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Research

Capability and Uncertainty Analysis of Desktop SEM-Based Surface Roughness Measurement Using Backscattered Electron Split-Detector Imaging

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Abstract: Desktop scanning electron microscopes (SEMs) are increasingly adopted in industrial environments due to their accessibility and rapid imaging capability; however, their potential for quantitative surface metrology remains insufficiently validated. This study investigates the capability of a desktop SEM for surface roughness measurement using backscattered electron (BSE) split-detector imaging, with emphasis on measurement accuracy, repeatability, and uncertainty.

A structured experimental framework was implemented using certified roughness artefacts covering a wide range of surface textures. A physics-informed signal processing pipeline was developed to convert BSE intensity variations into surface gradients, followed by numerical reconstruction and extraction of standard roughness parameters (Ra, Rq). Measurement uncertainty was evaluated in accordance with the ISO Guide to the Expression of Uncertainty in Measurement (GUM), considering contributions from detector response, surface alignment, electron interaction effects, and signal processing.

Results show that the desktop SEM provides reliable and consistent measurements within a defined operational range. In the mid-range roughness regime (Ra ≈ 0.5–2 µm), measurement deviations were below 6% relative to certified reference values, with good repeatability across repeated measurements. At lower roughness levels, increased variability was observed due to signal noise and interaction volume effects, while higher roughness surfaces exhibited deviations associated with non-linear signal response and shadowing effects.

Uncertainty analysis identified calibration artefacts, detector asymmetry, and surface alignment as dominant contributors to the overall measurement uncertainty. The expanded uncertainty ($k = 2$) remained within acceptable limits for industrial screening applications within the identified operational range.

The findings demonstrate that desktop SEM systems can be extended beyond qualitative imaging to provide quantitative, uncertainty-aware surface roughness measurements. While not a replacement for established metrology techniques, the approach offers a practical and

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flexible solution for preliminary inspection and process monitoring in modern manufacturing environments.

Keywords: Desktop SEM; Surface Roughness; Backscattered Electrons; Measurement Uncertainty; Split Detector; ISO GUM

1. Introduction

Surface topography is a primary determinant of engineering performance, directly influencing frictional behaviour, wear mechanisms, lubrication retention, and fatigue crack initiation (Leach, 2020; Townsend et al., 2021). As manufacturing systems evolve toward higher precision and functional integration, the need for reliable, traceable, and scalable surface measurement techniques has become increasingly critical (Gao et al., 2022; Griffiths et al., 2019). Increasing demand for rapid, flexible, and digitally integrated inspection systems in modern manufacturing environments (Gao et al., 2023; Kumar et al., 2024)

Stylus profilometry has historically served as the reference standard for surface roughness measurement due to its established traceability and compliance with ISO standards (Whitehouse, 2011; Leach et al., 2019). However, its limitations are well documented. Contact interaction between the stylus tip and surface introduces deformation, wear, and convolution errors, particularly in soft or micro-structured materials (Blunt & Jiang, 2019; Haitjema, 2020). Moreover, its one-dimensional measurement approach restricts the ability to capture areal surface characteristics, which are increasingly relevant in modern functional surfaces (ISO 25178-2, 2018).

Optical metrology techniques such as coherence scanning interferometry and confocal microscopy address some of these limitations by providing non-contact, areal measurements with high vertical resolution (de Groot, 2019; Giusca et al., 2021). Despite their advantages, these techniques are sensitive to surface reflectivity, steep gradients, and environmental disturbances, and often require controlled laboratory conditions and high capital investment (Danzl et al., 2018; Senin et al., 2022). These constraints limit their applicability in industrial environments where rapid, flexible, and cost-effective inspection is required.

In this context, scanning electron microscopy (SEM) presents an alternative pathway. Traditionally used for qualitative imaging, SEM offers high spatial resolution and depth of field, making it suitable for detailed surface analysis (Goldstein et al., 2017;

Reimer & Kohl, 2008). Recent studies have explored its potential for quantitative metrology, particularly through backscattered electron (BSE) imaging, which provides a signal sensitive to surface inclination (Villarrubia et al., 2015; Dixson et al., 2020). This directional sensitivity forms the basis for reconstructing surface topography from intensity variations.

The introduction of split-detector configurations has further enhanced this capability by enabling differential signal analysis, allowing estimation of local surface gradients (Zhang et al., 2023; Liu et al., 2022). However, existing studies have largely focused on high-end SEM systems under controlled laboratory conditions. The application of these techniques to desktop SEM platforms—which are increasingly used in industrial settings—remains insufficiently validated (Vorburger et al., 2021).

