

Article

Evaluation of Gap and Flush Inspection Algorithms in a Portable Laser Line Triangulation System Through Measurement System Analysis (MSA)

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Abstract

The shift toward Industry 5.0 places human-centred and digitally integrated metrology at the core of modern manufacturing, particularly in the automotive sector, where portable Laser Line Triangulation (LLT) systems must combine accuracy with operator usability. This study addresses the challenge of operator-induced variability by evaluating how algorithmic strategies and mechanical support features jointly influence the performance of a portable LLT device derived from the G3F sensor. A comprehensive Measurement System Analysis was performed to compare three feature extraction algorithms—GC, FIR, and Steger—and to assess the effect of a masking device designed to improve mechanical alignment during manual measurements. The results highlight distinct algorithm-dependent behaviours in terms of repeatability, reproducibility, and computational efficiency. More sophisticated algorithms demonstrate improved sensitivity and feature localisation under controlled conditions, whereas simpler gradient-based strategies provide more stable performance and shorter processing times when measurement conditions deviate from the ideal. These differences indicate a trade-off between algorithmic complexity and operational robustness that is particularly relevant for portable, operator-assisted metrology. The presence of mechanical alignment aids was found to contribute to improved measurement consistency across all algorithms. Overall, the findings highlight the need for an integrated co-design of algorithms, calibration procedures, and ergonomic aids to enhance repeatability and support operator-friendly LLT systems aligned with Industry 5.0 principles.

Keywords: laser line triangulation system; measurement system analysis; gap and flush measurement



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1. Introduction

The evolution of manufacturing towards intelligent, adaptive, and human-centric paradigms has placed measurement technologies at the heart of industrial transformation. Industry 5.0, emphasizing the synergy between human expertise and advanced automation, requires quality control systems that are not only precise but also flexible, resilient, and capable of supporting customization and safety across diverse production environments [1,2].

This evolution is closely intertwined with the broader transition toward digitalization [3], which is redefining industrial processes across sectors through smart technologies,

interconnected systems, and data-driven decision-making. Measurement systems are no longer isolated or purely manual instruments; they are becoming integrated platforms capable of real-time analysis, remote monitoring, and seamless communication with other digital assets. By combining advanced measurement capabilities with intelligent digital frameworks, manufacturers can achieve greater efficiency, traceability, and adaptability—laying the foundation for production environments that fully embody the principles of Industry 5.0 [4].

Within this broader transformation, the automotive sector exemplifies how digital metrology is reshaping traditional quality control practices. The integration of advanced sensors and automated inspection routines has become essential to meet the increasingly stringent aesthetic and functional requirements of modern vehicles [5]. Dimensional checks such as gap and flush—used to assess the alignment and surface continuity between adjacent body components—play a vital role in ensuring both visual appeal and aerodynamic performance. Their accurate detection is now a critical step in digitalized assembly lines, where precision and repeatability must coexist with speed and flexibility [6]. Gap refers to the lateral distance between two neighbouring surfaces, while flush quantifies the vertical offset between them. Historically, these measurements were performed manually using gauges and visual inspection, but such methods are increasingly inadequate in the face of tighter tolerances and the need for traceability. Laser triangulation has emerged as a robust alternative, offering non-contact, high-resolution data acquisition suitable for both in-line and off-line applications [7].

Recent research has explored various implementations of portable triangulation systems [8], including smartphone-integrated sensors [9–11] and robotic-mounted devices [12]. These solutions have demonstrated promising results in terms of mobility and integration with digital ecosystems [13]. However, a persistent challenge remains: the variability introduced by human operators when using handheld systems. While systematic errors can be minimized through calibration and design, operator-induced deviations continue to affect measurement reliability, especially in manual modes [14].

In manual measurement contexts, the role of the operator becomes a critical variable influencing the reliability of the acquired data. Even when using high-precision instruments, the absence of standardized handling procedures or real-time feedback mechanisms can lead to inconsistencies in positioning, orientation, and the interpretation of results. These uncertainties, often subtle and difficult to detect, can compromise the validity of the analysis and hinder process optimization [15].

To mitigate these risks, it is essential to equip operators with advanced support techniques that enhance measurement repeatability and reduce subjective influence. This includes the integration of algorithmic guidance systems, ergonomic fixtures, and intelligent interfaces capable of assisting the user during acquisition. By embedding such tools into the measurement workflow, the system can actively compensate for human variability, ensuring that the data collected reflect the true geometry of the components rather than the nuances of operator behaviour.

In response to this challenge, the present study builds on the existing G3F sensor, a portable Laser Line Triangulation (LLT) system previously reported in the literature for automotive applications [16], and introduces a novel contribution: a comparative analysis of three dedicated algorithms for gap and flush measurement. The key innovation of this work lies in evaluating these algorithms through a rigorous Measurement System Analysis (MSA), which systematically assesses their accuracy, repeatability, and reproducibility under varying operational conditions. While the G3F system itself is already established, this study provides new insights into the relative performance of the algorithms, highlighting how differences in mathematical modelling, signal processing strategies, and sensitivity to

environmental factors affect measurement reliability. This MSA-based comparison offers a robust framework for benchmarking laser-based gap and flush measurement techniques in real-world automotive scenarios.

Beyond this algorithmic comparison, this study also examines a modification of the G3F system in which a masking device is mounted to facilitate measurement by the operator. By contrasting the standard G3F sensor with the masked version, the research assesses not only algorithmic performance but also how hardware adaptations can influence measurement ease, precision, and reliability. This dual-level evaluation—algorithmic and hardware-assisted—provides a comprehensive framework for benchmarking laser-based gap and flush measurement techniques in real-world automotive scenarios.

Ultimately, the results of these analyses will provide a clear picture of both the measurement system's performance and the operator's influence on the process. By quantifying these effects and comparing algorithmic strategies, this study aims to advance the integration of intelligent measurement systems into human-centred manufacturing workflows, contributing to more resilient, adaptive, and user-friendly metrology solutions fully aligned with the principles of Industry 5.0.

This paper is organized as follows: Section 2 describes a summary of related works to select which algorithm to choose for deeper study; Section 3 describes the materials and methods; Section 4 presents the results; Section 5 presents the limitations of this study and conclusion.

