

TWO-STAGE ADAPTIVE NORMALIZATION BASED ON EXPONENTIAL MOVING AVERAGE FOR DC OFFSET AND VARIANCE NON-STATIONARITY COMPENSATION IN REAL-TIME VOLCANIC SEISMIC SIGNAL PRECONDITIONING

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Abstract

Volcanic seismic signals output by digitizers as raw counts carry the accumulated imperfections of the entire acquisition chain—specifically, significant DC offset and large-scale variability—thereby violating the stationarity assumption underpinning downstream estimation blocks. This study proposes a two-stage adaptive normalization architecture based on the Exponential Moving Average (EMA) to serve as a statistical pre-conditioning block before the Kalman Filter. The first stage removes the DC offset using a recursive mean estimator—analytically equivalent to a first-order high-pass filter—while the second stage performs Z-Score standardization based on a running estimate of the standard deviation. Testing was conducted on a 386.48-second vertical-channel recording from the Leker (LKR) station at Mount Semeru (sampled at 100 Hz; 38,649 samples), characterized by a DC offset of $-7,292.4$ counts and a variance dynamic ratio of 10.42. With an adaptation constant of 0.005, the effective cutoff frequency of 0.0796 Hz lies approximately eighteen times below the 1.42 Hz fundamental frequency of the harmonic tremor, resulting in a passband attenuation of only -0.035 dB. Results demonstrate that the estimator locks onto the bias with a discrepancy of 7.72 counts (0.070% of the signal's standard deviation), reduces the dynamic ratio to 1.52, and yields an output where 99.989% of samples fall within the ± 3 range. The Normalized Innovation Squared test confirms that the static covariance parameters of the Kalman Filter remain consistent with the normalized input, yielding a ratio of 1.17 compared to 17.10 for the raw input—an improvement factor of 14.6. The algorithm requires 8 bytes of state memory and 0.0104% processor utilization on an ARM Cortex-M4F at 48 MHz. In contrast, static normalization of the same recording requires 151.0 kB and cannot be implemented on that platform.

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INTRODUCTION

Indonesia's geological location within an active plate convergence zone makes it the country with the highest number of active volcanoes in the world. This setting necessitates a monitoring

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system that is not only scientifically accurate but also capable of continuous operation and responsiveness to activity changes on timescales ranging from minutes to seconds. Among various monitoring modalities, seismic methods play a pivotal role by recording the direct manifestations of magmatic fluid movement and fragmentation processes within the volcanic edifice, even when weather conditions obstruct visual observation. The eruption of Mount Semeru in December 2021 demonstrated that the practical value of a monitoring system is ultimately determined by its processing latency; accurate information that arrives too late loses much of its mitigation value (Kristianto et al., 2023). Minson et al. (2018) showed that the timeliness of ground motion estimates is a critical factor in determining the continued meaningfulness of early warnings.

The seismic data used in this study were obtained from geophysical sensors monitoring the volcanic activity of Mount Semeru in East Java Province. The volcano's activity is monitored by stations equipped with Mark Products L4-C (1 Hz) short-period vertical seismometers. Seismic signals are transmitted via telemetry to the Sawur Volcano Observatory, where they are recorded on both analog drum recorders (Kinematics PS-2) and digital data loggers (Hakusan Datamark LS-7000). Since November 2005, the Center for Volcanology and Geological Hazard Mitigation, in collaboration with the Sakurajima Volcano Research Center, has operated a broadband seismometer (STS-2, Streckeisen), a water-tube tiltmeter, and a biaxial tiltmeter at a summit site located 0.7 km northeast of the Jonggring Saloka crater (Nakamichi et al., 2019). Overall, Mount Semeru is monitored by five seismic stations: Puncak (PCK), Kepolo (KPL), Tretes (TRS), Leker (LKR), and Besuk Bang (BSB). The dataset processed in this study consists of recordings from the LKR station.