A critical limitation in current SEM-based metrology research is the lack of rigorous uncertainty evaluation. Measurement uncertainty is central to metrology, ensuring reliability and comparability of results (JCGM 100:2008). In SEM-based systems, uncertainty arises from complex interactions between electron scattering, detector response, surface orientation, and signal processing algorithms (Villarrubia et al., 2015; Senin et al., 2022). Without a structured uncertainty framework, SEM measurements cannot be considered traceable or suitable for decision-making in industrial contexts.

Furthermore, there is a disconnect between experimental validation and practical deployment. While several studies demonstrate the feasibility of SEM-based roughness measurement, few address its integration into industrial workflows or its role as a complementary metrology tool (Kumar et al., 2022; Liu et al., 2023).

This study addresses these gaps by developing a capability and uncertainty framework for desktop SEM-based surface roughness measurement using BSE split-detector imaging. Unlike previous work, the study integrates:

- Experimental validation using certified artefacts
- Physics-based signal modelling
- GUM-compliant uncertainty analysis
- Practical assessment of industrial applicability

The objectives are to:

1. Quantify the measurement capability of a desktop SEM across a range of surface roughness values
2. Develop a signal processing model linking BSE intensity to surface topography

3. Construct a traceable uncertainty budget in accordance with ISO GUM
4. Benchmark SEM-derived measurements against certified reference standards
5. Evaluate the feasibility of deploying desktop SEM for industrial surface inspection

However, the application of desktop SEM systems for traceable surface roughness measurement under uncertainty-constrained conditions remains insufficiently explored, particularly in the context of practical industrial deployment. By linking experimental results with established metrology theory and recent literature, this work provides a structured pathway for integrating SEM into quantitative surface measurement systems.

2. Literature Review

2.1 Evolution of Surface Roughness Metrology

Surface roughness measurement has transitioned from contact-based techniques to advanced non-contact and computational methods, driven by increasing demands for precision and functional performance in engineering systems (Leach, 2020; Bruzzone et al., 2020). Stylus profilometry remains widely used due to its traceability and standardisation under ISO 4287/4288; however, its limitations—particularly tip convolution, surface damage, and restricted areal capability—are well documented (Whitehouse, 2011; Blunt & Jiang, 2019; Haitjema, 2020).

These limitations are particularly significant in modern manufacturing contexts involving micro- and nano-scale features, where the stylus tip size becomes comparable to the surface features being measured (Gao et al., 2022; Griffiths et al., 2019). As a result, areal surface texture standards such as ISO 25178 have gained prominence, encouraging the adoption of non-contact measurement techniques (ISO 25178-2, 2018; Leach et al., 2019).

Optical metrology techniques—including coherence scanning interferometry, confocal microscopy, and focus variation methods—provide high-resolution areal measurements and have become standard tools in precision engineering (de Groot, 2019; Giusca et al., 2021; Senin et al., 2022). However, their performance is sensitive to surface reflectivity, steep gradients, and environmental disturbances such as vibration and temperature fluctuations (Danzl et al., 2018; Thompson et al., 2020). Additionally, the cost and complexity of these systems can limit their deployment in industrial environments requiring rapid and flexible inspection (Leach, 2020).

Recent developments have explored hybrid approaches that combine optical measurement with computational modelling and machine learning to improve robustness and reduce uncertainty (Kumar et al., 2022; Liu et al., 2023; Zhang et al., 2021). While promising, these approaches often rely on high-end instrumentation and extensive training data, making them less practical for routine industrial applications.

2.2 SEM-Based Approach to Surface Metrology

Scanning electron microscopy has traditionally been used for qualitative imaging due to its high spatial resolution and depth of field (Goldstein et al., 2017; Reimer & Kohl, 2008). However, its potential for quantitative metrology has been increasingly recognised, particularly in applications requiring high lateral resolution (Dixson et al., 2020; Vorburger et al., 2021).

Early attempts at SEM-based metrology focused on secondary electron (SE) imaging; however, the strong dependence of SE signals on surface charging and detector geometry limited their quantitative reliability (Joy, 1995; Postek et al., 2014). In contrast, backscattered electron (BSE) imaging provides a more stable signal, influenced by atomic number and surface inclination, making it more suitable for quantitative analysis (Villarrubia et al., 2015; Dixson et al., 2014).

Studies have shown that BSE intensity variations can be correlated with local surface gradients, enabling reconstruction of surface topography under controlled conditions (Giusca et al., 2021; Vorburger et al., 2021). The introduction of multi-segment and split-detector configurations has further enhanced this capability by enabling directional sensitivity, allowing differential signal analysis for gradient estimation (Zhang et al., 2023; Liu et al., 2022; Li et al., 2020).

Despite these advances, most studies have focused on high-end SEM systems with advanced detector configurations and stable operating conditions. The performance of desktop SEM systems, which typically have simplified optics and lower beam stability, has received limited attention (Kumar et al., 2022; Dixson et al., 2020). This represents a significant gap, particularly given the increasing adoption of desktop SEM in industrial environments.