2. Related Works for Algorithm Selection

The main novelty of this study is the systematic evaluation of the trade-off between measurement accuracy and processing time on an embedded platform using well-established stripe extraction algorithms. Although numerous works address laser stripe detection for Laser Line Triangulation (LLT) systems, quantitative studies that jointly assess metrological performance and computational cost within a unified benchmarking framework remain scarce, particularly for portable and embedded industrial applications. In the existing literature, algorithm selection is often driven either by accuracy considerations alone or by application-specific constraints, without an explicit comparison of how different methods balance precision, robustness, and execution time on the same hardware platform. As a result, practical guidelines for algorithm selection under real-time and resource-constrained conditions are still limited. This study aims to fill this gap by providing a fair and reproducible benchmark in which accuracy, repeatability, reproducibility, and processing time are evaluated simultaneously.

In particular, a review of the literature [17] reveals that stripe extraction algorithms for Laser Line Triangulation (LLT) system are generally categorized based on their approach to finding the centre, balancing accuracy against computational cost. The most common and fundamental methods cited are centroid-based algorithms (like the Grey Centroid—GC) [18] and Hessian-based algorithms (like the Steger method) [19]. Many recent studies focus on developing new algorithms and Artificial Intelligence (AI) techniques that modify or combine these methods to achieve higher accuracy. However, these enhancements often introduce further mathematical operations, increasing the processing time, which is unsuitable for the embedded system targeted in this work. An additional intermediate algorithm in terms of computational cost can join with the GC and Steger methods to perform the benchmark task, namely the Finite Impulse Response (FIR) algorithm [20]. Details of each algorithm chosen is described in Section 3.5 (Algorithms).

A recent study [14] employed the GC algorithm and performed a Gauge Repeatability and Reproducibility (GRR) analysis, reporting a gap GRR of 0.099 mm and a flush GRR of 0.075 mm on a real vehicle. In that work, the algorithms were executed on a smartphone

platform, and the measured cycle time per point was reported as 11 s; however, no details are provided on how this time was obtained. The main differences between [14] and the present study concern the hardware platform (professional embedded system versus smartphone), the filtering kernel size, the thresholding method, and the feature extraction algorithm applied to the profile. Further details of the proposed methodology are reported in Section 3 (Materials and Methods).

In recent years, machine learning (ML) and AI have emerged as promising approaches to improve the accuracy and adaptability of LLT systems. Instead of relying purely on analytical models, AI-based methods can learn the mapping between image intensity distributions and stripe centre positions directly from data. Neural network architectures, such as convolutional neural networks (CNNs), have been trained to detect laser stripe centres with sub-pixel accuracy even under challenging conditions like varying surface reflectivity, ambient illumination, or partial occlusion [21]. Other approaches exploit deep regression models and autoencoders to denoise and enhance stripe profiles prior to extraction, thereby reducing sensitivity to sensor noise and optical distortions. Recent studies further show that integrating a neural network segmentation stage to isolate the stripe region, followed by sub-pixel centre extraction on the cleaned area, achieves higher accuracy and lower computational cost compared to full-image Hessian methods [22]. This combination of semantic segmentation and geometric refinement enables robust operation under difficult optical conditions while concentrating computation on the relevant region and minimizing stray light artifacts.

While these AI-driven solutions can significantly improve robustness and accuracy, they often require substantial computational resources and large training datasets, making them less suitable for real-time embedded implementations. Nevertheless, they represent a growing research direction for adaptive and self-calibrating triangulation sensors that can outperform traditional model-based algorithms in uncontrolled environments.

3. Materials and Methods

3.1. Methodology

The methodology adopted in this study has been structured to provide a clear and systematic assessment of the portable LLT system under investigation. The block diagram reported in Figure 1 shows the measurement procedure adopted. First, the sensing technology related to LLT is introduced, with a detailed description of the G3F sensor and the experimental test developed for gap and flush measurements on an automotive body. Subsequently, the image processing pipeline is presented, including the image pre-processing phase and the gap and flush extraction stage, where three different algorithms are introduced and discussed, highlighting their operating principles and implementation within the measurement workflow.

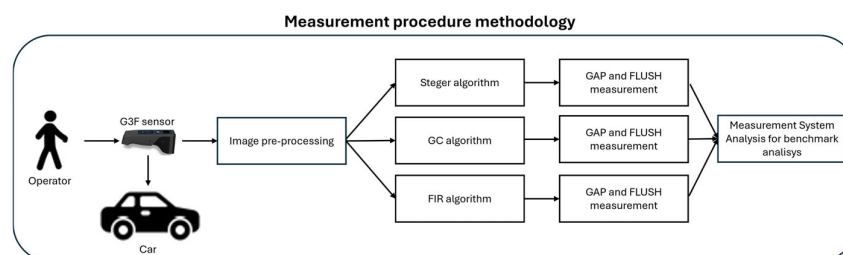


Figure 1. Block diagram describing measurement system methodology.

Finally, a Measurement System Analysis (MSA) is performed to assess the performance of the proposed algorithms, evaluating measurement uncertainty, repeatability,

reproducibility, and processing time, in order to compare their accuracy and computational efficiency [23].

This structure enables a comprehensive understanding of how hardware setup, measurement system performance, and algorithmic strategies jointly influence the reliability of gap and flush measurements in automotive applications. Within this framework, the flush value is equal to the distance between the straight line of a reference surface and the edge point on the other side; in practice, both the reference line and the edge point are geometric features that must be detected. The gap value is evaluated as the distance between the circles of surfaces; these circles are likewise geometric features extracted from the measurement data. Figure 2 shows two adjoining components (solid lines) together with these geometric definitions of gap and flush [9].