A conventional approach to simultaneously removing DC offset and normalizing scale is static statistical normalization—specifically, subtracting the mean and dividing by the standard deviation calculated over the entire recording. While this procedure is common and entirely adequate for post-event analysis, it entails a fundamental violation of causality: the mean and standard deviation are functions of the entire set of samples, including those not yet available at the moment a decision must be made. For the recording under study, applying static normalization necessitates buffering 38,649 samples, resulting in a decision latency of 386.48 seconds.

This research therefore proposes the Exponential Moving Average as a recursive estimator for these two statistical moments, structured within a two-stage normalization architecture. This scheme was selected for three mutually reinforcing reasons. First, it is perfectly causal, resulting in zero algorithmic latency. Second, it features $O(1)$ computational complexity per sample and $O(1)$ memory requirements, enabling direct implementation on embedded devices at the station. Third, its adaptation constant provides analytically tractable, explicit control over the trade-off between tracking speed and estimation stability.

The contributions of this research are formulated as follows: (1) quantitative characterization of statistical anomalies in raw seismic counts from the LKR station; (2) formulation and analysis of a two-stage adaptive normalization architecture, including the derivation of the transfer function, time constant, and effective cutoff frequency; (3) a spectral-separation-based criterion for selecting the adaptation constant that ensures baseline removal without significant distortion of the seismic signal band; (4) empirical validation and verification of the consistency of static covariance parameters within the Kalman Filter block; and (5) identification of the analytical limit for the variance envelope contraction rate, along with its implications for post-event sensitivity.

LITERATURE REVIEW

In the field of seismology, this sensitivity is even more critical. Zhu and Beroza (2019) and Zhu et al. (2022) employed mean subtraction and division by the standard deviation as standard preprocessing steps, while other models normalized data against the maximum absolute amplitude (Ross et al., 2018; Mousavi et al., 2020). These seemingly minor differences carry significant consequences. Xiao et al. (2021) identified that the limitations of the Earthquake Transformer model when handling low-SNR seismograms stemmed from noise affecting the normalization process itself, rather than solely from the network architecture. The most explicit evidence comes from a study on phase pickers in the Hakone volcanic region, which demonstrated that normalizing against the maximum value caused low-amplitude events within the same detection window to be treated as

noise and consequently go undetected (Kim et al., 2023). Wang et al. (2023) recommend explicit data standardization to mitigate the impact of variability on model performance.

Min-Max normalization maps signals to a fixed range via a linear transformation, offering the advantages of simple implementation and guaranteed output bounds. However, its scaling relies entirely on two extreme values, meaning a single outlier is sufficient to distort the entire mapping. In the recordings studied, the amplitude range spanned from $-67,153$ to $+67,219$ counts due to a single period of strong tremor; consequently, all quiet segments would be compressed into a narrow band, losing effective resolution. Furthermore, minimum and maximum values are not known *a priori* in continuous data streams, rendering this scheme non-causal. While offline Z-score normalization is more robust against outliers and preserves the distribution shape, it relies on a single pair of parameters applicable to the entire realization. This assumption of stationarity fails in non-stationary seismic environments, as noise statistics estimated from quiet segments do not apply to signal-bearing segments. Indeed, this pattern dominates volcanic monitoring: Tan et al. (2024) noted that volcanic tremors are characterized by highly variable amplitude, duration, and onset.

Sliding-window normalization offers a middle ground that restores causality. Tanaka et al. (2022) developed this method for electromyography-based motion prediction, reporting that it eliminates the need for offline calibration and adapts to slow baseline and amplitude shifts, albeit with an additional computational overhead of approximately 18.6%. Nevertheless, memory requirements remain proportional to the window length, latency persists, and the choice of window length presents an unresolved bias-variance dilemma.