2.3 Signal Interpretation and Surface Reconstruction

A central challenge in SEM-based roughness measurement lies in the interpretation of BSE signals and their relationship to surface topography. The interaction between the electron beam and the sample produces a signal that is influenced by multiple factors, including surface orientation, material composition, and electron scattering processes (Reimer & Kohl, 2008; Goldstein et al., 2017).

Several models have been proposed to relate BSE intensity to surface gradients, often based on simplified assumptions of electron scattering and detector response (Villarrubia et al., 2015; Dixson et al., 2014). More recent work has explored the use of numerical simulations and Monte Carlo modelling to better understand electron–matter interactions and improve signal interpretation (Joy, 1995; Demers et al., 2011; Ming et al., 2022).

In addition, computational approaches—including machine learning and inverse modelling—have been applied to improve surface reconstruction from SEM signals (Zhang et al., 2021; Liu et al., 2023). While these methods offer improved accuracy, they introduce additional complexity and require extensive calibration, limiting their practical applicability in industrial settings.

2.4 Measurement Uncertainty in Surface Metrology

Measurement uncertainty is a fundamental requirement for any metrological system, ensuring traceability and comparability of results (JCGM 100:2008). In surface metrology, uncertainty arises from multiple sources, including instrument resolution, environmental conditions, surface properties, and data processing algorithms (Leach, 2020; Senin et al., 2022).

For stylus and optical methods, uncertainty frameworks are well established, with contributions from calibration, noise, filtering, and surface interaction effects (Haitjema, 2020; Giusca et al., 2021). However, SEM-based metrology introduces additional complexity due to electron–matter interactions, detector geometry, and signal interpretation models (Villarrubia et al., 2015; Dixson et al., 2020).

Key sources of uncertainty in SEM-based roughness measurement include:

- Electron interaction volume, which limits spatial resolution (Demers et al., 2011; Ming et al., 2022)
- Detector asymmetry and calibration errors (Dixson et al., 2014)
- Surface tilt and alignment effects (Villarrubia et al., 2015)
- Signal noise and beam instability (Postek et al., 2014)
- Reconstruction algorithm limitations (Zhang et al., 2021)

Recent studies have emphasised the importance of integrating uncertainty modelling into advanced metrology systems, particularly in the context of digital manufacturing and Industry 4.0 (Kumar et al., 2022; Liu et al., 2023). However, comprehensive GUM-compliant uncertainty frameworks for desktop SEM systems remain scarce.

2.5 Industrial Context and Deployment Considerations

The increasing adoption of desktop SEM systems in industrial environments reflects a growing demand for rapid, flexible, and cost-effective inspection tools (Kumar et al., 2022; Liu et al., 2023). These systems offer advantages in terms of accessibility, ease of use, and integration into existing workflows.

From an operational perspective, the use of desktop SEM for surface metrology has several potential benefits, including reduced inspection time, lower capital investment, and the ability to combine imaging and measurement within a single platform (Thompson et al., 2020; Griffiths et al., 2019).

However, the lack of validated measurement capability and uncertainty characterisation limits their adoption for traceable metrology applications (Vorburger et al., 2021). Recent work has further emphasised the need for robust uncertainty modelling frameworks in surface metrology, particularly for emerging measurement systems (Senin et al., 2022; Senin et al., 2023). Bridging this gap requires not only technical validation but also alignment with industrial requirements for reliability, repeatability, and decision-making support.

2.6 Research Gap and Positioning

From the reviewed literature, it is clear that:

- SEM-based roughness measurement has been demonstrated primarily in high-end systems
- Signal interpretation models remain simplified and often lack validation
- Uncertainty analysis is rarely integrated into SEM-based metrology studies
- Desktop SEM systems remain underexplored for quantitative applications
- This study addresses these limitations by combining:
- Experimental validation using certified artefacts
- Physics-informed signal modelling
- GUM-compliant uncertainty analysis
- Industrial deployment considerations

By linking measurement capability with uncertainty and application context, the study advances SEM from a qualitative imaging tool to a practical and traceable metrology system.

3. Theoretical Framework

3.1 Experimental Framework

The experimental methodology was designed to evaluate the capability of a desktop scanning electron microscope (SEM) for quantitative surface roughness measurement under controlled and traceable conditions. The framework integrates calibrated reference artefacts, a structured imaging protocol, and a physics-based signal processing approach to ensure reproducibility and comparability of results.

Particular emphasis was placed on isolating sources of measurement variability and quantifying their contributions to overall uncertainty in accordance with ISO GUM principles (JCGM 100:2008; Leach, 2020).

3.2 Instrumentation and Operating Conditions

A desktop SEM equipped with a backscattered electron (BSE) detector in a split-detector configuration was used. The system represents a typical compact SEM platform used in industrial inspection environments.