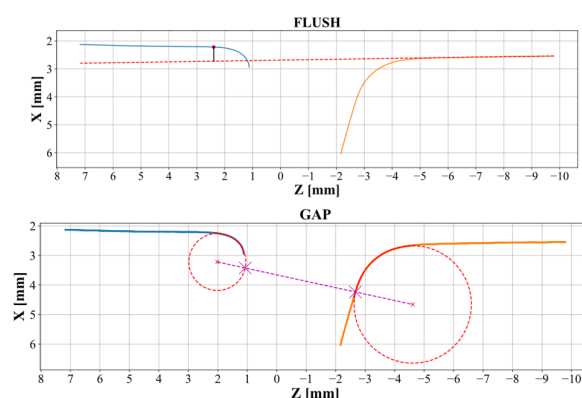


Figure 2. Flush and Gap definitions. The left profile is identified in blue and the right profile in orange. The extracted features are highlighted in red: the circle for the gap and the straight line for the flush. The distance between the two identified gap centers, shown in purple, is included to improve visualization.

3.2. Core Technology: Laser Stripe Detection and Centre Estimation

The core task of an LLT sensor is to accurately determine the centre of the laser stripe in each column of the image, as this information forms the basis for the subsequent reconstruction of the observed object's profile. The laser beam profile can typically be approximated by a Gaussian distribution; therefore, along each image column j , the intensity of the laser line in the image can be represented as $I(i, j)$, where i denotes the pixel position within the column. After applying an appropriate intensity threshold, only pixels whose values exceed this threshold are retained as part of the laser stripe, as demonstrated in Figure 3 for (1). These selected pixels define the region of interest on which sub-pixel localization algorithms are applied to compute the stripe centre.

$$I(i, j) : i \in [k; n] \ \& \ I(i, j) \geq \text{threshold}. \quad (1)$$

In this context, it is essential to determine which laser stripe extraction algorithm is most suitable for real-time processing on an embedded system. The analysis will focus on several well-known algorithms, evaluating their performance in terms of precision and processing time when executed on a low-power CPU. The objective is to quantify the trade-off between measurement uncertainty and computational cost for a general-purpose LLT sensor controlled by a System-on-Module (SoM) platform.

Additionally, this study aims to assess how ergonomic modifications of the sensor influence its overall performance, and how these effects compare to the performance variations introduced by different centre detection algorithms.

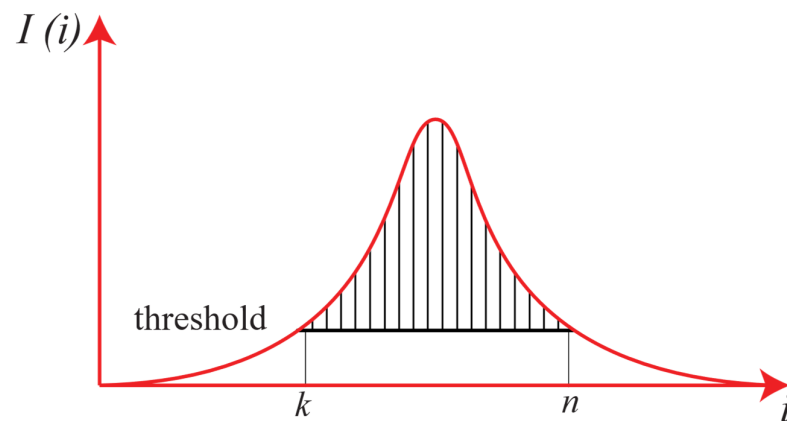


Figure 3. Gaussian profile with a threshold that determines where the laser stripe starts.

3.3. Measurement Setup

In this work, the G3F sensor from U-Sense.IT srl is used (Figure 4a), which is a manual, wireless, portable laser profilometer. To obtain the LLT Field of View (FOV), the components shown in Figure 5 are required:

- A laser source (blue in the figure) that projects a thin, straight-light plane;
- A camera, composed of a CMOS sensor combined with a lens system (represented as the yellow pyramid frustum).

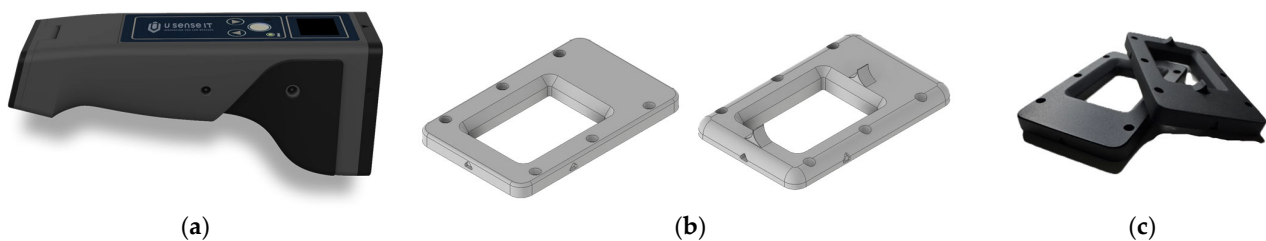


Figure 4. (a) G3F sensor; (b) standard soft sensor front panel (left) and prototype panel with alignment teeth (right); (c) real front panels.

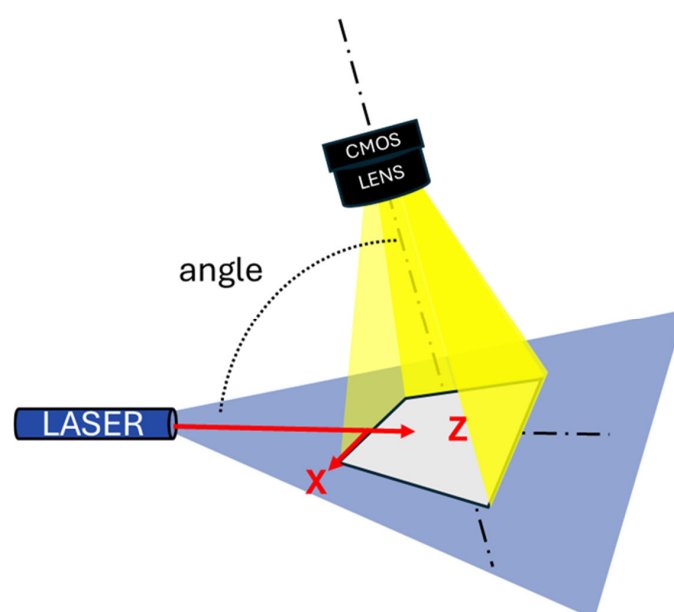


Figure 5. LLT FOV definition (grey) as interception of camera pyramid frustum FOV (yellow) and laser plane (bright blue).