Recent trends in seismic instrumentation favor low-cost, high-density networks, shifting part of the processing load to the sensor level. Hu et al. (2021) documented this ongoing instrumentation revolution, while Fu et al. (2019) reported a Class C MEMS sensor with a dynamic range exceeding 87 dB, capable of detecting M 3.1–3.6 earthquakes within a 50 km radius. In the volcanic domain, Sosa et al. (2024) implemented seismic event detection for Mount Copahue on a low-end SoC-FPGA device, demonstrating the feasibility of edge-based seismo-volcanic processing. Indonesia is moving in a similar direction through the development of an Internet of Things-based volcano monitoring system (Eva et al., 2021).

The strongest argument for adaptive normalization stems from the characteristics of the downstream estimator. The adaptive Kalman filtering literature consistently documents that noise parameter mismatches lead to accuracy degradation and even filter divergence (Song et al., 2022; Wang et al., 2021). Ye et al. (2023) noted that the Sage–Husa estimator is prone to producing non-positive-definite matrices when operating amidst anomalous noise, while Kruse et al. (2025) added that poor initialization adversely affects noise covariance estimation. Two strategies exist to address this issue: making the filter itself adaptive through online estimation, or stabilizing input statistics prior to the filter. This study adopts the second strategy, an approach that has not yet been systematically explored in the seismo-volcanic monitoring literature.

Table 1. Comparison of normalization scheme characteristics for real-time seismic signals

Criteria	Min-Max	Offline Z-Score	Sliding Window	EMA (proposed)
Causality	Non-causal	Non-causal	causal	causal
Algorithmic latency	N/f_s	N/f_s	L/f_s	0
Memory requirements	$O(N)$	$O(N)$	$O(L)$	$O(1)$
Mean and variance adaptation	No	No	Yes	Yes
Spectral characterization	None	None	implicit	Closed analytics
Microcontroller compatibility	Low	Low	Medium	High

METHODS

This study employs a quantitative approach based on numerical simulation, validated against actual seismic data. The algorithm is implemented as a sample-by-sample simulation that precisely replicates the execution flow of a real-time embedded system: each sample is processed once, sequentially, without access to subsequent samples. This constraint is strictly enforced at every stage to ensure the simulation results represent performance that is truly realizable on hardware. The processing channel architecture comprises four sequential blocks: ADC acquisition, Stage 1 (DC blocker), Stage 2 (Z-score standardization), and a Kalman filter followed by a detection block.

Table 2. Dataset specifications and descriptive statistics of the recordings

Parameter	Value	Parameter	Value
Station	Leker (LKR)	Global average	-7,292.4 counts
Sampling rate, f_s	100 Hz	Global standard Deviation	11,047.4 counts
Number of samples, N	38,649	Amplitude range	[-67,153, +67,219]
Recording duration	386.48 s	Minimum word width	18-bit (Signed)
Fundamental frequency	≈ 1.42 Hz	Dynamic ratio σ (10 s)	10.42×

The data used consist of vertical-channel recordings from the Leker station at Mount Semeru, with specifications as presented in Table 2. Data extraction was performed on the seismic amplitude and time columns; samples that could not be converted into numerical values were eliminated before simulation. No filtering, smoothing, or corrections of any kind were applied before the normalization block, ensuring the algorithm's performance could be evaluated against the raw counts in their original state.

Stage 1: Adaptive DC Offset Removal

The first stage eliminates the DC component resulting from the accumulation of imperfections in the acquisition chain. The mean is estimated recursively using the first-order difference equation in Equation (1), yielding a centered signal as the output, as shown in Equation (2).

$$\hat{\mu}[n] = \alpha_\mu x[n] + (1 - \alpha_\mu) \hat{\mu}[n - 1] \quad (1)$$

$$x_c[n] = x[n] - \hat{\mu}[n] \quad (2)$$

Here, $x[n]$ is the n -th raw count sample, $\hat{\mu}[n]$ is the estimated moving average, and α_μ is the adaptation constant. For implementation, it is more efficient to write equation (1) in an algebraically equivalent incremental form—as shown in equation (3)—which saves one multiplication operation and maps directly to a fused multiply-accumulate instruction.

