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Improving accuracy of differential parameter extraction from noisy measurement data

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Abstract. The paper addresses the problem of enhancing the accuracy of differential analysis of integral characteristics of semiconductor structures under conditions of experimental noise. It is shown that standard measurement methods with a linear voltage step lead to significant errors in calculating the dimensionless sensitivity, manifesting themselves as non-physical oscillations that complicate the identification of charge transport mechanisms. A comparative analysis of three data processing methods is conducted: the optimal step method, polynomial approximation (Savitzky–Golay filter), and adaptive filtering based on the Kalman algorithm. It is established that application of the optimal step method based on logarithmic current sampling avoids differentiation artifacts without introducing phase delays characteristic of smoothing methods. The proposed approaches are tested on experimental current-voltage characteristics of OLED structures, confirming their suitability for precise diagnostics of electrophysical parameters of semiconductor devices.

Keywords: current-voltage characteristic, dimensionless sensitivity, differential analysis, optimal step method, Savitzky–Golay filter, Kalman filter, semiconductor structure.

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1. Introduction

Most experimental measurements in physics, particularly in semiconductor physics, are integral in nature, as they reflect the generalized response of a material or structure to external stimuli. Integral characteristics serve as a primary tool for investigating the electrical, optical, and structural parameters of semiconductor systems. In particular, measurements of current-voltage (*I–U*) characteristics enable determination of barrier height, series resistance, charge transport mechanisms, and key efficiency parameters of photovoltaic devices (V_{oc}, I_{sc}, FF, η) [1]. The family of the integral characteristics also includes frequency and impedance dependences, which are employed to analyze dynamic processes in structures and devices. Capacitance-voltage (*C–U*) characteristics are used to determine charge carrier concentration, depletion region width, barrier height, and defect states [2].

To resolve the fine features of the integral characteristics, differential processing methods are employed, enabling identification of local features and hidden patterns in the behavior of semiconductor structures. Recent studies demonstrate the effectiveness of combined methods such as logarithmic transformations ($\ln I/\ln U$) for determining the ideality factor and saturation current [2, 3], derivative analysis for determining the breakdown voltage [4], and equivalent circuit modeling for analyzing capacitance steps in the spectra of thin-film solar cells [5].

Among these methods, dimensionless sensitivity (DS) occupies a special place: $\alpha = d(\lg y)/d(\lg x)$ characterizes the slope of the function $y(x)$ on a double-logarithmic scale. This quantity finds application across diverse scientific fields: in engineering as a quality factor, in mechanics as relative velocity or acceleration, and in climatology as Radiation Amplification Factor (RAF) describing changes in biologically active UV radiation due to ozone layer depletion. In the case of *I–U* characteristics, DS can be expressed as the ratio of static resistance $R = U/I$ to differential resistance $dR = dU/dI$, or as the ratio of differential conductance $\sigma = dI/dU$ to static conductance $\sigma = I/U$. However, due to the high DS sensitivity, spurious oscillations often arise, which hinders proper interpretation of obtained results.

To mitigate these artifacts, statistical processing and smoothing techniques are required.

The most common approaches include the moving average method [6], the Savitzky–Golay filter [7], spectral smoothing (Fourier filtering) [8, 9], and Kalman filter-based algorithms [10]. Choice of a particular method depends on the spectral characteristics of the signal and the requirement to preserve the curve morphology.

The purpose of this study is to model accurancy in determining dimensionless sensitivity, analyze the origins of noise in its characteristics, and identify optimal smoothing and filtering techniques to enhance the informativeness of theoretical and experimental data analysis.

2. Concept of dimensionless sensitivity

The concept of dimensionless sensitivity has been utilized since the 1960s. Over time, interest in this approach has steadily increased, driven by its universality and dimensionless nature. The dimensionless-sensitivity approach facilitates comparison of processes across varying ranges of arguments and functions and enables identification of parameters and functional form of non-periodic dependences, whether of physical or other origins.

In the scientific literature, this quantity appears under various designations depending on the specific field of application: dimensionless coefficient, sensitivity coefficient, differential slope, or power-law exponent.

The dimensionless sensitivity method is typically employed when the argument or function varies over several orders of magnitude, necessitating use of logarithmic scales. In particular, this method is widely applied in the analysis of *I–U* characteristics of semiconductor materials and structures [11–17].

2.1. Theoretical basis

Fundamentally, the numerical value of the dimensionless sensitivity

$$\alpha(x) = \frac{d(\lg y)}{d(\lg x)} = \frac{x}{y}\cdot\frac{dy}{dx} \tag{1}$$

defines the power-law exponent in the expression $y(x) = x^{\alpha}$. Consequently, the terms "differential slope" and "exponent" are considered equivalent hereinafter. Analogously, the quantity $\gamma(x)$

$$\gamma(x) = \frac{d(\lg \alpha)}{d(\lg x)} = \frac{x}{\alpha}\cdot\frac{d\alpha}{dx} \tag{2}$$

defines the exponent in the exponential expression $y(x) = \exp(x^{\alpha})$. Transitioning from infinitesimal increments dy and dx in Eqs. (1) and (2) to finite differences Δy and Δx yields the following expressions:

$$\alpha\left(\frac{x_n + x_{n+1}}{2}\right) = \frac{x_{n+1} + x_n}{x_{n+1} - x_n}\cdot\frac{y_{n+1} - y_n}{y_{n+1} + y_n}, \tag{3}$$

$$\gamma\left(\frac{x_k + x_{k+1}}{2}\right) = \frac{x_{k+1} + x_k}{x_{k+1} - x_k}\cdot\frac{\alpha_{k+1} - \alpha_k}{\alpha_{k+1} + \alpha_k}, \tag{4}$$

where $x_k = (x_{n+1} + x_n)/2$.

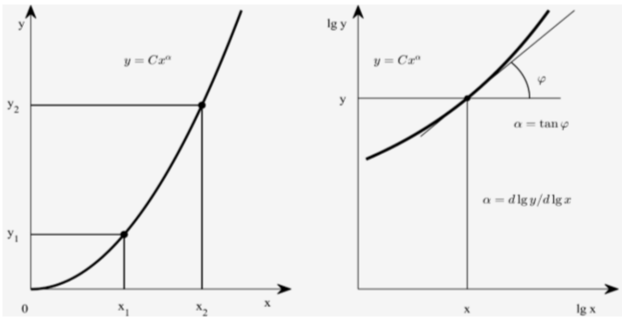

Fig. 1. Geometric definition of the dimensionless sensitivity for a function $y = f(x)$ at a point x.

