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EFFICIENT SIGNAL SMOOTHING AND IMPULSE COMPUTATION IN HIGH-RESOLUTION PRESSURE MEASUREMENTS

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Abstract: *This paper presents a data processing approach for smoothing noisy experimental signals and estimating impulse through numerical integration. Large pressure–time datasets are first reduced using controlled subsampling while preserving critical peak values. High-frequency noise is then attenuated using a Savitzky–Golay smoothing filter, applied selectively after the signal maximum to avoid distortion of physically meaningful features. Impulse values are computed by integrating the processed signals using the composite trapezoidal rule following the removal of non-physical negative values. The proposed methodology improves numerical stability and repeatability compared to raw data processing while remaining computationally efficient and suitable for large-scale experimental pressure or force measurements.*
Keywords: *Signal smoothing; Savitzky–Golay filter; Numerical integration; Trapezoidal rule; Impulse calculation.*

1. INTRODUCTION

High-resolution pressure signals generated by explosive and other high-energy transient events exhibit strong broadband noise, abrupt growth, and large data volumes, complicating post-processing and often leading to unstable impulse estimation when conventional filtering and integration methods are applied directly. In experimental mechanics and blast diagnostics, impulse is obtained from the pressure–time integral; however, noise-induced oscillations, particularly near the peak region, can significantly bias this calculation. Existing smoothing techniques are typically applied uniformly over the entire signal duration, which may distort peak amplitude and temporal structure critical for explosion-generated signals [1–3]. Despite extensive research, application-oriented frameworks specifically designed for such signals remain limited [4,5].

This work proposes a purpose-built processing framework that applies selective Savitzky–Golay smoothing exclusively after the signal maximum, combines controlled subsampling with peak retention to reduce computational cost, and employs composite trapezoidal integration for stable impulse estimation. The framework enables repeatable and computationally efficient impulse analysis for high-energy transient measurements.

2. RESEARCH STAGES

2.1 Acquisition of data

During a series of experiments aimed at optimizing the formulation of thermobaric explosive compositions, multiple candidate chemical structures were synthesized and tested.

The objective was to measure the pressure–time response generated by each composition at distances of 1 m, 2 m, and 3 m from the detonation point.

The experimental setup consisted of three PCB 102B06 piezoelectric pressure sensors positioned at the specified distances. Following each detonation, high-resolution time-series data were recorded, capturing the sensor vibrations induced by the resulting shock wave.

The main characteristics of the experimental dataset and acquisition system are summarized in Table 1.

The measurements were stored as spreadsheet files containing the pressure signals for

subsequent signal processing and impulse analysis.

Table 1

Summary of the Experimental Dataset and Acquisition Parameters

Parameter	Description
Pressure sensors	PCB Piezotronics 102B06 piezoelectric pressure sensors
Sensor pressure range	Up to 34.5 MPa
Sensor sensitivity	1.45 mV/kPa
Sampling frequency	1 MHz
Acquisition resolution	16-bit analog-to-digital conversion
Number of sensors	3 (positioned at 1 m, 2 m, and 3 m from the detonation point)
Number of explosion tests	Multiple tests per explosive composition
Signal duration	Entire positive and post-peak pressure phase
Measurement uncertainty	±2% of full-scale output
Data volume per channel	1–4 million samples per test

All explosive experiments were conducted in authorized laboratory facilities and in full compliance with applicable safety protocols, regulatory requirements, and institutional guidelines governing the handling and testing of energetic materials.

2.2 Literature review

Previous studies have proposed a wide range of smoothing and numerical integration techniques for noisy experimental signals. However, most methods are designed for stationary or weakly non-stationary data and are applied uniformly across the entire signal duration. In thermobaric explosion measurements, pressure signals are highly asymmetric, with a rapid growth phase followed by a noise-dominated decay, making global smoothing approaches prone to peak distortion and biased impulse estimation.

Traditional smoothing methods such as moving averages and Gaussian filters are computationally efficient but attenuate sharp transients [1,3]. Frequency-domain low-pass filters may introduce phase distortion in non-stationary signals [2,6], while wavelet-based techniques are computationally intensive and sensitive to parameter selection [4]. Polynomial-based Savitzky–Golay filtering offers improved peak preservation and noise suppression [1,2,7], yet is typically applied globally. For impulse estimation, higher-order integration schemes are sensitive to noise, whereas the composite trapezoidal rule provides superior robustness and numerical stability for large experimental datasets [8–10].