An angle is formed between the optical axis of the camera and that of the laser. The interception of the camera's FOV with the laser plane defines the sensor's trapezoidal measurement area [24].

The G3F sensor interacts with the contact surface through a soft front panel positioned in front of the optical assembly (the design of the soft panel is shown on the left in Figure 4b,c). The repeatability of the contact point has the greatest influence on the overall measurement uncertainty, as previously investigated in [16]. In this paper, an improvement in performance achieved through a more ergonomic and cost-effective design is presented. In this revised design, alignment teeth for both the gap and the flush have been added to the front panel, as shown on the right side in Figure 4b,c. This modification represents a low-cost design enhancement that improves positioning repeatability and user handling.

Table 1 describes the G3F FOV, defined along the Z-axis from the trapezoidal minor base at $Z = 0$ mm to the major base at $Z = 12$ mm. The plane at $Z = 0$ mm corresponds to measurements performed in contact with the sensor front panel, while the major base is located 12 mm away from it. Figure 6a shows the orientation of the axes with respect to the sensor front panel, and Figure 6b shows the sensor's FOV.

Table 1. Sensor's FOV description.

	$Z = 0$ mm	$Z = 12$ mm
X range	± 8.5 mm	± 11 mm
X Resolution	$7\ \mu\text{m}$	$9\ \mu\text{m}$
Z Resolution	$9\ \mu\text{m}$	$9\ \mu\text{m}$

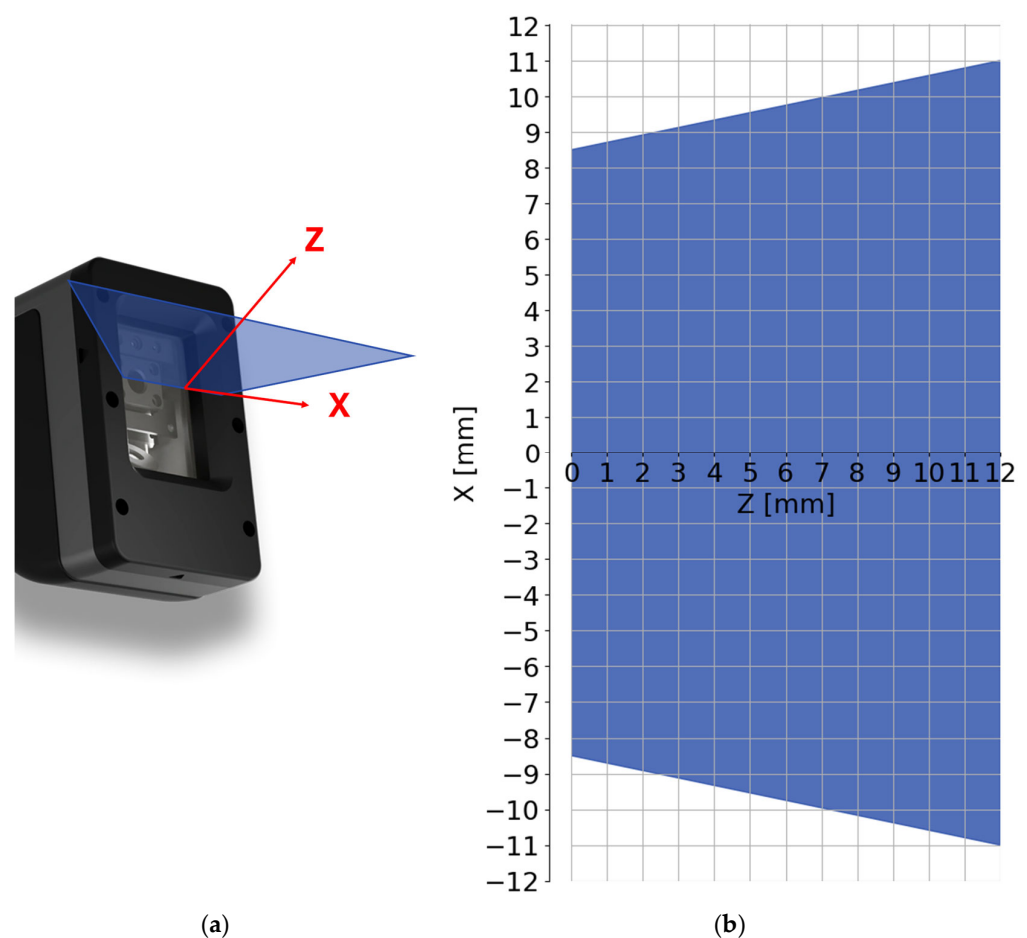


Figure 6. (a) The orientation of the FOV on the sensor; (b) the shape of the sensor FOV in millimetres.

3.4. Measurement Test Procedure

To perform this benchmark task in a controlled manner, a single set of images was used. Images were acquired from 14 different points on the same car, 7 for each side as shown in Figure 7, by four different operators. Each operator acquired the same point 3 times in a random order. This set was acquired under two distinct working conditions (“with” and “without alignment teeth”). Using the same image set ensures that all three algorithms are tested against the exact same input data, allowing for a direct comparison of their GRR performance and processing speed.

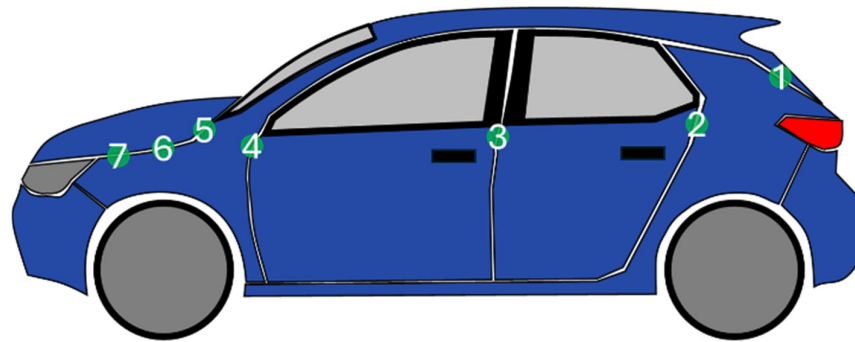


Figure 7. Seven measurement sequence points are shown in green on the car’s left side. On the right side, the same seven points are positioned in corresponding locations.