$$\hat{\mu}[n] = \hat{\mu}[n - 1] + \alpha_\mu (x[n] - \hat{\mu}[n - 1]) \quad (3)$$

Equation (1) represents a first-order IIR filter with the transfer function given in Equation (4). Due to the subtraction operation in Equation (2), the cascade of (1) and (2) is overall equivalent to the high-pass filter in Equation (5), which has a zero at $z = 1$, thereby ensuring perfect DC rejection.

$$H_{LP}(z) = \frac{\alpha_\mu}{1 - (1 - \alpha_\mu)z^{-1}} \quad (4)$$

$$H_{HP}(z) = 1 - H_{LP}(z) = \frac{1 - z^{-1}}{1 - (1 - \alpha_\mu)z^{-1}} \quad (5)$$

For α_μ much smaller than unity, the continuous-domain approximation yields the -3 dB cutoff frequency, time constant, and equivalent window length as given by equations (6) through (8), respectively.

$$f_c \approx \frac{\alpha_\mu f_s}{2\pi} \quad (6)$$

$$\tau = \frac{1}{\alpha_\mu f_s} \quad (7)$$

$$N_{eff} = \frac{2 - \alpha_\mu}{\alpha_\mu} \approx \frac{2}{\alpha_\mu} \quad (8)$$

Substituting $\alpha_\mu = 0.005$ and $f_s = 100$ Hz yields $\tau = 2.00$ s, $N_{eff} = 399$ samples (or 3.99 s), and $f_c = 0.0796$ Hz. The results of the magnitude response evaluation are presented in Table 3. This cutoff frequency lies approximately eighteen times below the observed fundamental tremor frequency. Consequently, seismic signal components within the observation band are transmitted with less than 0.04 dB of attenuation. Thus, the choice of the adaptation constant is not the result of empirical tuning, but rather a design decision satisfying the spectral separation criterion defined in Equation (9). For $f_0 = 1.42$ Hz and $f_s = 100$ Hz, this criterion establishes an upper bound for α_μ that is significantly lower than 0.089, the value of 0.005 satisfies this requirement with a margin of a factor of eighteen.

$$\alpha_\mu \ll \frac{2\pi f_0}{f_s} \quad (9)$$

Table 3. Equivalent high-pass filter magnitude response ($\alpha = 0,005$; $f_s = 100$ Hz)

Frequency (Hz)	H _{HP}	Attenuation (dB)	Interpretation
0.05	0.5297	-5.519	Baseline strip, pressed
0.10	0.7798	-2.161	Transition
0.50	0.9850	-0.131	Band-pass
1.42	0.9959	-0.035	Tremor fundamental
4.25	0.9973	-0.023	Overtone

Stage 2: Dynamic Variance-Based Z-Score Standardization

The second stage normalizes the amplitude scale against a running estimate of the standard deviation. Since the centered signal has a zero mean as a result of Stage 1, the square of the centered signal can be used directly as an estimator of instantaneous power without requiring a second mean subtraction, as shown in equations (10) through (12).

$$\hat{\sigma}^2[n] = \alpha_v x_c^2[n] + (1 - \alpha_v) \hat{\sigma}^2[n - 1] \quad (10)$$

$$\hat{\sigma}[n] = \sqrt{\hat{\sigma}^2[n]} \quad (11)$$

$$z[n] = \frac{x_c[n]}{\hat{\sigma}[n]} \quad \text{for } \hat{\sigma}[n] > \varepsilon; \quad z[n] = 0 \quad (12)$$

A numerical threshold of $\varepsilon = 10^{-4}$ is applied to prevent division singularities during periods of total signal silence. This estimator is negatively biased during rapid transition patterns because the variance estimate lags behind actual energy changes by a time constant of $\tau_v = 1/(\alpha_v f_s)$.