2.3 Methodology

The methodology was organized into a sequence of interdependent stages to ensure an objective and systematic approach to the research objectives. A multi-criteria analysis was first employed to guide the selection of signal smoothing and numerical integration techniques for explosion-generated pressure data, avoiding arbitrary methodological choices and ensuring compliance with both physical and numerical requirements.

Performance indicators relevant to high-energy transient signals—including noise suppression, signal shape preservation, numerical stability, implementation complexity, processing time, and impulse accuracy—were evaluated. Criterion weights were determined using the FRISCO method, and candidate filtering and integration techniques were ranked accordingly to enable transparent method selection.

The selected methods were then implemented within a dedicated processing pipeline comprising controlled data reduction, selective post-peak smoothing, physically constrained signal conditioning, and numerical impulse computation. Each stage was validated through sensitivity analysis and statistical evaluation of repeatability and accuracy, ensuring a reproducible and physically consistent framework for impulse estimation in thermobaric explosion experiments.

2.3.1 Multi-Criteria Analysis

Based on the characteristics of explosion-generated pressure signals and recent signal-processing research, a multi-criteria analysis was employed to guide the objective selection of filtering and integration techniques. High-energy transient signals are dominated by broadband noise and non-stationary behavior, requiring noise reduction methods that preserve peak

amplitude and temporal structure [11], [12]. Comparative studies indicate that effective smoothing must balance noise suppression with signal morphology preservation, with Savitzky–Golay and related polynomial filters offering a favorable compromise compared to moving-average and Butterworth methods in high-noise applications [13].

Accordingly, the following criteria were selected as the most relevant for evaluating candidate methods:C1 – Noise suppression: the ability to reduce parasitic fluctuations and high-frequency noise;C2 – Signal shape preservation: the extent to which true signal features, particularly peak values, are retained;C3 – Numerical stability: the absence of spurious oscillations or numerical artifacts during processing;C4 – Implementation complexity: the ease of implementation, coding, and practical use;C5 – Processing time: the computational efficiency and execution speed; C6 – Impulse accuracy: the precision of the final impulse estimation obtained from the processed signal.

The determination is completed by calculating the weighting coefficients.

The weighting coefficients γi were calculated using the FRISCO method, which derives criterion weights from pairwise comparison scores obtained on a three-level Latin scale. In this scale, a value of 1 indicates that a criterion is more important than the compared criterion, a value of 0.5 indicates equal importance, and a value of 0 indicates lower importance. The scale is presented in Table 2. This discrete scale was selected to limit subjectivity and ensure consistency in expert judgment, as recommended in rank-based multi-criteria decision-making frameworks.

For each criterion, the total score p was computed as the sum of its row values in the pairwise comparison matrix. The FRISCO formula was then applied to transform these scores into weighting coefficients γi taking into account the relative ranking position of each criterion, the number of criteria it outperformed, and its distance from both the highest-ranked and lowest-ranked criteria. This formulation enhances discrimination between closely ranked criteria while preserving the ordinal structure of the ranking.

Table 2

Comparison Table

	C1	C2	C3	C4	C5	C6	P
C1	0,5	1	1	1	1	0	**4,5**
C2	0	0,5	1	1	1	0	**3,5**
C3	0	0	0,5	1	1	0	**2,5**
C4	0	0	0	0,5	1	0	**1,5**
C5	0	0	0	0	0,5	0	**0,5**
C6	1	1	1	1	1	0,5	**5,5**

The resulting weighting coefficients were not normalized to sum to unity, as the FRISCO method produces relative weights intended for direct multiplication with normalized performance scores. In this context, normalization is not required, since the final ranking of alternatives depends on relative weighted sums rather than absolute weight magnitudes. The adopted numerical scale and weighting approach therefore provide sufficient resolution to differentiate criteria importance while maintaining transparency and reproducibility in the evaluation process.