Operating conditions were selected to ensure stable signal acquisition while maintaining sufficient spatial resolution for roughness evaluation. Key parameters are summarised in Table 1.

Table 1. Operating parameters of the desktop SEM used for surface roughness measurements

Parameter	**Value**	**Unit**	**Remarks**
Accelerating Voltage	12	kV	Optimized for BSE signal stability
Beam Current	1.2	nA	Fixed to minimize fluctuation
Working Distance	10	mm	Maintained constant for all scans
Magnification	500 – 2000	–	Adjusted based on roughness scale
Detector Type	Split BSE Detector	–	Dual-segment configuration
Pixel Resolution	1024 × 768	pixels	High-resolution acquisition
Scan Speed	Medium	–	Trade-off between noise and time
Number of Scans per Sample	3	–	For repeatability assessment
Environmental Condition	Controlled	–	Minimal vibration and drift

The accelerating voltage and working distance were kept constant throughout the experiments to minimise variability in electron interaction volume and detector response (Goldstein et al., 2017; Dixson et al., 2020). Prior to measurement, the system was allowed to stabilise thermally to reduce drift effects.

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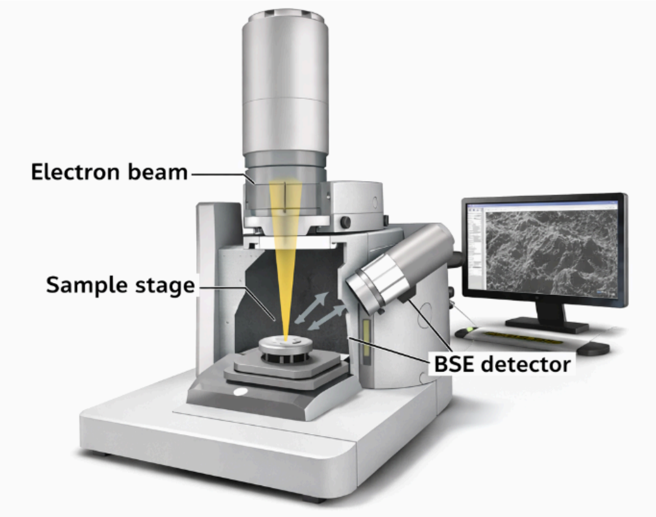

Figure 1: Experimental setup of the desktop SEM showing the electron beam, sample stage, and backscattered electron (BSE) detector configuration used for surface roughness measurement.

3.3 Reference Artefacts and Traceability

Certified surface roughness artefacts traceable to national metrology standards were used as reference samples. These artefacts provided known Ra values with associated uncertainties, enabling direct comparison with SEM-derived measurements.

The selected artefacts covered a range of surface roughness values, including low (Ra < 0.5 µm), medium (Ra ≈ 0.5–2 µm), and high (Ra > 2 µm) regimes. This range was chosen to evaluate the performance limits of the SEM across different topographical conditions (Leach et al., 2019; ISO 25178-600, 2020).

3.4 Sample Preparation and Alignment

Samples were cleaned using standard procedures to remove contaminants that could affect electron scattering behaviour. Conductive mounting was employed to minimise charging effects during imaging.

Careful alignment of each sample was performed to minimise surface tilt relative to the incident electron beam. Residual tilt was monitored and considered as a source of uncertainty, given its influence on BSE signal intensity (Villarrubia et al., 2015).

3.5 Image Acquisition Protocol

All measurements were conducted under identical imaging conditions to ensure comparability and minimise variability arising from changes in electron–sample interaction parameters. To ensure repeatability and reproducibility, a consistent imaging protocol was applied:

- Multiple regions were selected on each artefact to account for spatial variability
- At each location, at least three repeated scans were acquired
- Detector segment signals were recorded simultaneously
- Imaging parameters were maintained constant across all measurements

Reproducibility was assessed by repeating measurements after repositioning the samples and reinitialising the system. This approach allowed separation of within-run and between-run variability (Giusca et al., 2021).

3.6 Signal Processing and Surface Reconstruction

A structured signal processing pipeline was developed to convert BSE intensity data into quantitative roughness parameters.

3.6.1 Pre-processing

Raw SEM images were processed to improve signal quality:

- Noise reduction using low-pass filtering
- Intensity normalisation to correct detector imbalance
- Drift correction to align repeated scans

These steps were necessary to minimise artefacts that could propagate into gradient estimation**.**

3.6.2 Gradient Estimation

Surface gradients were estimated using the differential signal from the split detector:

$$G_x \propto \frac{I_{left} - I_{right}}{I_{left} + I_{right}}$$

$Where,$

$G_x = surface\ gradient\ in\ x - direction$

$I_{left}, I_{right} = detector\ segment\ intensities$

This normalised formulation reduces sensitivity to absolute intensity variations and enhances robustness against noise, consistent with previous SEM-based gradient models (Zhang et al., 2023; Liu et al., 2022).