As reported in the manual [23], a minimum number of 10 points should be acquired. In the same manual, the examples are recorded by two or three operators. To increase the statistical relevance, we conducted the study with four operators chosen considering four distinct levels of technology knowledge: producer knowledge, high technology knowledge, medium technology knowledge, and basic technology knowledge.

3.5. Algorithms

The measurement obtained by LLT is based on image acquisition. This context makes it possible to leverage standard Computer Vision pre-processing strategies to improve the robustness and accuracy of the data, primarily by reducing noise.

However, the industrial environment introduces numerous challenges that complicate the reliable extraction of the laser stripe centre. The primary challenges include the following:

- Image noise: requiring de-noising strategies (e.g., Gaussian, mean, or median filtering [17]);
- Surface irregularities: such as specular reflections or abrupt changes in colour or material;
- Laser stripe variations: where surface irregularities cause fluctuations in the stripe’s thickness and intensity, producing heterogeneous regions in the image.

There are three main processing stages that influence the final measurement value. The first stage, image pre-processing, addresses noise and background identification [17]. The output of this stage is a denoised and properly cropped image, optimized for subsequent analysis. The second stage comprises laser stripe extraction. After applying the calibration functions, this stage produces one or more profiles representing the reconstructed geometry. To extract the laser stripe centreline with high precision, we employ the GC, Steger, and FIR algorithms. Finally, the third stage consists of feature extraction from the obtained profiles. In this phase, the relevant geometric features are computed to produce the final measurement output.

3.5.1. Image Pre-Processing

After analysing the noise present in the images acquired by the sensor, it is observed that the noise is predominantly impulsive rather than Gaussian. This is evident in Figure 8, where high-intensity white dots appear in proximity to darker dots. This type of noise, known as *salt-and-pepper noise*, is characterized by frequent dark spots in bright areas and bright spots in dark areas across the image. Given these characteristics, the median filter emerges as the most suitable choice, as confirmed in the literature [25,26]; in this work, a median filter with a 5×5 kernel is adopted and the resulting improvements in the uniformity of the laser stripe are illustrated on the right in Figure 9.

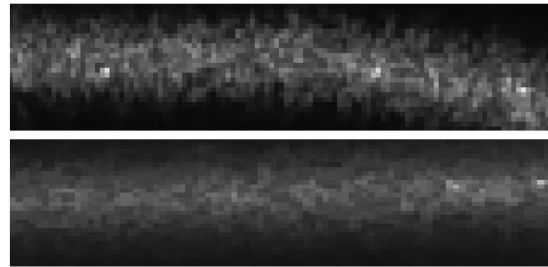


Figure 8. Two different images acquired by the sensor zoomed in on the laser stripe. It is possible to see bright points immersed in the laser stripe next to dark points, showing impulsive noise.

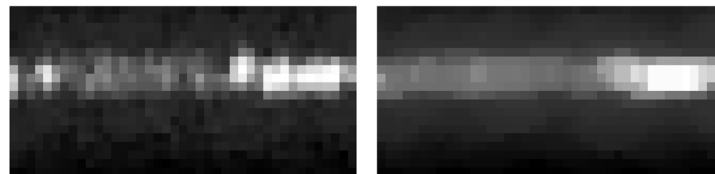


Figure 9. The left shows the raw portion of the image, and the right shows the same portion after using the median filter.

To increase the speed of laser stripe extraction and improve detection, the Otsu thresholding method is applied to set to zero all points outside the ROI [22]. The Otsu method is an automatic thresholding technique that assumes that the image is composed of two main pixel classes: foreground and background. For each possible threshold value, the image is divided into these two classes and the inter-class variance is computed, which measures how well separated the grey-level distributions of the two classes are. The optimal threshold maximizes this variance, as it corresponds to the best possible separation between foreground and background in terms of pixel intensity, and it is a standard algorithm available within openCV library and well explained in the documentation available in [27]. The positions of the first and last pixels with intensity $I(i, j) \neq 0$ (above the Otsu threshold) in each column are located by scanning the image from top to bottom, and the corresponding row indices are recorded as i_1 and i_2 .

To enhance the stability of subsequent stripe centre extraction, the ROI is obtained considering only row indexes where pixel intensities are non-zero and is then expanded by 10 pixels both upward and downward. Therefore, the upper and lower boundaries of the ROI are defined as $(i_1 - 10)$ and $(i_2 + 10)$, respectively.

3.5.2. Stripe Extraction Algorithms: GC, Steger, and FIR

The GC algorithm finds the $i_{\text{stripe}-j}$ for each column j , i.e., the i row in the j column where the laser stripe is founded, following the equation for each consecutive pixel with intensity $I(i, j)$ that exceeds the threshold, as shown in Figure 10, and following Formula

(2) with sub-pixel accuracy that calculates the weighted average row above the threshold, where the weights are the levels of intensities $I(i, j)$:

$$i_{\text{stripe}-j} = \frac{\sum_{i=k}^n I(i, j) i}{\sum_{i=k}^n I(i, j)}. \quad (2)$$

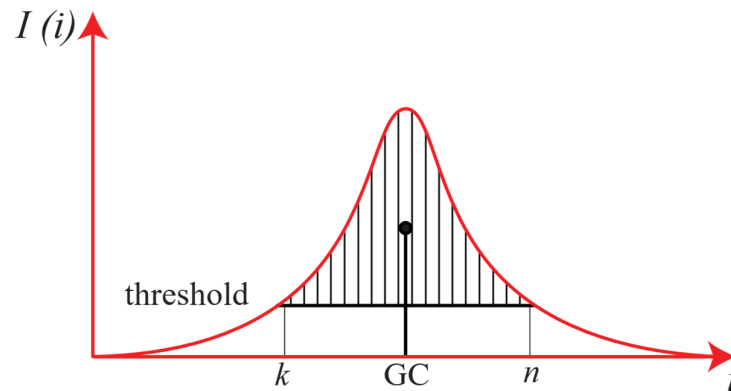


Figure 10. Representation of GC method for laser stripe extraction. Only values above threshold are considered. There are $n - k$ black vertical lines representing pixels i rows above threshold.

