be served with a valid edge position (totally scan: 1,100 profiles). The maximum deviation of the correctly detected edges was 12 pixel.

TABLE II  
TRUE POSITIVE RATE OF DETECTION OF EVERY METHOD.

Methods	$\pm 3Pixel$	$\pm 10Pixel$	$\pm 12Pixel$
Model-Fitting	85.7%	93.4%	94.3%
Local Weighted-Voting	81.5%	84.4%	86.7%
Gradient-Accumulation	65.3%	87.4%	94.3%
Combined pos. detections	80.4%	97.5%	99.3%

## VI. CONCLUSION AND FUTURE WORK

The research project “REDUX” which is partly presented, aims to close the gap between laboratory research and flexible industrial production. The approach of an automated CAD-based path planning and a sensor-guided seam following applied for the sewing process realizes lot-size-one production. The approach proposed in this work, detecting the carbon fibre edges by acquiring and analyzing a laser-stripe profile, presents a very robust way to compensate carbon fibre draping uncertainties.

For seam following three different methods are introduced to detect and track the edge in the presence of outliers and artifacts in noisy range data. The experiments show that a two out of three voting over these three methods achieves a detection result of 99.3% and the edges are located within  $0.65mm$ , which is totally sufficient for the sewing process, where draping is only accurate to a few centimeters. Also consider that for production it is not necessary that the edge can be detected correctly in each individual profile. Profiles

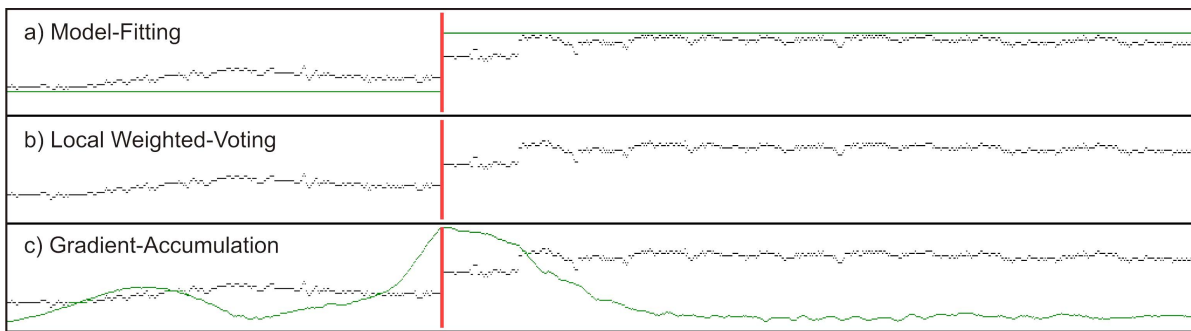


Fig. 7. All three different methods applied on a double edge: a) Model-Fitting b) Local Weighted-Voting c) Gradient-Accumulation.

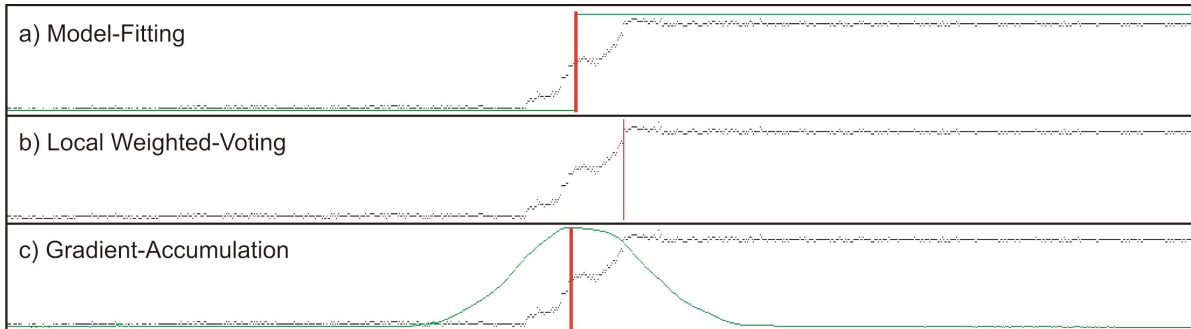


Fig. 8. All three different methods applied on a slant edge: a) Model-Fitting b) Local Weighted-Voting c) Gradient-Accumulation.

are obtained every  $0.02\text{mm}$  where several missed edges can be easily compensated.

The presented method shows very high reliability. Thus the approach for edge detection and localization is suited for use in related industrial applications under difficult conditions.

Further work will deal with the development and the prototype's integration of a new laser range sensor with three laser-stripes to increase the robustness and predictability of the edge tracking system. Therefore, a new calibration method will be needed to replace the lookup-table with an analytic solution.

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