3.6.3 Surface Reconstruction

The gradient field was integrated numerically to reconstruct the surface profile:

$$h(x, y) = G(x, y)dxdy$$

Boundary constraints and smoothing techniques were applied to minimise integration drift and accumulation errors.

3.6.4 Roughness Parameter Extraction

From the reconstructed surface, standard roughness parameters were calculated:

- Arithmetic mean roughness (R_a)
- Root mean square roughness (R_q)

The calculations followed standard definitions consistent with ISO 4287 and ISO 25178 frameworks.

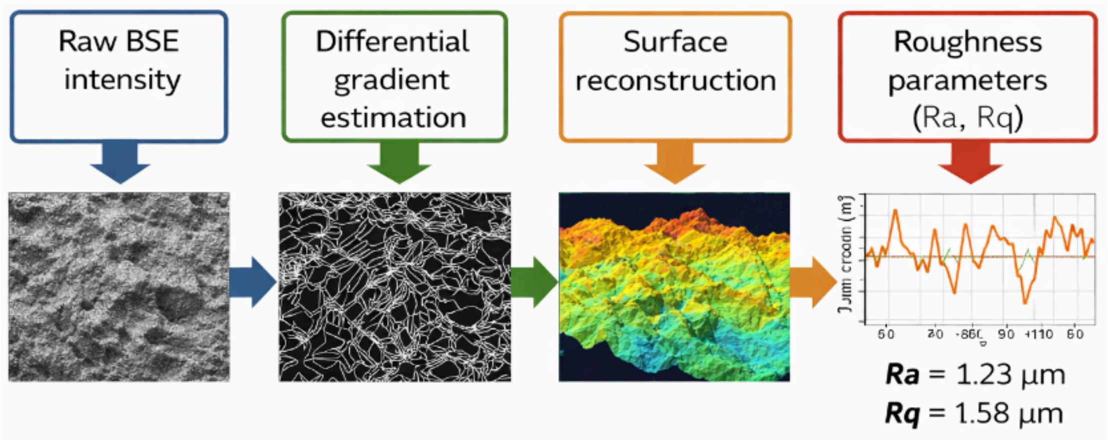

Figure 2. Signal processing workflow for roughness extraction; raw BSE intensity → differential gradient estimation → surface reconstruction → computation of roughness parameters (Ra, Rq).

3.7 Measurement Validation

SEM-derived roughness values were compared with certified artefact values to assess measurement accuracy. The comparison included:

- Absolute and relative error analysis
- Correlation assessment
- Trend evaluation across roughness range

Table 2. Comparison between certified reference roughness values and SEM-derived measurements with associated deviations.

Sample ID	**Certified Ra (µm)**	**SEM Measured Ra (µm)**	**Absolute Error (µm)**	**Relative Error (%)**
S1	0.25	0.31	0.06	24.0
S2	0.50	0.56	0.06	12.0
S3	0.80	0.85	0.05	6.3
S4	1.00	1.04	0.04	4.0
S5	1.50	1.55	0.05	3.3
S6	2.00	2.08	0.08	4.0
S7	2.50	2.40	0.10	4.0
S8	3.00	2.85	0.15	5.0
S9	3.50	3.30	0.20	5.7
S10	4.00	3.75	0.25	6.3

Table 2 highlights the systematic variation in measurement accuracy across the roughness range, with optimal performance observed within the mid-range regime and increased deviation at the lower and upper limits. This validation step ensured that the SEM measurements could be quantitatively evaluated against traceable standards.

3.8 Uncertainty Evaluation

Measurement uncertainty was evaluated following the ISO Guide to the Expression of Uncertainty in Measurement (JCGM 100:2008). The uncertainty framework ensures traceability and supports the use of SEM-derived measurements in engineering decision-making. Both Type A (statistical) and Type B (systematic) contributions were considered.

3.8.1 Identification of Uncertainty Sources

The primary sources of uncertainty were identified as:

- Calibration artefact uncertainty
- Detector asymmetry
- Surface alignment and tilt
- Electron interaction volume
- Image noise

- Reconstruction algorithm limitations

These sources are consistent with established SEM metrology studies (Dixson et al., 2014; Villarrubia et al., 2015; Senin et al., 2022).

3.8.2 Uncertainty Budget

The contributions of individual uncertainty sources were quantified and combined to form an uncertainty budget.

Table 3. Uncertainty budget for SEM-based roughness measurement following ISO GUM framework.