The Steger method requires knowledge of the input parameter σ , which is related to stripe width and is used in the Gaussian filtering step. The algorithm then computes the Hessian matrix of the image and calculates its eigenvalues to identify the stripe profile with sub-pixel accuracy using the Taylor expansion along the normal direction, as described by Steger [19] and Zaho et. al. [28].

The Finite Impulse Response (FIR) algorithm is selected as an intermediate solution between GC and Steger, as it relies on a per-column convolution that is more computationally demanding than the Grey Centroid method but less complex than Steger. An important advantage of the FIR approach is that it applies a low-pass filter $h(i)$ during the computation of the derivative along each column j . It is possible to demonstrate that, considering vector $x(i)$, a filtered vector obtained with the convolution between the filter and the original vector (3) is equal to the vector convolved with the derived filter, as shown in (4), which means that the derivate must be calculated only once by the program after the filter definition [20]. Then, it is possible to calculate the i row with sub-pixel precision by finding the zero crossing, as shown in Figure 11, following Equation (5) where $p_0 = (x_0; y_0)$ is the last positive point of $dy(i)/di$ before the zero crossing and $p_1 = (x_1; y_1)$ is the first negative point.

$$y(i) = x(i) * h(i); \quad (3)$$

$$\frac{dy(i)}{di} = x(i) * \frac{dh(i)}{di}; \quad (4)$$

$$i_{\text{stripe}j} = x_0 - \frac{y_0(x_1 - x_0)}{y_1 - y_0}. \quad (5)$$

The filter is designed following the steps shown in Figure 12. Since the images are affected by impulsive noise, a Hamming window $h(i)$, as shown in Figure 12a, is chosen as the smoothing component. The derivate kernel d/di in Figure 12b is designed with a relatively large support to further mitigate the influence of local noise. Kernel $h'(i)$ designed to reduce noise and find the zero crossing is represented in Figure 12c. The filter size was set to 21 based on empirical observation of the laser stripe in the acquired images, whose maximum width was approximately 21 pixels, ensuring that the filter fully covered the stripe.

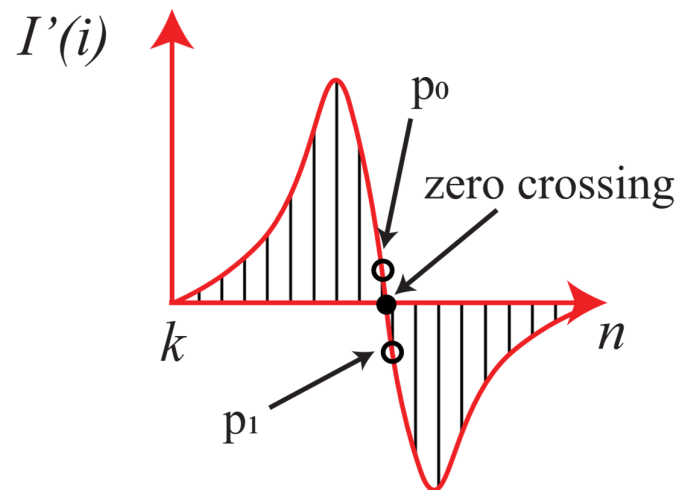


Figure 11. Graphical representation of FIR peak algorithm. Only for intensities above threshold is convolution computed.

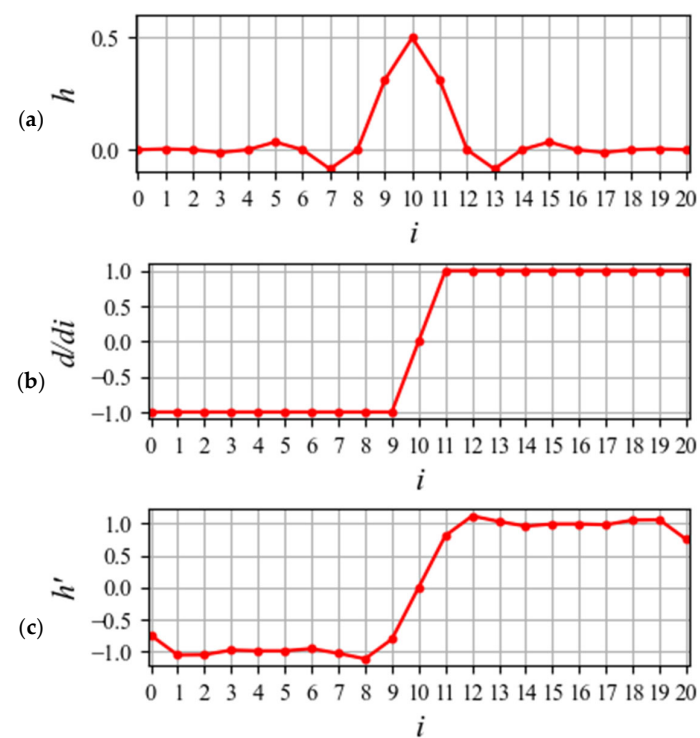


Figure 12. (a) Hamming filter with 21 parameters and cutoff of 0.5. (b) Derivate kernel. (c) FIR filter designed for this paper.

After finding the points, the laser stripe is obtained by linking each point with a scanning procedure: starting from the left, the point is joined to another if the distance between them is lower than the threshold.

All of this is performed in the sensor space with a plane of axes i and j . In order to transform sensor coordinates i and j into real-world coordinates x and z , the calibration functions $x(i, j)$, $z(i, j)$ provided by the sensor are used. Calibration is not discussed in this paper; however, it consists of direct calibration using a reference geometrical artifact which is moved in the 3D space [17].

3.5.3. Feature Extraction

In this paragraph, a feature extraction code is provided to evaluate gap and flush using the definition provided in Section 3.1 (Methodology). First, the parameters are set and Savitsky–Golay filtering [29] can be performed on the profile to extract the second-grade derivate Z'' that is calculated for both the left and right profile. As such, we can divide the profile into a straight line obtained considering second-derivative values below a threshold and an arc of a circle considering values above the same threshold. The hypothesis is that each profile is composed of at least one line and an arc of a circle. Lines and circles are evaluated for each profile according to the following pseudocode (Algorithm 1). A reference surface is chosen to evaluate gap and flush, as shown in Figure 2.