The weighting coefficients γi can be calculated using several formulas. For practical use, the FRISCO formula was selected, which has been internationally recognized as highly effective and is widely used [14]:

$$\gamma_{i=}\frac{p+\Delta p+m+0.5}{-\Delta p'+\frac{N_{crt}}{2}} \quad (1)$$

where:

p represents the sum of points obtained (row-wise) by the criterion under consideration;

Δp is the difference between the score of the considered criterion and the score of the criterion at the last level; if the considered criterion is itself at the last level, then Δp=0;

m denotes the number of criteria surpassed (outperformed in terms of score) by the considered criterion;

Ncrt represents the total number of criteria considered;

Δp′ is the difference between the score of the considered criterion and the score of the criterion

at the first level (resulting in a negative value); if the considered criterion is located at the first level, then $\Delta p'=0$.

The resulted weighted coefficients are presented in Table 3.

Table 3

Weighting coefficients obtained using the FRISCO method.

Criterion	p	γ_i
C6	5,50	5,33
C1	4,50	3,25
C2	3,50	2,00
C3	2,50	1,16
C4	1,50	0,57
C5	0,50	0,125

Following determination of the FRISCO weighting coefficients, alternative signal processing strategies were evaluated using a normalized 1–10 scoring scale based on noise suppression, signal fidelity, numerical stability, implementation complexity, processing time, and impulse accuracy. Scores were assigned using theoretical considerations and observed performance on representative datasets, and overall performance was obtained by weighting the scores with the corresponding coefficients, as summarized in Tables 4 and 5.

Table 4

Consequence matrix and total scores of filtering methods

	$\gamma_{1=3,25}$	$\gamma_{2=2,00}$	$\gamma_{3=1,16}$	$\gamma_{4=0,57}$	$\gamma_{5=0,125}$	$\gamma_{6=5,33}$	TOTAL
Moving Average ($N \times \gamma_i$)	19,50	8,00	8,12	5,13	1,125	26,65	68,525
Sav-Gol ($N \times \gamma_i$)	29,25	20,00	10,44	4,56	1,00	53,33	118,58
Butter-worth ($N \times \gamma_i$)	26.00	16,00	8,12	3,42	0,75	42,64	96,93
Chebyshev ($N \times \gamma_i$)	29,25	10,00	6,96	2,85	0,75	37,31	87,12
Kalman ($N \times \gamma_i$)	32,50	20,00	11,60	2,28	0,50	47,97	114,85

Based on the multi-criteria evaluation, the Savitzky–Golay filter achieves the highest overall score among the filtering methods, primarily due to its superior performance in noise suppression, signal shape preservation, and impulse accuracy.

Table 5

Consequence matrix and total scores of integration method

	$\gamma_{1=3,25}$	$\gamma_{2=2,00}$	$\gamma_{3=1,16}$	$\gamma_{4=0,57}$	$\gamma_{5=0,125}$	$\gamma_{6=5,33}$
Nummerical Integration ($N \times \gamma_i$)	12.00	6,96	5,13	1,125	31,98	52,065
Trapezoidal ($N \times \gamma_i$)	16.00	9,28	4,56	1,00	47,97	78,81
Simpson ($N \times \gamma_i$)	18.00	8,12	2,28	0,50	47,97	76,87

Among the numerical integration techniques, the trapezoidal rule provides the best balance between accuracy, numerical stability, and computational efficiency, justifying its selection within the proposed processing framework.

2.3.2 Overview of the Processing Pipeline

The proposed processing pipeline consists of four main stages:

- controlled data reduction,
- selective signal smoothing
- physically constrained signal conditioning
- numerical impulse estimatio

Each stage was designed to balance computational efficiency with physical fidelity and numerical stability, and all parameter choices were evaluated through sensitivity analysis.

2.3.3 Application of the Savitzky–Golay Filter

The Savitzky–Golay filter was applied using a symmetric window, but restricted exclusively to the post-peak segment of the signal. Specifically, the global maximum of the pressure–time signal was first identified, and the signal was segmented into a pre-peak (growth) region and a post-peak (decay) region. No smoothing was applied to the pre-peak region.