Unlike the mean adaptation constant—which is determined by spectral separation criteria—selecting the variance adaptation constant involves a different set of trade-offs. A high value yields rapid energy envelope tracking and a highly stationary output but carries a risk of "over-whitening": the standard deviation estimate begins to track the signal itself rather than just its envelope, thereby erasing the peak characteristics that define transient events. Sensitivity test results in Table 4 reveal a clear pattern. Dynamic range stabilization improves monotonically as the adaptation constant increases; however, excess kurtosis decreases monotonically, indicating a more uniform output distribution and the progressive erasure of transient structures. A value of 0.005 was selected because it reduced the dynamic ratio from 10.42 to 1.52 while maintaining kurtosis at a level that still preserves the representation of transient structures.

Table 4. Output sensitivity to the variance adaptation constant

α_v	τ_v (s)	CV(σ local)	Dynamic ratio	Excess kurtosis
— (raw signals)	—	0.4980	10.42	—
0.001	10.0	0.2110	2.41	-0.18
0.005 (chosen)	2.0	0.0764	1.52	-0.66
0.020	0.5	0.0216	1.13	-0.91
0.050	0.2	0.0094	1.05	-1.13

State Initialization and Warm-up Period

To ensure full causality, this study employs an initialization scheme that relies on no information from future data—specifically, $\hat{\mu}[-1] = x[0]$ dan $\hat{\sigma}^2[-1] = 0$. While a scheme based on known mean values converges slightly faster—achieving a settling time of 0.12 seconds versus 0.54 seconds—it introduces look-ahead bias that invalidates the claim of causality; consequently, it was not used. Based on these results, a formal warm-up period of five times the variance time constant was established—equivalent to 10 seconds or the first 1,000 samples—during which the output is marked as invalid and not passed to the Kalman Filter block.

Analysis of Implementability on ARM Cortex-M4F

The reference platform employed is the Renesas RA4M1 microcontroller—as found on the Arduino UNO R4 board—featuring a 48 MHz Arm Cortex-M4 core equipped with a Floating-Point Unit (FPU), 32 kB of SRAM, and 256 kB of flash memory. It should be noted that the unit supports only single-precision arithmetic; double-precision operations are executed via software emulation with a computational cost one to two orders of magnitude higher, necessitating the declaration of all state variables as `float`. The adequacy of single-precision arithmetic was verified through comparative simulations on the full dataset: the maximum output difference between `binary32` and `binary64` arithmetic was merely 6.40×10^{-6} , with an RMS value of 1.29×10^{-6} . This numerical stability can be analytically explained, as the relative increment per update is on the order of 5×10^{-3} —approximately four orders of magnitude above the `binary32` machine epsilon—thereby preventing catastrophic cancellation in the accumulator.

A fixed-point implementation was rejected due to dynamic range limitations. Raw amplitudes reach $\pm 67,219$ counts, causing the squared centered signal to reach 5.55×10^9 , which exceeds the range of a 32-bit signed integer by a factor of 2.6. Consequently, a fixed-point implementation would require a 64-bit accumulator and manual scaling management—complexities that negate its performance advantages given the availability of a hardware floating-point unit. The algorithm's computational budget comprises eight single-cycle operations, one `VSQRT.F32` instruction and one `VDIV.F32` instruction (each requiring 14 cycles), and approximately twelve cycles for load, store, and control operations, totaling around 50 cycles per sample. At a core frequency of 48 MHz, this figure equates to $1.04 \mu\text{s}$ per sample; thus, relative to a sampling period of $10,000 \mu\text{s}$, processor utilization is merely 0.0104%, as shown in Equation (13). This margin of more than four orders of magnitude leaves almost the entire time budget available for the Kalman Filter block, ADC acquisition, and telemetry.