Algorithm 1. Finding features for one side (left or right).

Input: profile (x, z) , linearSide, min_line_length $l_{\min}$

Output: features $\rightarrow$ line, arc, edge point

- (1) If linearSide = right: reverse (x, z) .
 - (2) Set window_length = $l_{\min}$; polyorder = 3; derivative order = 2. Set min_circle_length $c_{\min}$. Set step st.
 - (3) Compute Savitsky–Golay second derivative on signal
 - (4) Build Boolean mask $B = \{|d_i| < \tau\}$. Split B into contiguous runs; drop runs of length $l < l_{\min}$. Pick first run with length $l > l_{\min} \rightarrow$ line indices $\mathcal{L}$ (with optional trimming for very long lines)
 - (5) Let edge index i^* be last index in $\mathcal{L}$
 - (6) Circle search starting at $s = i^* + 1$.
 - (7) For windows $[s, e]$ of length $l \geq c_{\min}$ with growth/shift rules:
 - (a) Fit 3-point describing the arc $\rightarrow$ center C , radius r , length l_r , angle θ .
 - (b) If $r < r_{th}$ and $N_{outliers} \leq N_{max-outliers}$: mark as “arc” and try to extend e with st or shift window forward of st.
 - (8) Choose the best arc minimizing a cost function based on C , r , l_r and θ .
-

3.6. Measurement System Analysis

This paper presents a benchmark to compare three different laser stripe extraction algorithms. The evaluation is based on two fundamental and equally important metrics: measurement uncertainty and processing time.

Processing time is a critical parameter, as the target G3F system is embedded and runs on a low-power SOM processing unit (based on the i.MX 8M family) designed for flexibility and low power consumption.

To robustly quantify measurement uncertainty, a GRR study was conducted, in accordance with standard MSA procedures, emulating a standard industrial process. This study is performed using the range method [23]. The range is calculated according to Equation (6):

$$R_{p,o} = \max(x_{o,p,t}) - \min(x_{o,p,t}), \quad (6)$$

where $x_{o,p,t}$ is the measure performed by operator o at point p in trial t . The GRR study breaks down the total variation in the measurement system into two primary components:

1. Repeatability uncertainty based on Equipment Variation (EV): the variation observed when a single operator measures the same part multiple times; this uncertainty is influenced by the uncertainty of the sensor and the uncertainty of the measurement method and is evaluated as

$$EV = \bar{R} \cdot K_1, \quad (7)$$

where $\bar{R}$ is the average value of all ranges $R_{p,o}$ and K_1 is a statistical coefficient that depends on the number of trials.

2. Reproducibility uncertainty based on Appraiser Variation (AV): the variation that arises when different operators measure the same part; this uncertainty indicates the utility of training operators to obtain the same measurement method. It is calculated as in (8),

$$AV = \sqrt{\left(X_{diff} \cdot K_2\right)^2 - \left(\frac{EV^2}{P \cdot T}\right)}, \quad (8)$$

where P is the number of points measured, T is the number of trials, K_2 is a constant that depends on the number of operators, and X_{diff} is the range obtained considering only average values of measures for each operator, $\bar{x}_o$.

Finally, GRR is calculated as the combination of both contributions:

$$GRR = \sqrt{EV^2 + AV^2}. \quad (9)$$

4. Results

To evaluate the performance and robustness of the proposed gap and flush algorithms, a comprehensive MSA was carried out under different operating conditions. This chapter presents the outcomes of that assessment, comparing AV, EV, GRR, and processing time for the three algorithms considered. The analysis is performed both with and without the masking device mounted on the G3F system, allowing us to isolate the effects of hardware assistance and operator interaction on the measurement process. Each algorithm was executed on the same G3F SoM, based on the i.MX 8M Plus processor, in order to ensure comparable and representative processing time results for embedded applications.

The results reported in the following figures provide a clear overview of how each algorithm behaves in practical use and highlight the conditions under which performance degradation may occur.

Figure 13 shows the difference in performance, AV, EV, GRR, and processing time between the GC, FIR, and Steger algorithms while the prototyped front panel is used when measuring gap and flush. Figure 14 shows the same benchmark when the front panel is not mounted; here, it is possible to see a net decrease in performance for the FIR and Steger algorithms in gap analysis and for all the algorithms for flush analysis.

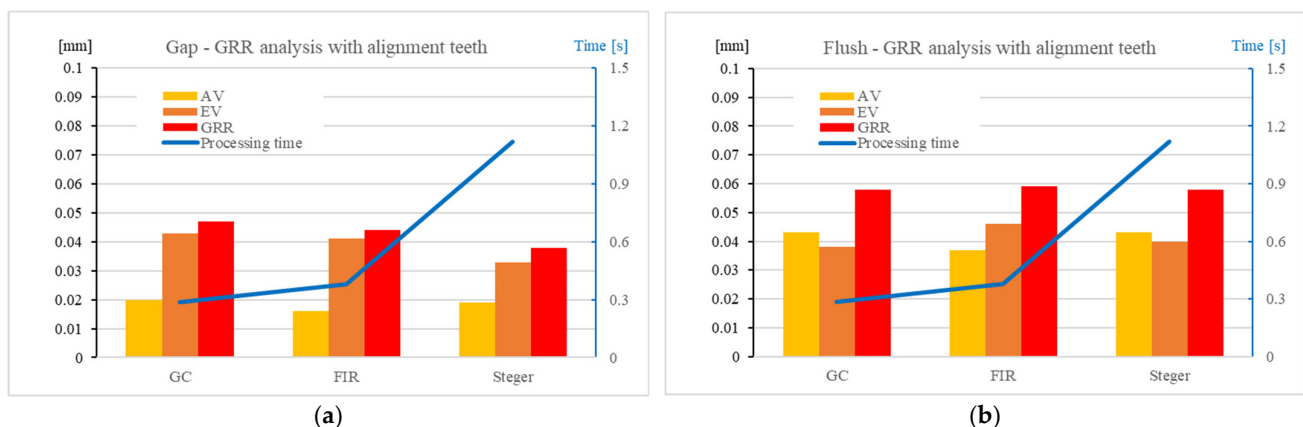


Figure 13. Uncertainty and processing time benchmark using three different algorithms when front panel with alignment teeth is used to measure gap (a) and flush (b).