2.2. Geometric interpretation

Geometrically, for each point x, the DS value α corresponds to the exponent of the power function $y = Cx^{\alpha}$ passing through the coordinate origin and two adjacent points of the data array $y(x)$. Fig. 1 illustrates the geometric interpretation of the dimensionless sensitivity for the function $y = f(x)$. Equivalently, α can be determined as the tangent of the curve's inclination angle in the immediate vicinity of point x when the data are plotted in double-logarithmic coordinates, $\lg y = f(\lg x)$ [14].

2.3. Measurement error and measurement step effect

It is conventionally assumed that reducing the measurement step enhances the accuracy of numerical differentiation. However, the results of differential analysis indicate a contrary trend: an excessively small step leads to a significant increase in the statistical error component and the emergence of spurious oscillations in the $\alpha(U)$ and $\gamma(U)$ characteristics [11, 14]. The uncertainty in determining the differential slope is directly dependent on the measurement errors of the argument x and the function $y(x)$. A qualitative representation of the error dispersion is illustrated in Fig. 2.

Fig. 2 demonstrates that decreasing the measurement step $(x_{n+1} - x_n)$ increases the amplitude of oscillations in the calculated function $\alpha(x)$, whereas increasing the step suppresses these oscillations. However, this simultaneously compromises the resolution of the DS representation. Furthermore, lower measurement precision induces a greater error in determining α. Consequently, selecting the optimal step size is crucial.

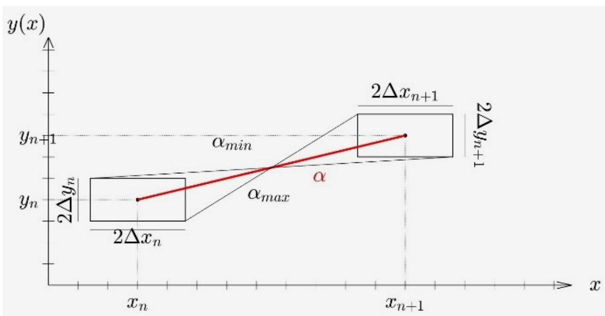

Fig. 2. Qualitative view of the spread of the differential slope error at two points (x_n and x_{n+1}) of an integral characteristic.

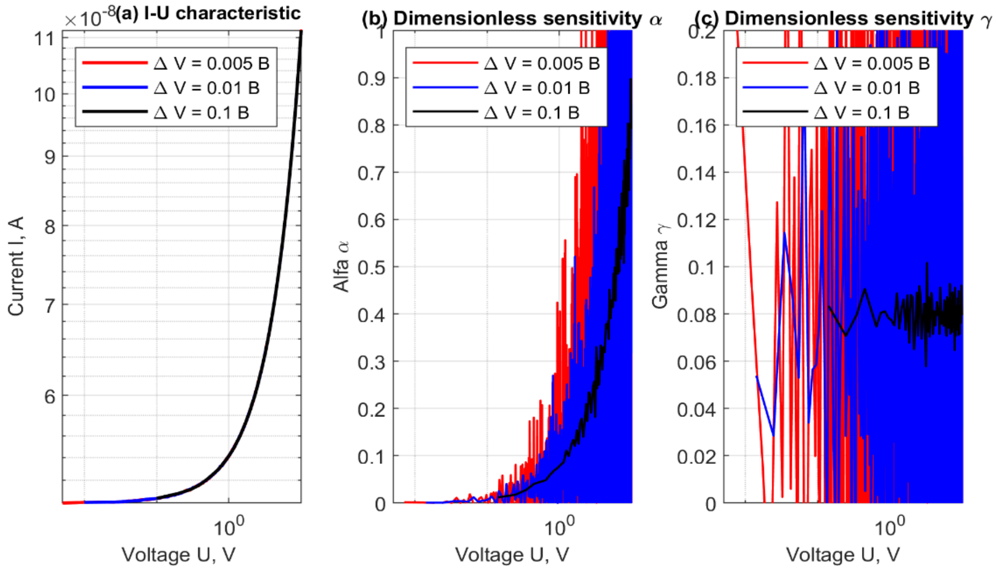

Fig. 3. *I–U* characteristics (*a*) and dimensionless sensitivities $\alpha(x)$ (*b*) and $\gamma(x)$ (*c*) for three measurement step values: $\Delta U = 0.005$ V, $\Delta U = 0.01$ V, and $\Delta U = 0.1$ V.

Analytical examination of power-law dependences of the form $I = CU^{\alpha}$ indicates that minimization of the total error is achieved when the data points are uniformly distributed on a logarithmic scale, *i.e.*, when the voltage change follows a geometric progression. The mathematical determination of the optimal measurement step for integral characteristics to minimize the DS error was presented in [11, 14]. The optimal-step approach ensures a constant distance (equidistance) between points on the $\log I = f(\log U)$ plot, which minimizes spurious oscillations of the differential slope and enables determination of the exponent α with high accuracy over a wide range. The optimal step method is particularly effective when analyzing *I–U* characteristics, where the current varies by several orders of magnitude [11, 14].

3. Motivation and illustration

For exponential dependences typical of diode *I–U* characteristics, the standard linear voltage step (ΔU = const) proves ineffective [11, 14]. At low voltages, current variations are negligible, whereas at high voltages they span several orders of magnitude. Furthermore, selection of the measurement step is a critical factor determining stability of the differential analysis.

To demonstrate the impact of the measurement step size on the accuracy of determining the dimensionless sensitivity, an exponential relationship was employed to simulate the theoretical *I–U* characteristic curve of a semiconductor diode $I = 5\times10^{-8}\exp(0.08\times U)$.

In the MATLAB environment, *I–U* characteristics and the corresponding $\alpha(U)$ and $\gamma(U)$ dependences were generated for three measurement step values: $\Delta U = (0.005$ V, 0.01 V and 0.1 V). The values of $\alpha(U)$ and $\gamma(U)$ were calculated according to Eqs. (3) and (4). The simulation results are presented in Fig. 3a–3c.