Platform acuan yang dipakai adalah mikrokontroler Renesas RA4M1 sebagaimana terpasang pada papan Arduino UNO R4, dengan inti Arm Cortex-M4 berfrekuensi 48 MHz yang dilengkapi *Floating Point Unit*, SRAM 32 kB, dan memori *flash* 256 kB. Perlu ditegaskan bahwa unit tersebut hanya menyediakan presisi tunggal; operasi presisi ganda dieksekusi melalui emulasi perangkat lunak dengan kebutuhan satu hingga dua orde magnitudo lebih tinggi, sehingga seluruh variabel keadaan harus dideklarasikan sebagai *float*. Kecukupan presisi tunggal dibuktikan melalui simulasi ganda pada dataset penuh: selisih maksimum keluaran antara aritmetika *binary32* dan *binary64* hanya $6,40 \times 10^{-6}$ dengan nilai RMS $1,29 \times 10^{-6}$. Stabilitas numerik ini dapat diterangkan secara analitik, sebab inkremen relatif per pembaruan berorde 5×10^{-3} , yakni sekitar empat orde magnitudo di atas *epsilon* mesin *binary32*, sehingga pembatalan katastrofik pada akumulator tidak terjadi.

$$U = \frac{1,04 \mu\text{s}}{10.000 \mu\text{s}} \approx 0,0104 \% \quad (13)$$

Table 5. Buffer memory requirements relative to the reference platform's SRAM capacity (32 kB)

Scheme	Requirement	Towards SRAM	Status
Offline Z-Score (N = 38,649)	151.0 kB	472%	Cannot be embedded
Sliding window (L = 1,000)	3.9 kB	12.2%	Acceptable, 10 s latency
EMA (2 float32 states)	8 byte	0.024%	Accepted, zero latency

The first row of Table 5 represents not merely a comparison of efficiency, but a statement regarding structural feasibility. Offline Z-score normalization for recordings of this length cannot be implemented on the reference platform because the required buffering exceeds the SRAM capacity by a factor of 4.72—a hard constraint that cannot be overcome through software optimization. Performance evaluation in the subsequent section employs metrics such as offset residuals, the local standard deviation coefficient of variation, the dynamic ratio within a 10-second window, excess kurtosis (to detect over-whitening), and passband attenuation, alongside the Normalized Innovation Squared test to assess the consistency of static covariance parameters.

RESULTS AND DISCUSSION

All figures in this section are based on direct measurements of the simulation output. Unless otherwise stated, statistics are calculated after a 10-second warm-up period.

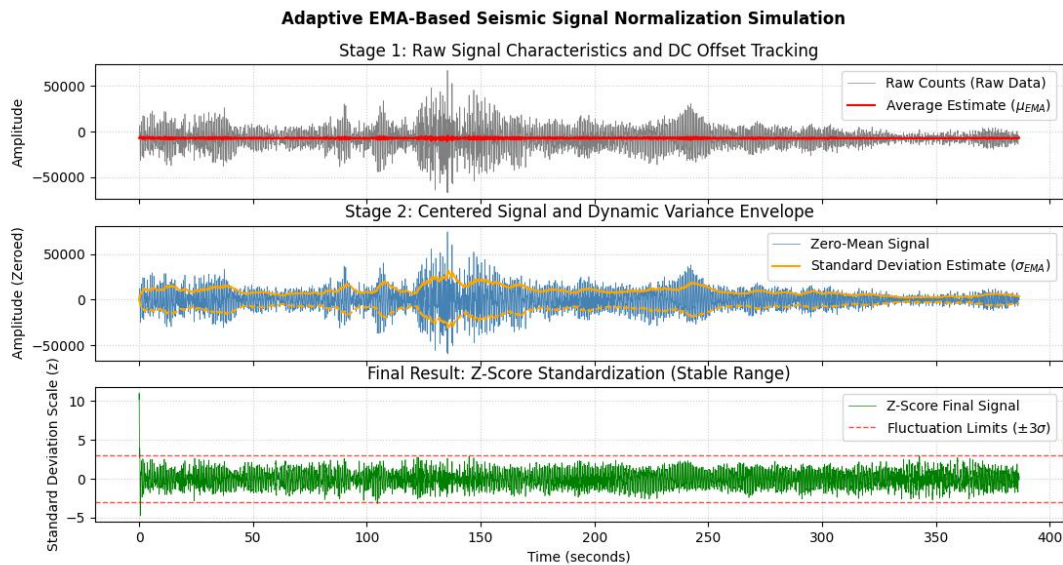


Figure 1. Simulation results of adaptive EMA-based seismic signal normalization. Top panel: raw signal and DC offset tracking. Middle panel: centered signal and dynamic variance envelope. Bottom panel: final Z-score signal with $\pm 3\sigma$ thresholds.