Within the post-peak segment, the Savitzky–Golay filter operates with its standard symmetric window centered at each sample point. However, the window is constrained to remain entirely within the post-peak data range. Near the segmentation boundary (immediately after the peak), the filter window is automatically truncated by the algorithm to avoid incorporating pre-peak samples. As a result, no information

from the growth phase or peak region contributes to the smoothing process.

This approach ensures that the physically meaningful growth phase and peak amplitude are preserved exactly, while noise-dominated oscillations in the post-peak region are effectively attenuated. The filter is therefore not applied asymmetrically in a causal sense, but rather symmetrically within a deliberately restricted post-peak domain, combining the numerical advantages of symmetric Savitzky–Golay filtering with physically motivated signal segmentation.

2.3.4 Data Reduction and Subsampling Strategy

High-resolution pressure signals from thermobaric explosive events typically contain 1–4 million samples per channel, making full-resolution processing computationally inefficient without significant gains in impulse accuracy. To reduce data volume while preserving physically relevant information, uniform subsampling was applied.

Several subsampling ratios (1:25, 1:50, 1:100, and 1:200) were evaluated by comparing impulse values from subsampled signals with those obtained from full-resolution data. A ratio of 1:100 was selected, as it limited impulse deviation to below 1.5% while reducing computational time by approximately two orders of magnitude. The subsampling ratio can be adjusted for different events if required, and the global maximum pressure point was explicitly preserved to prevent peak attenuation.

2.3.5 Treatment of Negative Pressure Values

Negative pressure values observed in the post-peak region are primarily associated with rarefaction effects, sensor ringing, and wave reflections, and they do not contribute to the forward momentum transfer imparted by the blast wave. In classical blast mechanics, impulse is defined as the time integral of the positive-phase overpressure, as this phase governs structural loading, damage mechanisms, and momentum transfer to surrounding media.

Consequently, the negative phase is commonly neglected in impulse calculations unless specific suction-related effects are under investigation. This convention is well established in both theoretical and experimental blast research, where impulse metrics are consistently derived from the positive overpressure history only. Authoritative blast engineering references explicitly state that the positive-phase impulse represents the physically relevant quantity for explosion-induced loading and should be evaluated independently of negative pressure excursions.

Accordingly, negative pressure values were set to zero prior to numerical integration to compute the positive-phase impulse, in accordance with established blast mechanics theory and experimental practice [11,12,22].

2.3.6 Quantitative Comparison with Alternative Smoothing and Integration Strategies

To validate the proposed processing framework, a quantitative comparison was performed against commonly used smoothing and numerical integration techniques, following established approaches for high-noise transient pressure measurements [13], [15]. The evaluation was based on experimental pressure signals recorded during thermobaric explosion tests.

Five smoothing methods—moving average, Savitzky–Golay, Butterworth, Chebyshev, and Kalman filtering—were applied to identical subsampled datasets using literature-recommended parameter ranges to ensure consistency and fairness [2], [4], [17]. Performance was assessed using standard quantitative metrics: Noise Reduction Ratio (NRR), Peak Preservation Error (PPE), Impulse Deviation (ID), and average computational time per signal (CT), as defined in prior comparative studies [3].

The reference impulse was defined as the impulse computed from the full-resolution pressure signal with minimal preprocessing, serving as a physically meaningful experimental benchmark. The reference signal was retained at full sampling rate, without smoothing or filtering, negative pressure values were set to zero to isolate the positive-phase contribution, and the impulse was computed using the composite trapezoidal rule. This reference does not represent an

analytical ground truth but provides a reproducible baseline for evaluating the effects of smoothing, subsampling, and parameter selection on impulse accuracy. The Savitzky–Golay filter yields the lowest impulse deviation while maintaining effective noise suppression and moderate computational cost, consistent with recent comparative studies [3]. Although the Kalman filter provides slightly higher noise reduction, its substantially greater computational cost and implementation complexity limit its suitability for large experimental datasets [1], [2], [7].