The obtained $\alpha(U)$ and $\gamma(U)$ dependences demonstrate that decreasing the measurement step leads to an increase in the amplitude of oscillations in α values, thereby complicating interpretation of the DS characteristic. While these oscillations may be less apparent in the $\alpha(U)$ plot, they become significantly more pronounced in the $\gamma(U)$ dependence.

Consequently, an excessively small step size, commensurate with the measurement uncertainty, results in amplification of random errors and instability of the results. In summary, the uncertainty in determining the dimensionless sensitivity increases at excessively small measurement intervals and decreases as the step size increases. At this, however, an overly large step leads to a loss of resolution. Therefore, in cases where spurious oscillations in $\alpha(x)$ and $\gamma(x)$ hinder the analysis, application of data smoothing techniques is recommended.

4. Filtering techniques

To mitigate noise effects and enhance the precision of experimental data processing, various filtering, smoothing and approximation techniques are employed. Selection of a specific approach is governed by the spectral characteristics of the signal, the nature of the dependence under study and the requirements for preserving the curve morphology.

4.1. Time-domain smoothing methods

One of the most fundamental and effective processing techniques is the Moving Average (MA) method. This approach involves sequential averaging of a group of adjacent data points, which effectively suppresses high-frequency noise. For a discrete signal y_i with a window size N, the smoothed value is defined as

$$\bar{y}_i = \frac{1}{N}\sum_{k=i-N/2}^{i+N/2} y_k \,.$$

The advantage of this method lies in its simplicity of implementation. However, a significant drawback is potential distortion of peaks and shifting of extrema, which can be critical when analyzing fine features of characteristics.

A more advanced approach is the Savitzky–Golay filter [18, 19], which performs smoothing through local polynomial approximation of the data. Unlike the moving average technique, this method preserves the signal morphology and amplitude and also facilitates calculation of derivatives [20]. In its general form, it involves determining polynomial coefficients that minimize the error between the experimental and approximated points within a local window. The Savitzky–Golay method is frequently employed in the analysis of *I–U*, capacitance, and spectral characteristics, where preserving local features of the curve is essential.

4.2. Spectral filtering methods

In cases where noise exhibits a periodic or harmonic structure, application of spectral methods is advisable. Fourier filtering relies on the Fast Fourier Transform (FFT) to convert the signal into the frequency domain, suppress high-frequency components, and then apply an inverse transform to recover the filtered signal. This technique enables precise separation of noise components from the underlying trend; however, it requires careful selection of the cut-off frequency to prevent loss of useful information.

4.3. Statistical and adaptive methods

Statistical methods include median filtering, a technique that effectively eliminates impulse (peak) noise without distorting the shape of smooth curve segments.

A prominent example of adaptive approaches is the Kalman filter [21]. This method estimates the current state of the signal based on the statistical properties of prior measurements and noise, while accounting for the anticipated dynamic characteristics of the signal evolution [22, 23]. This approach proves particularly effective in processing continuous experimental data, for instance, during real-time *I–U* characteristic measurements.

Consequently, application of filtering and smoothing techniques enables a substantial reduction in errors during calculation of dimensionless sensitivity and other differential parameters. Combination of local and adaptive approaches yields more stable and physically reliable results, particularly in the analysis of experimental *I–U* and *C–U* characteristics of semiconductor structures.

5. Filtering of noisy experimental data

Quality diagnostics of semiconductor structures rely on analysis of integral characteristics (current-voltage, capacitance-voltage, spectral *etc.*). However, fundamental electrophysical parameters are often concealed within fine features of these curves, which become apparent only upon differentiation.

A critically important parameter is the DS, which enables identification of charge carrier transport regimes. The primary challenge lies in the fact that during differentiation of experimental data, negligible measurement noise, which is imperceptible on the integral curve, is transformed into significant spurious oscillations on the differential plots. This phenomenon considerably complicates physical interpretation. Solution of this problem involves application of signal filtering techniques.

This article compares three approaches to process noisy experimental data: the optimal step method, polynomial approximation (Savitzky-Golay filter), and the Kalman filter. All the approaches involve post-processing of "raw" data obtained with a standard linear measurement step.

To visually demonstrate the results and facilitate comparative analysis, experimental *I–U* characteristics of organic light-emitting diode (OLED) structures are utilized (Fig. 4a). Specifically, we employed a comercially available yellow-emitting thermally activated delayed fluorescence (TADF) emitter, N-(4-tert-butylphenyl)1,8-naphthalimide-9,9-dimethyl-9,10-dihydroacridine (NAI-DMAC). The optimized device architecture for the yellow-emitting OLED was as follows: ITO (120 nm)/TAPC doped with 20 wt.% MoO3 (10 nm)/TAPC (35 nm)/TCTA (5 nm)/TCTA:CN-T2T (1:1) doped with 1 wt.% NAI-DMAC (20 nm)/CN-T2T (50 nm)/LiF (1.2 nm)/Al (120 nm), where ITO is indium tin oxide (transparent anode), TAPC and TCTA are hole-transport materials, CN-T2T is the electron-transport/host material, and the LiF/Al bilayer forms the low-work-function cathode. [24, 25] The experimental dataset consisted of 300 data points within an applied voltage range of 0 to 5 V. It is noteworthy that fluctuations in the *I–U* characteristics may appear negligible or invisible to the naked eye. However, upon calculating the dimensionless sensitivity, even the smallest noise components can induce oscillations in the $\alpha(U)$ dependence, as observed in Fig. 4b.

5.1. Optimal step method

Previous studies [11] have demonstrated that minimization of noise impact on the results of differential analysis must be incorporated as early as the experimental design phase. The theoretically grounded "optimal step" method is based on selecting measurement points in such a manner as to ensure their uniform distribution on a logarithmic current scale. This approach enables minimization of errors in calculating differential parameters without the necessity for additional mathematical filtering.