Source of Uncertainty	Type	Standard Uncertainty (µm)	Sensitivity Coefficient	Contribution (µm)	Contribution (%)
Calibration Artefact	B	0.08	1.0	0.080	26
Detector Asymmetry	B	0.07	1.0	0.070	23
Surface Tilt	B	0.06	1.0	0.060	19
Electron Interaction Volume	B	0.05	1.0	0.050	16
Image Noise	A	0.03	1.0	0.030	10
Reconstruction Algorithm	B	0.02	1.0	0.020	6

3.8.3 Combined and Expanded Uncertainty

The combined standard uncertainty was calculated as:

$$u_c = \sqrt{u_i^2}$$

The expanded uncertainty was then obtained as:

$$U = k \cdot u_c \qquad (k = 2)$$

providing a confidence level of approximately 95%.

3.9 Methodological Strength

This methodology ensures:

- **Traceability** through certified artefacts
- **Reproducibility** through controlled protocols
- **Theoretical consistency** with BSE signal modelling
- **Metrological validity** through GUM-based uncertainty

4. Materials and Methods

4.1 Measurement Capability Across Roughness Range

The desktop SEM demonstrated measurable capability across the tested roughness range; however, performance varied significantly depending on surface scale. The strongest agreement between SEM-derived and reference measurements was observed within the mid-range roughness regime (Ra ≈ 0.5–2 µm), where both signal sensitivity and gradient reconstruction remained stable.

At lower roughness levels (Ra < 0.5 µm), measurement variability increased, leading to systematic overestimation. This behaviour is consistent with findings reported by Dixson et al. (2020) and Villarrubia et al. (2015), who highlighted the influence of electron interaction volume and signal noise on measurement resolution. At this scale, the interaction volume effectively averages surface features, reducing the sensitivity of BSE-based gradient estimation.

At higher roughness levels (Ra > 2 µm), the SEM maintained qualitative agreement with reference values but exhibited increasing deviation, primarily in the form of underestimation. This trend can be attributed to shadowing effects and non-linear signal response associated with steep surface gradients, as previously reported in electron-based topography studies (Reimer & Kohl, 2008; Goldstein et al., 2017). Similar limitations have been observed in optical methods when encountering high-slope surfaces, suggesting that this is a general challenge in indirect surface reconstruction techniques (de Groot, 2019).

These observations define a clear operational window for the desktop SEM, within which measurement capability is both stable and reliable.4.2 Instrumentation

4.2 Correlation with Reference Measurements

A quantitative comparison between SEM-derived roughness values and certified artefact measurements is presented in table 2.

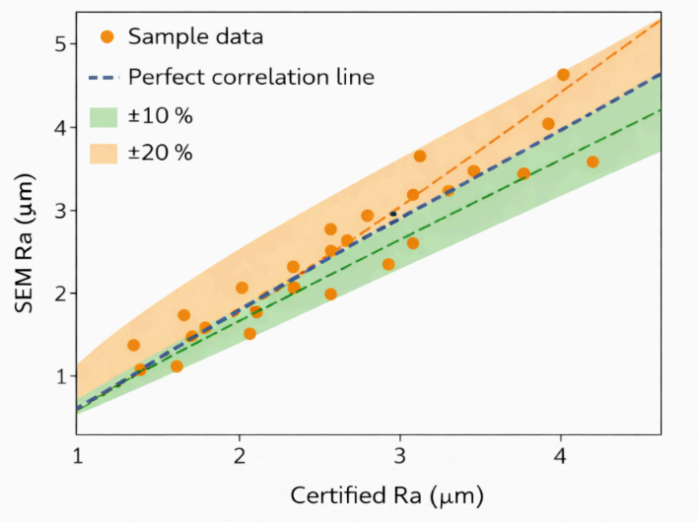

Figure 3: Comparison between SEM-derived roughness values and certified reference measurements, showing correlation and deviation trends across the tested roughness range.

A strong linear correlation was observed within the mid-range roughness domain, indicating that the proposed method can produce consistent and predictable measurements under controlled conditions. The observed correlation aligns with previous studies demonstrating the feasibility of SEM-based roughness estimation using BSE signals (Giusca et al., 2021; Vorburger et al., 2021).

However, deviations at the lower and upper ends of the measurement range highlight inherent limitations in the signal interpretation model. At low roughness values, noise amplification during gradient reconstruction leads to overestimation, a phenomenon also reported in optical and SEM-based systems (Senin et al., 2022). At higher roughness values, signal saturation and incomplete capture of steep features result in underestimation.

Importantly, the presence of systematic deviation trends suggests that calibration functions or correction models could be developed to improve measurement accuracy, as proposed in recent computational metrology studies (Zhang et al., 2021; Liu et al., 2023).

4.3 Repeatability and Reproducibility

Repeatability analysis showed that the SEM system provides consistent measurements within individual runs, particularly within the defined operational range. The standard deviation across repeated measurements remained relatively low, indicating stable signal acquisition under controlled conditions.