Table 6

Quantitative comparison of smoothing methods

Method	NRR (%)	PPE (%)	ID (%)	CT (ms)
Moving average	62.10	14.80	9.50	3.00
Savitzky–Golay	78.40	2.10	1.80	6.00
Butterworth	73.20	6.40	5.20	9.00
Chebyshev	75.50	11.30	6.80	10.00
Kalman	81.60	1.90	2.60	21.00

Three numerical integration methods—direct numerical integration, the composite trapezoidal rule, and Simpson's rule—were evaluated, as commonly adopted in experimental mechanics and transient signal analysis [8], [9], [18], [19]. Performance was assessed in terms of impulse stability (IS), defined as the standard deviation of impulse values across repeated trials, subsampling sensitivity (SS), defined as the impulse deviation induced by varying subsampling ratios, and computational time (CT). These metrics directly quantify numerical robustness and efficiency under noise-dominated conditions and are summarized in the corresponding tables.

Table7

Quantitative comparison of integration methods

Method	IS (%)	SS (%)	CT (ms)
Numerical integration	**6.30**	**7.10**	**5.0**
Trapezoidal rule	**1.20**	**1.50**	**4.0**
Simpson's rule	**3.80**	**4.90**	**6.0**

The composite trapezoidal rule demonstrates superior numerical stability and minimal sensitivity to subsampling, in agreement with findings reported in recent numerical analysis and applied mechanics literature [9], [10], [20].

These properties make it particularly suitable for large, noise-affected experimental datasets.

2.3.7 Sensitivity Analysis and Error Evaluation

A sensitivity analysis was conducted to evaluate the influence of Savitzky–Golay (SG) filter parameters on impulse estimation. Window lengths between 51 and 251 samples and polynomial orders from 2 to 5 were examined, consistent with ranges reported in recent signal-processing studies [13], [15]. For each parameter combination, the impulse computed from the selectively smoothed signal was compared with a reference impulse obtained from minimally smoothed full-resolution data. Equation (2) provides a dimensionless measure of impulse error, enabling direct comparison across datasets with different absolute impulse magnitudes and facilitating objective parameter selection.

$$\varepsilon_J = \frac{|J_{SG} - J_{ref}|}{J_{ref}} \times 100\% \qquad (2)$$

The relative impulse error, defined in Eq. (2), quantifies the normalized deviation between the processed and reference impulse and provides a direct measure of parameter-induced error. Small window sizes (below 75 samples) resulted in insufficient noise suppression and increased impulse variability, while large windows (above 200 samples) caused over-smoothing and attenuation of physically meaningful signal features. Polynomial orders greater than 4 did not improve accuracy and occasionally introduced boundary oscillations.

A window length of 155 samples and a polynomial order of 3 minimized impulse error, maintaining $\varepsilon J<2\%$ across all datasets. This configuration was therefore adopted for subsequent analysis.

2.3.8 Impact of Subsampling on Impulse Accuracy

The effect of subsampling on impulse estimation accuracy was evaluated by comparing impulses computed from subsampled signals against those obtained from full-resolution data. Subsampling ratios of 1:25, 1:50, 1:100, and 1:200 were analyzed, with the global pressure maximum explicitly preserved in all cases.The impact of subsampling on impulse accuracy was evaluated using a relative impulse deviation metric. This deviation is defined in Eq. (3) as the

normalized difference between impulses computed from subsampled and full-resolution signals.

$$\delta_I = \frac{|I_{sub} - I_{full}|}{I_{full}} \times 100\% \quad (3)$$

The results show that subsampling ratios up to 1:100 introduce impulse deviations below 1.5%, while significantly reducing computational cost. In contrast, a ratio of 1:200 resulted in impulse deviations exceeding 4%, indicating a loss of relevant signal information. These findings demonstrate that the selected subsampling strategy represents an optimal compromise between accuracy and efficiency. [21].

2.3.9 Error Propagation and Repeatability

Repeatability was evaluated across multiple explosion tests and sensor channels. The standard deviation of impulse values remained below 2.1%, confirming the numerical stability of the proposed configuration [11], [16]. No systematic bias was observed across repeated measurements, indicating that the combined effects of smoothing and subsampling do not compromise impulse accuracy [7–9], [11].

Sensitivity analysis confirms that both Savitzky–Golay filter parameters and subsampling ratio significantly influence impulse estimation. Selecting these parameters through quantitative error evaluation rather than heuristic choice ensures reproducible and physically consistent impulse computation for explosion-generated pressure signals [1], [2], [16].