For exponential dependences typical of the *I–U* characteristics of diode structures, use of a standard linear voltage step (ΔU = const) proves ineffective for the reasons discussed above. The sampling density is therefore a critical parameter: as the simulations in Section 6 indicate, an excessively small step leads to an increase in the statistical error component, manifesting itself as spurious oscillations in the dimensionless

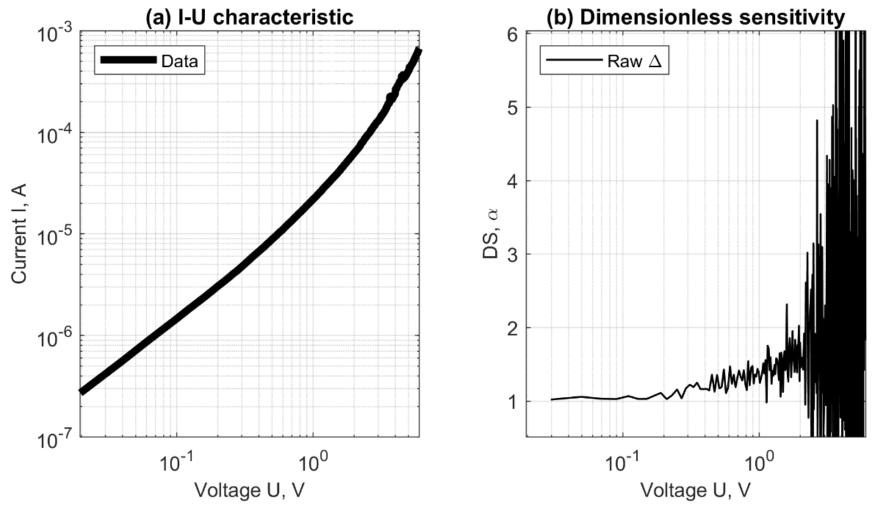

Fig. 4. (*a*) experimental *I–U* characteristic and (*b*) dimensionless sensitivity of OLED structure.

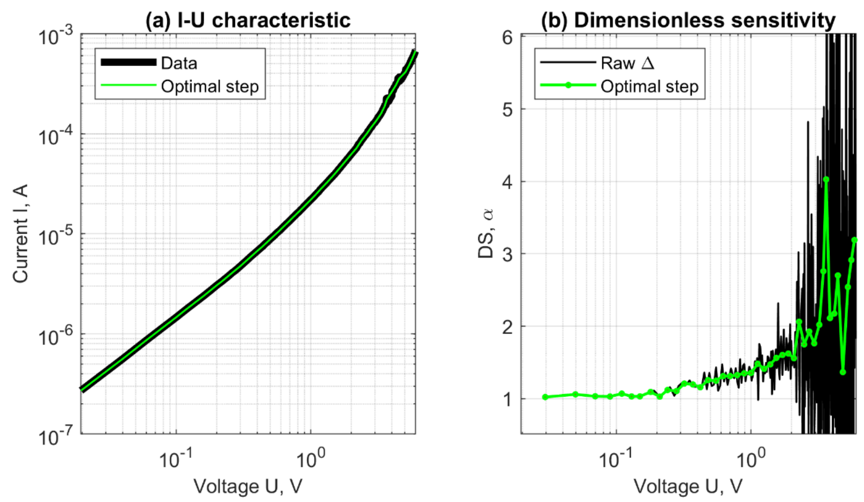

Fig. 5. *I–U* characteristic (*a*) and dimensionless sensitivity (*b*) with optimal step method.

sensitivity plots [11, 14], whereas an insufficient number of points results in a loss of resolution and smoothing of local features of the *I–U* characteristic.

5.1.1. Practical implementation of the method

Within this research framework, an optimal step method is proposed for post-processing of existing experimental datasets. The implementation algorithm follows the methodology outlined in [14] to compute theoretically optimal step size, subsequently resampling (decimating) an initial high-density data array. Only the values corresponding to the calculated logarithmic voltage grid are selected from the experimental data.

A key advantage of this approach lies in the fact that it exclusively processes original experimental data points unlike smoothing techniques that generate new values through approximation. This characteristic ensures elimination of smoothing artifacts such as peak displacement or blurring of sharp transitions, which is crucial for accurate identification of charge transport mechanisms.

Furthermore, unlike filtering methods that may introduce phase delays, the optimal step method guarantees zero phase lag fully preserving precise voltage positions of physical features.

Based on the resampled dataset obtained *via* the optimal step method, the dimensionless sensitivity value α(*U*) was recalculated. Comparative analysis of the results (Fig. 5) reveals a significant reduction in the level of high-frequency fluctuations. This enables clear identification of charge transport mechanisms within the structure such as transitions between conduction regimes, trap filling, and carrier injection phenomena. In the original noisy characteristics, these features were obscured by fluctuations, preventing precise determination of electrophysical parameters.

As demonstrated by the comparative results presented below (Fig. 8, Table 1), the optimal step method is not only conceptually valid for measurement design but also serves as an effective data filtering tool, enhancing the information content of differential analysis.

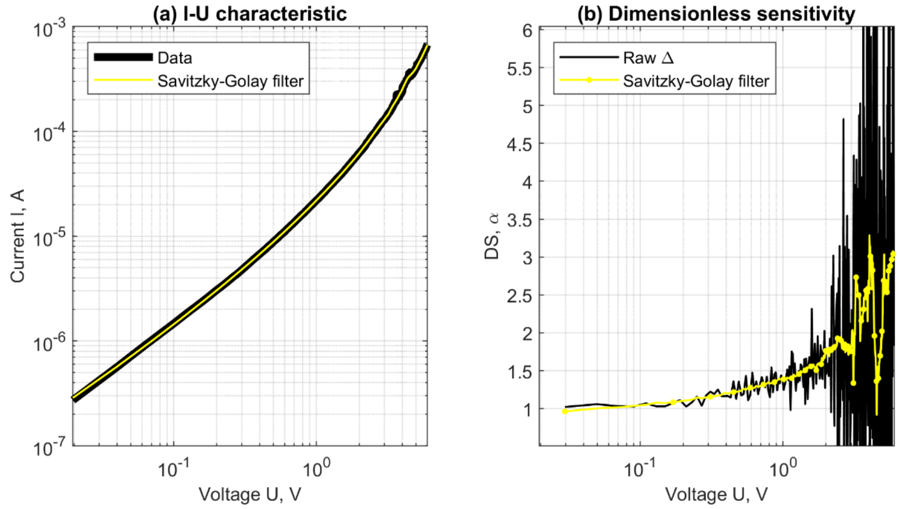

Fig. 6. *I–U* characteristic (*a*) and dimensionless sensitivity (*b*) with the Savitzky–Golay filter.