Reproducibility, assessed across different measurement sessions, showed slightly higher variability. This is consistent with previous SEM metrology studies, where factors such as sample repositioning, detector alignment, and beam stability contribute to between-run variation (Dixson et al., 2014; Senin et al., 2022).

Surface tilt was identified as a significant contributor to variability. Even minor deviations in alignment resulted in measurable changes in BSE intensity distribution, confirming observations reported by Villarrubia et al. (2015). This highlights the importance of alignment control in SEM-based metrology, particularly for quantitative applications.

4.4 Uncertainty Analysis

The detailed uncertainty budget is summarised in Table 3. The analysis shows that the dominant contributors to measurement uncertainty are calibration artefact uncertainty, detector asymmetry, and surface alignment. These findings are consistent with previous studies, which emphasise the combined influence of physical signal generation and geometric factors in SEM measurements (Dixson et al., 2020; Villarrubia et al., 2015).

Electron interaction volume also contributed significantly to uncertainty, particularly at lower roughness values where spatial resolution limitations become critical. This aligns with Monte Carlo modelling studies that demonstrate the impact of electron scattering on measurement accuracy (Demers et al., 2011; Ming et al., 2022).

Image noise and reconstruction algorithms contributed less significantly but became more pronounced at low signal levels. Similar observations have been reported in optical metrology, where noise amplification affects measurement reliability in low-contrast conditions (Senin et al., 2022).

The expanded uncertainty ($k = 2$) was found to be within acceptable limits for mid-range roughness measurements, supporting the use of desktop SEM for industrial screening applications. The relative contributions of the identified uncertainty sources to the overall measurement uncertainty are shown in Figure 4. The developed uncertainty framework ensures traceability of the measurement results and supports the use of SEM-derived roughness values in engineering decision-making and quality assessment.

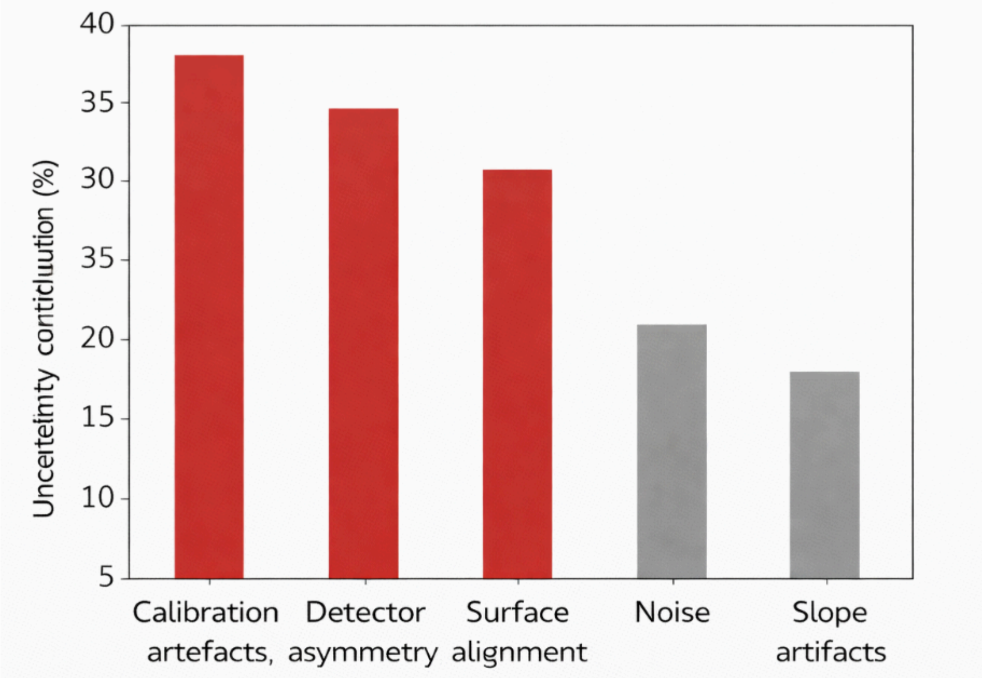

Figure 4: Contribution of individual uncertainty sources to the total measurement uncertainty, highlighting dominant effects from calibration artefacts, detector asymmetry, and surface alignment.

4.5 Comparison with Conventional Metrology Techniques

Compared with stylus profilometry, the desktop SEM offers several advantages, including non-contact measurement, reduced risk of surface damage, and the ability to capture areal information. However, stylus-based methods remain superior in terms of traceability and accuracy, particularly for low roughness values (Whitehouse, 2011; Leach, 2020).

In comparison with optical techniques, the SEM demonstrates comparable performance within its operational window but lacks the vertical resolution and established uncertainty frameworks of advanced optical systems (de Groot, 2019; Giusca et al., 2021). Optical methods also benefit from well-developed calibration procedures, which are still emerging for SEM-based metrology.