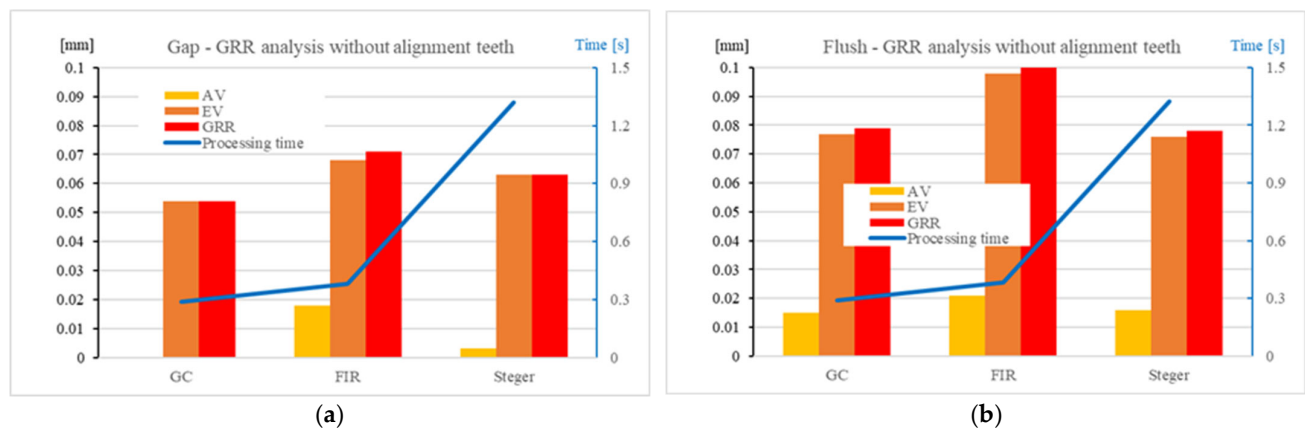


Figure 14. Uncertainty and processing time benchmark using three different algorithms when front panel without alignment teeth is used to measure gap (a) and flush (b).

Quantitative values of GRR and processing time measurements are reported in Table 2. In this case, the selected algorithm is the GC, with a processing time of 0.29 s, which is significantly lower than those of the other methods: Steger, with processing times of 1.12 s and 1.32 s with and without alignment teeth, respectively, and FIR, with a processing time of 0.38 s.

Table 2. Results of processing time and GRR for each algorithm, considering images acquired with and without alignment teeth.

Algorithm	Processing Time with Alignment Teeth	Processing Time Without Alignment Teeth	Gap GRR with Alignment Teeth	Gap GRR Without Alignment Teeth	Flush GRR with Alignment Teeth	Flush GRR Without Alignment Teeth
GC	0.29 s	0.29 s	0.047 mm	0.054 mm	0.058 mm	0.079 mm
FIR	0.38 s	0.38 s	0.044 mm	0.071 mm	0.059 mm	0.1 mm
Steger	1.12 s	1.32 s	0.038 mm	0.063 mm	0.058 mm	0.078 mm

The GC also is more robust to sudden changes in operating conditions. The results shown also have other, more general practical consequences: the measurement system without alignment teeth has an internal uncertainty high enough to absorb the uncertainty caused by operator changes. We can define $\Delta EV = EV_{alignment} - EV$ as the difference between the EV calculated with alignment teeth and the EV calculated without alignment teeth. Similarly, ΔAV is calculated. FIR and Steger have $\Delta AV > \Delta EV$. Considering the measurement of gap, for the GC algorithm, $\Delta AV = 0.02$ mm and $\Delta EV = -0.01$ mm; for the FIR algorithm, $\Delta AV = 0$ mm and $\Delta EV = -0.03$ mm; for the Steger algorithm, $\Delta AV = 0.02$ mm and $\Delta EV = -0.03$ mm. Selecting the GC algorithm also reduces the need to redefine the measurement process considering that it has the lowest $|\Delta EV|$.

5. Conclusions and Limitations

This study set out to evaluate how algorithmic strategies and mechanical support features jointly affect the performance of a portable LLT system for gap and flush assessment in automotive applications. Through a dedicated MSA procedure, the work investigated whether more advanced extraction algorithms effectively enhance measurement reliability when the system is operated manually, and how mechanical alignment aids contribute to overall robustness. The following conclusions synthesize the main findings and outline the implications for the development of portable, operator-friendly metrology solutions.

The results show that the performance of the LLT measurement system is influenced not only by the choice of the extraction algorithm but also—often more significantly—by

the mechanical conditions under which the measurement is performed. Although FIR and Steger algorithms incorporate more sophisticated processing techniques, their advantages decrease sharply when operator variability or suboptimal alignment conditions are present. The GC algorithm proved to be the most effective in this context: it consistently achieved lower processing times and maintained stable performance even when measurement conditions degraded.

The comparison between measurements taken with and without the alignment teeth on the front panel further highlights the dominant role of mechanical guidance. The absence of alignment features led to a marked increase in uncertainty—exceeding 30% for flush measurements—overshadowing the differences between algorithms. This finding demonstrates that, in portable metrology applications, mechanical support and ergonomic aids can have a stronger impact on repeatability and reproducibility than algorithmic complexity.

Future developments should therefore focus on improving both calibration and feature extraction. A promising direction is the integration of calibration procedures directly into the extraction stage, in a way that is coherent with the specific algorithm employed. Additionally, exploring mechanical modifications or user-assistance fixtures could further reduce operator influence and enhance the robustness of portable LLT systems.

Overall, this study demonstrates that achieving reliable, operator-assisted gap and flush measurements requires a balanced co-design of algorithms, calibration strategies, and mechanical support. Such an integrated approach aligns closely with the principles of Industry 5.0, where human-centred measurement systems must combine accuracy, repeatability, and usability to effectively support flexible and digitalized manufacturing environments.

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