5.2. Polynomial approximation method

Beyond approximation and modeling tasks, polynomial methods have been widely adopted in experimental data processing, specifically as a tool for extracting the signal of interest and mitigating noise [26]. In many practical cases, an experimental signal does not exhibit pronounced fluctuations. However, presence of even a weak noise component can significantly impact the results of subsequent mathematical processing, particularly when applying differential analysis methods. Polynomial approximation enables replacement of a discrete set of noisy data with a smooth analytical function that reflects the general trend of the signal behavior.

Global polynomial approximation is employed to estimate the trend of experimental dependences in cases where the primary objective is qualitative analysis of the variable's behavior rather than reproduction of local fluctuations [27]. Nevertheless, the efficiency of polynomial approximation heavily relies on selection of the polynomial order, as an excessively high degree may lead to emergence of spurious oscillations unrelated to the physical nature of the process.

Unlike global polynomial approximation, which is based on the least squares method, the method developed by Savitzky and Golay (1964) relies on local polynomial regression within a moving window. It ensures effective suppression of high-frequency noise with minimal distortion of peaks, inflection points and other local features. Consequently, the Savitzky–Golay filter remains a standard tool for application to real spectra (IR, Raman, UV-Vis), chromatograms, geoelectric signals and ECG/EEG data, where preserving amplitude-temporal characteristics of the useful component is critical [10, 28, 29].

In the experimental analysis of the *I–U* characteristics of semiconductor structures, particularly solar cells, Schottky diodes and heterojunctions, the Savitzky–Golay method is extensively used for smoothing noisy data to accurately separate the useful signal from the noise component. The method ensures preservation of the curve morphology, peak heights (*e.g.*, the maximum power point in the solar cells) and curvature in inflection regions, while significantly enhancing the Signal-to-Noise Ratio (SNR) [18, 19].

5.2.1. Practical implementation

To implement this approach, a MATLAB environment and its built-in digital signal processing algorithms (specifically sgolayfilt) were employed in this study. Application of the Savitzky-Golay filter to the experimental *I–U* characteristics of the OLED structure enabled data smoothing without distorting the underlying physical nature of the signal.

A critical stage in the processing involved selection of optimal filtering parameters: the polynomial order (k) and the smoothing window width (frame size). For the investigated *I–U* characteristics, a low-order polynomial (typically 2nd or 3rd order) and an adaptive window width were selected. This configuration effectively suppressed oscillations while preserving the steepness of the characteristic's slope.

Fig. 6 presents a comparison between the DS obtained by direct differentiation of the raw (unfiltered) data and the result obtained after applying the Savitzky–Golay filter. As can be seen from this figure, the Savitzky–Golay filter completely eliminated non-physical spurious oscillations in the $\alpha(U)$ plots, which were evident during direct differentiation. The resulting "clean" trend curve clearly visualizes transitions between conductivity regimes and enables reliable identification of the structure's electrophysical parameters without need for repeated or more complex measurements.

5.3. Adaptive Kalman filtering method

An alternative approach to experimental data smoothing, which is fundamentally distinct from local polynomial approximation methods, involves use of recursive estimation algorithms, with the Kalman filter being the most prominent one. Whereas the Savitzky–Golay

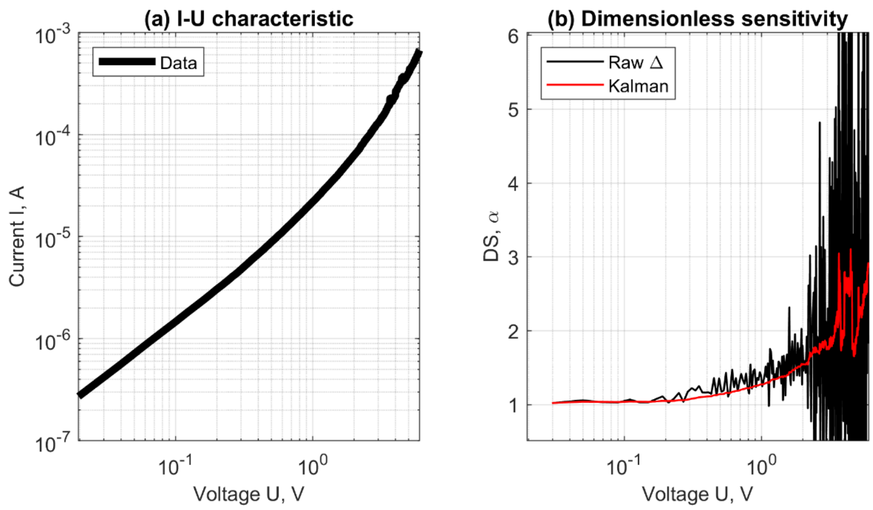

Fig. 7. *I–U* characteristic (*a*) and dimensionless sensitivity (*b*) with the Kalman filtering.

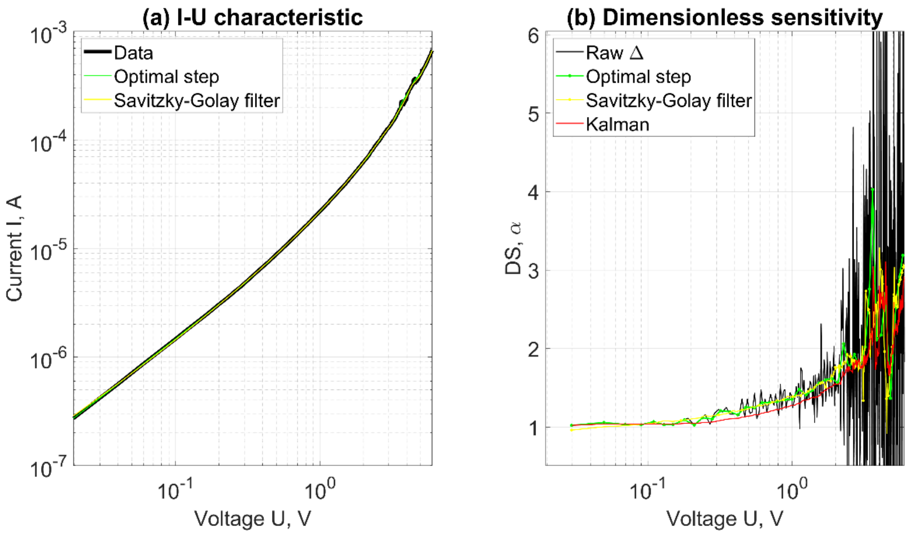

Fig. 8. *I–U* characteristic (*a*) and dimensionless sensitivity (*b*) with all methods.