2.4 Software Implementation and Availability

The proposed processing framework was implemented as a dedicated software tool developed in Python, leveraging established scientific computing libraries for numerical processing and data handling. The implementation is platform-independent and was tested on Windows and Linux operating systems. The software processes high-resolution pressure time-series data stored in standard spreadsheet formats and executes the complete pipeline, including data reduction, selective post-peak smoothing, physically constrained signal conditioning, numerical integration, and statistical evaluation.

At the time of submission, the software is available for internal research use and can be provided to reviewers upon reasonable request. Future work will focus on extending the implementation toward a user-friendly interface and broader distribution for experimental research applications.

3. RESULTS

Impulse values were computed using five smoothing techniques applied to identical datasets: moving average, Savitzky–Golay, Butterworth, Chebyshev, and Kalman filtering. The composite trapezoidal rule was used consistently for integration to isolate the effect of smoothing**.**

Table 8

Impulse accuracy and variability for smoothing methods

Method	Mean Impulse (Ns)	Std. Dev. (Ns)	Relative Error (%)
Reference (full-resolution)	**12.84**	**0.31**	**–**
Moving average	**11.62**	**0.88**	**9.50**
Savitzky–Golay	**12.61**	**0.27**	**1.80**
Butterworth	**12.18**	**0.56**	**5.20**
Chebyshev	**11.96**	**0.71**	**6.80**
Kalman	**12.50**	**0.34**	**2.60**

The Savitzky–Golay filter achieves the lowest relative error and the smallest variance, indicating superior impulse accuracy and repeatability. Although the Kalman filter performs comparably in terms of mean impulse value, it exhibits a higher computational cost and implementation complexity, limiting its suitability for large datasets.

Using Savitzky–Golay–processed signals, three numerical integration methods were evaluated: direct numerical integration, composite trapezoidal rule, and Simpson's rule.

Table 9

Impulse stability and sensitivity of integration methods

Method	Mean Impulse (Ns)	Std. Dev. (Ns)	Subsampling Sensitivity (%)
Numerical integration	12.09	0.76	7.10
Trapezoidal rule	12.61	0.15	1.50
Simpson's rule	12.48	0.47	4.90

The trapezoidal rule demonstrates the highest numerical stability and the lowest sensitivity to subsampling, confirming its suitability for impulse estimation in noisy experimental conditions.

Repeatability and uncertainty metrics were computed using impulse estimates obtained from six independent explosion tests conducted at three sensor locations (1 m, 2 m, and 3 m). The total sample size was therefore

$$n = N_{tests} \times N_{sensors} = 6 \times 3 = 18 \quad (4)$$

Equation (4) reflects the aggregation of independent measurements across six explosion tests and three sensor locations, yielding a total sample size of 18 impulse estimates. Only trials with complete and artifact-free recordings across all sensor channels were included in the statistical analysis.

The coefficient of variation (CV) was computed as:

$$CV = \frac{\sigma}{J} \times 100\% \quad (5)$$

where J denotes the sample mean impulse and σ is the sample standard deviation calculated using Bessel's correction. Equation (5) expresses the relative dispersion of impulse values with respect to their mean and provides a dimensionless indicator of repeatability independent of impulse magnitude.

The 95% confidence interval (CI) for the mean impulse was calculated under the assumption of independent measurements and approximately normally distributed errors, using the Student t-distribution:

$$\bar{J} \pm t_{0.975,n-1} \frac{\sigma}{\sqrt{n}} \quad (6)$$

where $t_{0.975,17}$ corresponds to the critical value for n−1=17 degrees of freedom.

Equation (6) employs the Student's t-distribution, which is appropriate for small sample sizes and unknown population variance, providing a statistically rigorous uncertainty estimate. Independence was assumed because each explosion test constituted a distinct experimental event and each sensor channel represented a separate measurement location.

Approximate normality of the impulse estimates was assumed based on the central limit theorem for aggregated experimental measurements. Repeatability was quantified using the standard deviation and coefficient of variation across the 18 impulse estimates. Where relevant, repeatability metrics were also evaluated separately for each sensor distance.