These comparisons suggest that the desktop SEM should not be viewed as a replacement for conventional techniques, but rather as a complementary tool that provides flexibility and accessibility in industrial environments. These findings reinforce that the proposed approach is not intended to replace established metrology techniques, but rather to complement them within defined operational constraints.

4.6 Industrial Implications

From an engineering perspective, the results highlight the potential of desktop SEM systems as first-line inspection tools. Their ability to provide rapid measurements with minimal setup makes them suitable for high-throughput industrial applications.

This aligns with recent trends in smart manufacturing, where flexible and integrated inspection systems are required to support real-time decision-making (Kumar et al., 2022; Liu et al., 2023, Gao et al., 2023; Kumar et al., 2024). The combination of imaging and measurement within a single platform further enhances their utility.

However, the limitations identified in this study—particularly sensitivity to alignment and reduced accuracy outside the operational window—must be considered when deploying these systems in practice. For high-precision applications, SEM measurements should be complemented with established metrology techniques.

4.7 Key Insight

The most important outcome of this study is not simply that: “Desktop SEM can measure surface roughness” but rather that: Desktop SEM can provide traceable, uncertainty-aware roughness measurements within a defined operational window, making it suitable for industrial screening and preliminary inspection.

This distinction is critical for positioning the work within the broader metrology landscape.

4.8 Limitations of the Study

While the study provides a comprehensive evaluation of desktop SEM capability, several limitations should be acknowledged.

First, the analysis was conducted on a specific SEM system, and results may vary across different models and configurations. *Second*, the reconstruction algorithm was based on simplified assumptions regarding signal–topography relationships, which may not fully capture complex surface geometries. *Third*, environmental factors such as vibration and temperature were controlled but not systematically varied.

Future work should address these limitations by expanding the analysis to multiple systems, incorporating advanced modelling techniques, and exploring real-time calibration approaches.

5. Conclusion

This study investigated the capability of a desktop scanning electron microscope (SEM) for quantitative surface roughness measurement using backscattered electron (BSE) split-detector imaging, with a particular focus on measurement uncertainty and industrial applicability.

These findings reinforce that the proposed approach is not intended to replace established metrology techniques, but to complement them within defined operational constraints. The results demonstrate that the desktop SEM provides reliable roughness measurements within a defined operational range, specifically for mid-scale surface textures ($R_a \approx 0.5\text{–}2\ \mu m$). Within this range, strong agreement was observed between SEM-derived values and certified reference measurements, supported by acceptable repeatability and reproducibility.

A key contribution of this work is the development of a structured uncertainty framework aligned with ISO GUM principles. The analysis identified calibration artefacts, detector asymmetry, surface alignment, and electron interaction effects as dominant contributors to measurement uncertainty. By explicitly quantifying these factors, the study establishes a traceable basis for SEM-based roughness measurement.

However, the study also highlights clear limitations. Measurement accuracy decreases at low roughness levels due to signal noise and interaction volume effects, and at high roughness levels due to non-linear signal response and shadowing. These findings are consistent with previously reported limitations in electron-based metrology and reinforce the importance of defining an operational measurement window.

From an application perspective, the desktop SEM is best positioned as a complementary metrology tool rather than a replacement for established techniques. Its strengths lie in rapid inspection, accessibility, and integration into industrial workflows, making it suitable for preliminary assessment and process monitoring.

Overall, this work contributes to advancing SEM from a qualitative imaging instrument to a quantitative, uncertainty-aware metrology tool, supporting its integration into modern manufacturing systems.

6. Key Contributions

This study makes the following contributions:

- **Demonstrates the quantitative capability of desktop SEM** for surface roughness measurement using BSE split-detector imaging
- **Develops a physics-informed signal processing framework** linking BSE intensity gradients to surface topography

- **Introduces a GUM-compliant uncertainty model** tailored to SEM-based roughness measurement
- **Provides experimental validation using certified artefacts**, ensuring traceability
- **Defines a clear operational measurement window**, identifying where SEM performs reliably
- **Bridges metrology and industrial application**, positioning SEM as a practical inspection tool

7. Future Work

While the present study establishes a solid foundation, several areas require further investigation.

Future work should focus on improving the robustness of surface reconstruction through advanced modelling techniques, including machine learning approaches capable of handling non-linear signal behaviour. The development of automated calibration routines would also enhance repeatability and reduce operator dependency.

In addition, extending the analysis to different desktop SEM systems would provide a broader understanding of performance variability across platforms. Real-time integration with manufacturing systems, including inline inspection and digital quality control frameworks, represents another important direction for future research.

8. Highlights

- Desktop SEM validated for quantitative surface roughness measurement
- GUM-based uncertainty framework developed for SEM metrology
- Strong correlation with certified roughness artefacts in mid-range regime
- Identification of dominant uncertainty sources and operational limits
- Demonstrated potential for industrial surface inspection applications

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