method operates on a fixed data window treating the data as a static set of points, the Kalman filter treats the analysis of the *I–U* characteristic as a dynamic process that evolves with changing voltage. The foundations of the method were established in the seminal work by R.E. Kalman [10], who proposed a recursive solution of the discrete linear filtering problem. The core principle of the algorithm lies in optimal estimation of the system's state vector based on noisy measurements by minimizing the mean squared error.

The filtering process proceeds in two stages:

- Prediction: The algorithm extrapolates the state value to the subsequent step based on the previous estimate and the known physical model of the process.
- Update: The incoming measurement is utilized to correct the predicted value, incorporating a weighting coefficient (the Kalman Gain), which is determined by the ratio of the model uncertainty to the measurement noise [30].

In the context of semiconductor physics and *I–U* characteristic analysis, application of the Kalman filter enables effective separation of the signal of interest (actual conduction current) from the additive noise of the measurement instrumentation. A key advantage of the method is that it does not require storing the entire measurement history, rendering it computationally efficient. Furthermore, unlike simple low-pass filters, which may introduce phase delays and smooth out sharp physical features (*e.g.*, the breakdown region or abrupt changes in the conduction mechanism), a properly tuned Kalman filter is capable of rapid adaptation to trend changes [21].

5.3.1. Practical implementation

Practical implementation of the method for processing the *I–U* characteristic in this study utilizes a linear model, where the system "state" comprises the current value and its derivative. This yields a reconstructed *I*(*U*) dependence with a significantly reduced noise level, suitable

Table 1. Qualitative comparison between the methods under consideration.

Method	Complexity	Phase shift	Uses real points	Parametrization
Optimal step	Low	None	✓	1 (number of points)
Savitzky–Golay	Medium	None	✗ (approximation)	2 (window, order)
Kalman	High	Yes	✗ (stochastic)	2 (Q, R)

for subsequent differentiation and calculation of the dimensionless sensitivity $\alpha(U)$ without emergence of non-physical oscillations characteristic of raw experimental data. Fig. 7 presents a comparison between the dimensionless sensitivity obtained by direct differentiation of the raw data of the dimensionless sensitivity and the result obtained after applying Kalman filtering.

Fig. 8 clearly demonstrates the effectiveness of the proposed approach by comparing the performance of various processing techniques. The optimal step method is renowned for its direct adaptation to the underlying physical characteristics of the process. Unlike smoothing techniques, it fully preserves the original values of the experimental data points without modification. This is evident in the *I–U* characteristic (Fig. 8a), where the data are not "blurred" by filtering windows. Consequently, the positions and sequences of the peaks and inflection points on the graph precisely correspond to the actual voltage values. At the same time, the data edges exhibit no distortions typical of polynomial approximation methods. This is particularly evident when calculating DS, where significant oscillation artifacts are present in the raw data (Fig. 8b, black line). While conventional filters such as Savitzky–Golay or Kalman smooth these oscillations, they may introduce slight shifts or suppress fine details. In contrast, the uniform step on logarithmic scales provides mathematical robustness for dimensionless sensitivity calculations without these drawbacks. The algorithm does not require complex parameter settings (*e.g.* Q and R values for Kalman filtering or window size for Savitzky–Golay filtering), making it highly suitable for automated measurement applications. The key advantages and limitations of the considered methods, as illustrated by these results, are summarized in Table 1.

6. Experimental implementation of the optimal step method

The efficacy of the optimal step method is best evaluated based on actual experimentally measured current-voltage (*I–U*) curves. The application of the DS method for characterizing electrophysical properties of semiconductor diodes was proposed in [11]. In this study, an organic-inorganic hybrid structure was used as a laboratory sample to investigate the structure photoresponse and to identify specific charge transport and recombination mechanisms. (100)-oriented *n*-type structured silicon substrates with a resistivity of 2.7 Ω·cm were employed as the base. A carbazole derivative (DB74) deposited by spin coating served as the organic layer. The overall device structure was configured as follows: Aluminum contact / Silicon / DB74 / Contact (Silver paste). *I–U* characteristics in the dark and under illumination (30 mW/cm^2) were acquired using a standard automated Keithley measurement system with a measurement error of approximately 0.25% [31]. The system was pre-programmed to execute optimal voltage