Table 10

Summary comparison of impulse estimation performance

Processing Strategy	Relative Error (%)	Std. Dev. (Ns)	Processing Time (ms)
No smoothing	11.20	1.03	2
Global smoothing	6.7	0.59	5
Proposed method	1.8	0.27	6

The results demonstrate that selective post-peak noise suppression combined with controlled data reduction and physically constrained integration significantly stabilizes impulse estimates derived from high-resolution pressure signals. As summarized in Table X, the proposed program consistently yields impulse values with low dispersion and no systematic bias across all analyzed datasets, despite extreme noise levels and large data volumes. These results confirm the framework's effectiveness in mitigating the primary sources of numerical instability in explosion-induced measurements.

Beyond numerical performance, the contribution of this work lies in its practical applicability. The proposed program enables efficient processing of datasets containing millions of samples per channel while preserving physically meaningful signal features. By embedding domain-specific signal conditioning rules into an automated pipeline, the framework provides a reproducible and physically consistent solution for impulse estimation, clearly distinguishing it from generic signal-processing approaches used in experimental mechanics.

Novelty Statement

The novelty of the proposed pipeline lies in the systematic integration of domain-specific constraints into an automated impulse estimation framework tailored for explosion-generated pressure signals, rather than in the introduction of new filtering or integration algorithms. Unlike existing selective or adaptive filtering approaches that rely on heuristic windowing or local parameter adjustment, the proposed method enforces a physically motivated signal segmentation in which noise suppression is applied exclusively to the post-peak region,

preserving the growth phase and peak amplitude by design.

The pipeline uniquely combines selective post-peak Savitzky–Golay smoothing, peak-preserving subsampling, and positive-phase-constrained trapezoidal integration within a single reproducible workflow. By addressing post-peak noise amplification and data volume effects jointly, the framework improves impulse stability, repeatability, and computational efficiency, representing a practical advancement over existing selective filtering methods for high-energy transient measurements.

4. FURTHER RESEARCH

Future work will focus on adaptive smoothing strategies in which filter parameters are automatically adjusted based on local signal characteristics, reducing manual tuning and improving robustness across diverse datasets. Machine-learning-based denoising methods may also be investigated and compared with Savitzky–Golay filtering in terms of accuracy, interpretability, and computational cost.

Further developments include automated peak detection and event segmentation techniques, such as derivative-based or change-point analysis, to eliminate manual intervention and enhance repeatability. The methodology may also be extended into a user-friendly software package or graphical user interface to facilitate broader adoption.

5. CONCLUSIONS

This work presents a purpose-built software tool for noise suppression and impulse computation in high-resolution pressure measurements generated by explosive and other high-energy transient events. Unlike generic signal-processing pipelines, the proposed program is specifically designed to address the challenges of explosion-induced signals, including extreme noise levels, abrupt signal rise, and large data volumes.

A key contribution is the selective application of Savitzky–Golay smoothing exclusively to the post-peak region, enabling effective noise attenuation while preserving peak amplitude and temporal structure critical for impulse estimation. Combined with composite trapezoidal integration, the approach yields numerically stable and repeatable impulse values with high computational efficiency.

The results demonstrate that the developed program provides a reliable and reproducible solution for processing explosion-affected pressure data, constituting a practical contribution to experimental research on high-energy events. Future work will focus on real-time implementation and increased automation to extend applicability in operational measurement systems.

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Netezirea eficientă a semnalelor și calculul impulsului în măsurători de presiune de înaltă rezoluție

Rezumat: Această lucrare prezintă o metodă de procesare a datelor pentru netezirea semnalelor experimentale zgomotoase și estimarea impulsului prin integrare numerică. Seturile de date mari de presiune în funcție de timp sunt reduse prin eșantionare controlată, păstrând valorile critice ale vârfului. Zgomotul de înaltă frecvență este atenuat folosind un filtru Savitzky–Golay aplicat selectiv după valoarea maximă a semnalului, pentru a evita deformarea caracteristicilor fizice relevante. Valorile impulsului sunt calculate prin integrarea semnalului procesat cu regula trapezului compusă, după eliminarea valorilor negative . Metodologia propusă îmbunătățește stabilitatea numerică și consistența rezultatelor comparativ cu datele originale și rămâne eficientă din punct de vedere computațional, fiind adecvată pentru seturi mari de date experimentale de presiune sau forță.

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