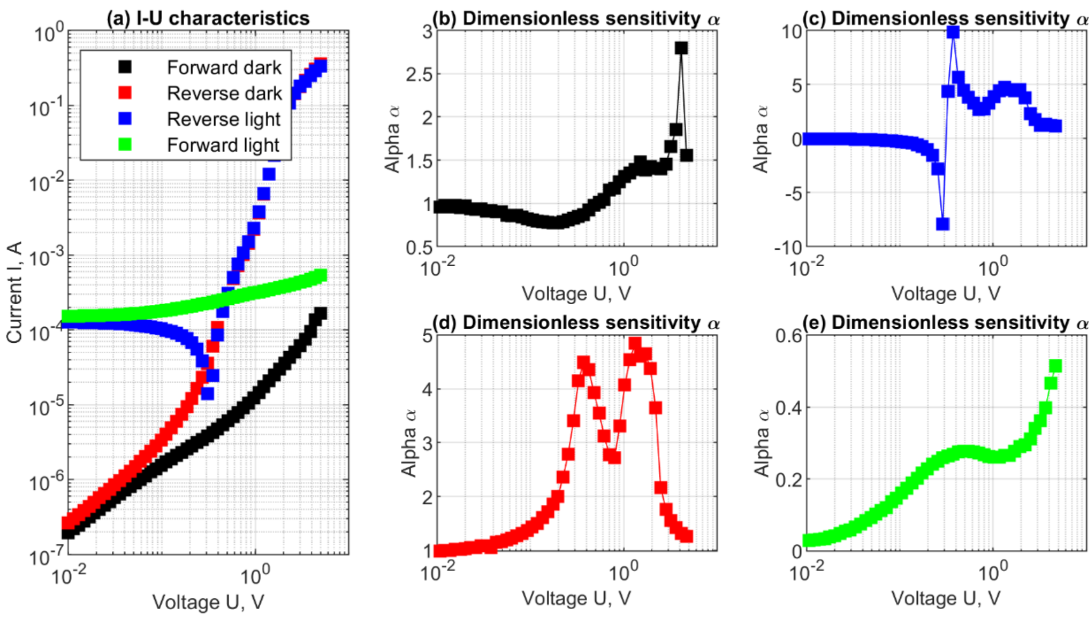

Fig. 9. *I–U* characteristic (*a*) and dimensionless sensitivity (*b–e*) of hybrid structure.

stepping in accordance with the theoretical specifications outlined in [11]. A dataset of 50 experimental points was obtained within an applied voltage range of 0.01 to 5 V. Subsequently, the data were analyzed based on the dimensionless sensitivity values.

Fig. 9a presents the initial *I–U* curve of the investigated structure plotted on a log-log scale. The dimensionless sensitivity value was calculated based on Eq. (3), yielding the $\alpha(U)$ dependence shown in Fig. 5b–5e on a semi-log scale.

The resulting $\alpha(U)$ curve is devoid of spurious oscillations indicating correctness of the measurement step selection and successful minimization of error. This characteristic facilitates reliable analysis of physical processes in the investigated structure specifically enabling identification of characteristic regions of recombination, rectification, and other charge transport mechanisms.

7. Conclusions

This study presents a comparative analysis of three approaches to mitigate noise artifacts in the differential analysis of semiconductor *I–U* characteristics: the optimal step method, polynomial approximation (Savitzky–Golay), and adaptive Kalman filtering.

The results demonstrate that while the Kalman filter provides effective noise suppression through stochastic estimation, it requires careful tuning of the covariance matrices Q and R noted in Table 1. Similarly, the Savitzky–Golay filter is sensitive to the window-size and polynomial-order selection discussed in Section 8.1. In contrast, the optimal step method exhibits a unique combination of precision and computational simplicity.

Unlike recursive algorithms or convolution-based filters, the optimal step method is deterministic and does not require complex parameter tuning. Its implementation reduces to a simple algebraic selection of data points based on a logarithmic criterion.

The novelty of this work lies in demonstrating that the optimal step method can be effectively applied not only at the experimental design stage but also as a powerful post-processing tool for pre-existing experimental datasets. This approach combines high efficiency with a clear experimental process, ensuring high-quality data acquisition and eliminating the need for further filtering and post-processing. Consequently, the optimal step method is recommended as the primary strategy for enhancing the reliability of dimensionless sensitivity analysis, providing a robust solution for the diagnostics of semiconductor structures without the risk of data distortion.

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References

1. Sze S.M., Li Y., Ng K.K. *Physics of Semiconductor Devices.* John Wiley & Sons, Hoboken, NJ, 2021.
2. Wangyang P., Huang X., Shi X. *et al.* Advances in Schottky parameter extraction and applications. *J. Mater. Sci. Technol.* 2025. **218**. P. 317–335. https://doi.org/10.1016/j.jmst.2024.08.037.
3. Park J., Yu C., Min S. *et al.* Extracting the inherent ideality factor of a diode from electrical current–voltage characteristics. *Electron. Lett.* 2023. **59**. P. e13046. https://doi.org/10.1049/ell2.13046.
4. Nagai A., Alispach C., Barbano A. *et al.* Characterization of a large area silicon photomultiplier. *Nucl. Instrum. Methods Phys. Res. A.* 2019. **948**. P. 162796. https://doi.org/10.1016/j.nima.2019.162796
5. Werner F., Siebentritt S. Buffer layers, defects, and the capacitance step in the admittance spectrum of a thin-film solar cell. *Phys. Rev. Appl.* 2022. **18**. P. 034033. https://doi.org/10.1103/PhysRevApplied.9.054047.
6. Zakamulin V., Rubio J.G. A digital signal processing approach to moving averages. In: *The Ultimate Moving Average Handbook.* Springer, 2025. Ch. 10. https://doi.org/10.1007/978-3-031-90907-8_10.
7. Lin X., Liang X., Li W. *et al.* Adaptive robust least-squares smoothing algorithm. *IEEE Trans. Instrum. Meas.* 2022. **71**. Art. No 8505218. https://doi.org/10.1109/TIM.2022.3210970.
8. Press W.H., Teukolsky S.A., Vetterling W.T., Flannery B.P. *Numerical Recipes: The Art of Scientific Computing.* 3rd ed. Cambridge University Press, New York, 2007.
9. Sainburg T., Zorea A. Domain general noise reduction for time series signals with spectral gating in the Fourier domain. *Sci. Rep.* 2025. **15**. Art. No 30905. https://doi.org/10.1038/s41598-025-13108-x.
10. Kalman R.E. A new approach to linear filtering and prediction problems. *J. Basic Eng.* 1960. **82**, No 1. P. 35–45. https://doi.org/10.1115/1.3662552.
11. Smertenko P., Fenenko L., Brehmer L., Schrader S. Differential approach to the study of integral characteristics in polymer films. *Adv. Colloid Interface Sci.* 2005. **116**, No 1-3. P. 255–261. https://doi.org/10.1016/j.cis.2005.05.005.
12. Mikhelashvili V., Eisenstein G., Garber V. *et al.* On the extraction of linear and nonlinear physical parameters in nonideal diodes. *J. Appl. Phys.* 1999. **85**, No 9. P. 6873–6883. https://doi.org/10.1063/1.370206.
13. Mikhelashvili V., Eisenstein G., Uzdin R. Extraction of Schottky diode parameters with a bias dependent barrier height. *Solid-State Electronics.* 2001. **45**, No 1. P. 143–148. https://doi.org/10.1016/S0038-1101(00)00227-6.
14. Smertenko P.S., Ciach R., Dotsenko Y.P. *et al.* Injection technique for the study of solar cell test structures. *Sol. Energy Mater. Sol. Cells.* 2003. **76**, No 4. P. 613–624. https://doi.org/10.1016/S0927-0248(02)00271-44.
15. Rizvi S.M.H., Mantri P., Mazhari B. Trap signature in steady-state current–voltage characteristics of organic diode. *J. Appl. Phys.* 2014. **115**, No 24. Art. No 244502. https://doi.org/10.1063/1.4884838.

16. Rizvi S.M.H., Mazhari B. Investigation of traps in thin-film organic semiconductors using differential analysis of steady-state current–voltage characteristics. *IEEE Trans. Electron. Devices.* 2018. **65**, No 9. P. 3907–3913. https://doi.org/10.1109/TED.2018.2849346.
17. Mantri P., Rizvi S.M.H., Mazhari B. Estimation of built-in voltage from steady-state current–voltage characteristics of organic diodes. *Org. Electron.* 2013. **14**, No 8. P. 2034–2038. https://doi.org/10.1016/j.orgel.2013.04.030.
18. Gallagher N.B. *Savitzky–Golay Smoothing and Differentiation Filter.* Eigenvector Research Inc., Manson, WA, 2020. https://doi.org/10.13140/RG.2.2.20339.50725.
19. Vermang B., Wätjen J.T., Fjällström V. *et al.* Employing Si solar cell technology to increase efficiency of ultra-thin Cu(In,Ga)Se_2 solar cells. *Prog. Photovolt.* 2014. **22**. P. 1023–1029. https://doi.org/10.1002/pip.2527.
20. Shao X., He X., Li Z. Strain fields measurement using frequency domain Savitzky–Golay filters in digital image correlation. *Opt. Laser Eng.* 2015. **65**. P. 93–101. https://doi.org/10.1088/1361-6501/acda53.
21. Zarchan P., Musoff H. *Fundamentals of Kalman Filtering: A Practical Approach.* 3rd ed. Progress in Astronautics and Aeronautics, vol. 240. AIAA, Reston, VA, 2013. https://doi.org/10.2514/4.102776.
22. Kim H., Kim D. A study on reducing the noise using the Kalman filter in digital holographic microscopy (DHM). *Journal of the Optical Society of Korea.* 2014. **18**, No 3. P. 232–239.
23. Hu H., Shen H., Pu Q. Design and implementation of high-precision voltage measurement system based on Kalman filter and automatic calibration technology. *Measurement.* 2022. **204**. Art. No 112126. https://doi.org/10.1016/j.measurement.2022.112126.
24. Zeng W., Lai H.-Y., Lee W.-K. *et al.* Achieving nearly 30% external quantum efficiency for orange–red organic light emitting diodes by employing thermally activated delayed fluorescence emitters composed of 1,8-naphthalimide-acridine hybrids. *Adv. Mater.* 2018. **30**, No 5. Art. No 1704961. https://doi.org/10.1002/ADMA.201704961.
25. Krucaite G., Beresneviciute R., Tavgeniene D. *et al.* New bipolar derivatives with diphenylsulfone or dibenzophenone as TADF based emitters for OLEDs. *Org. Electron.* 2024. **125**. Art. No 106981. https://doi.org/10.1016/j.orgel.2023.106981.
26. Matsuda T., Nakatsukasa Y. Polynomial approximation of noisy functions. *Numerische Mathematik.* 2025. **157**. P. 1285–1311. https://doi.org/10.1007/s00211-025-01485-4.
27. Pelz B., Belkadi A., Moddel G. Avoiding erroneous analysis of MIM diode current-voltage characteristics through exponential fitting. *Measurement.* 2018. **120**. P. 28–33. https://doi.org/10.1016/j.measurement.2018.01.054.
28. Maduakolam F.C., Dauda S.Y., Umar I. Analysis of Savitzky–Golay filter for electrocardiogram denoising using Daubechies wavelets. *ASEAN Science and Education Journal.* 2021. **1**, No 2. P. 34–48. https://doi.org/10.53797/aseana.v1i2.3.2021.
29. Angus F.J., Yiu W.K., Mo H. *et al.* Understanding the impact of SAM Fermi levels on high efficiency *p-i-n* perovskite solar cells. *J. Phys. Chem. Lett.* 2024. **15**. P. 10686–10695. https://doi.org/10.1021/acs.jpclett.4c02345.
30. Särkkä S. *Bayesian Filtering and Smoothing.* Cambridge University Press, Cambridge, 2016.
31. Mamykin S., Kuznietsova D., Roshchina N. *et al.* Self-organized films of carbazole derivatives on structured silicon substrates for photovoltaic application. *Proc. Int. Conf. EU PVSEC-41*, Vienna, Austria, Sept. 23–27, 2024. https://doi.org/10.4229/EUPVSEC2024/2BV.1.11.

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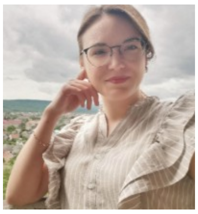

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Підвищення точності визначення диференціальних параметрів із зашумлених вимірювальних даних

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Анотація. У роботі розглядається проблема підвищення точності диференціального аналізу інтегральних характеристик напівпровідникових структур в умовах експериментальних шумів. Показано, що стандартні методи вимірювання з лінійним кроком напруги приводять до значних похибок при обчисленні безрозмірної чутливості, які проявляються у вигляді нефізичних осциляцій, що ускладнюють ідентифікацію механізмів переносу заряду. Проведено порівняльний аналіз трьох методів обробки даних: методу оптимального кроку, поліноміальної апроксимації (фільтр Савицького–Голея) та адаптивної фільтрації на основі алгоритму Калмана. Встановлено, що застосування методу оптимального кроку, основаного на логарифмічній вибірці струму, дозволяє уникнути артефактів диференціювання без внесення фазових затримок, характерних для методів згладжування. Запропоновані підходи були перевірені на експериментальних вольт-амперних характеристиках OLED-структур, що підтвердило їхню придатність для прецизійної діагностики електрофізичних параметрів напівпровідникових приладів.

Ключові слова: вольт-амперна характеристика, безрозмірна чутливість, диференціальний аналіз, метод оптимального кроку, фільтр Савіцького–Голея, фільтр Калмана, напівпровідникова структура.