Adaptive DC Offset Tracking

The top panel of Figure 1 presents the raw signal alongside the estimated mean trace. Visually, the trace appears as a nearly flat line embedded within the signal's amplitude band, remaining unaffected by the high-energy tremor periods occurring in the 120–160 second range. Quantitative evaluation confirms this visual impression. The estimator's long-term mean is $-7,300.14$ counts, while the true mean of the recording is $-7,292.41$ counts; the difference is merely 7.72 counts, equivalent to 0.070% of the signal's global standard deviation. Thus, the recursive estimator locks onto the bias component to three significant digits without ever accessing global statistics.

It must be candidly acknowledged that the mean estimate is not entirely immune to tremor amplitude. The trace exhibits a standard deviation of 564.08 counts, with an excursion range spanning from $-10,606.46$ to $-4,335.80$ counts. These fluctuations represent signal energy leakage into the estimator, the magnitude of which can be analytically predicted. The ratio of the fluctuation to the signal amplitude is 0.0511, corresponding to a rejection of -25.8 dB. This compares to the theoretical prediction derived from the transfer function in Equation (4), which yields a value of 0.0561 (or -25.0 dB) at the tremor's fundamental frequency of 1.42 Hz. The agreement between measured and predicted values falls within a 9% margin; the slight discrepancy is consistent with the fact that signal energy is distributed across multiple harmonic components, all of which undergo stronger attenuation. This agreement serves as a crucial cross-validation: the estimator's empirical behavior is fully explained by the first-order IIR filter model, demonstrating that the design is predictable rather than the result of fortuitous tuning.

Segment-by-segment analysis reveals that the fluctuations correlate with tremor energy in a sub-proportional manner. A 5.35-fold increase in signal energy—rising from a standard deviation of 3,810 in the quiet segment to 20,387 in the strong tremor segment—resulted in only a 3.77-fold increase in ripple, from 251.56 to 947.57 counts. This characteristic is advantageous because the ripple-to-signal ratio actually decreases in high-energy segments. Ultimately, the critical factor for the DC blocker function is not the absence of ripple, but the absence of accumulated bias; ripple oscillates around the true value and does not cause a systematic shift.

Variance Envelope Dynamics

The middle panel of Figure 1 displays the centered signal enclosed by the estimated standard-deviation envelope, exhibiting clear adaptive behavior: expanding in response to increasing tremor energy and narrowing as activity subsides. Quantitatively, the estimated standard deviation ranges from 2,066 to 32,335 counts, representing a dynamic ratio of 15.65. The envelope peaks at 135.7 seconds, coinciding with the period of strongest tremor, while the minimum value is reached at 337.9 seconds during the activity decay phase.

The most methodologically significant finding is the sharp asymmetry between the rates of envelope expansion and contraction. Measurements of the logarithmic rate of change yield a maximum value of +2.370 per second during the rising phase and -0.251 per second during the falling phase—an asymmetry factor of 9.4. This asymmetry is not an anomaly but a structural consequence of the form of equation (10). During the expansion phase, a single high-energy sample can immediately dominate the first term, meaning the rate of increase has no upper bound. Conversely, during the contraction phase, the variance decays geometrically, strictly limiting the rate of decrease as defined by equation (14). The measured value of -0.251 per second aligns with the theoretical limit of 0.250 per second, confirming that the estimator operates precisely at its analytical decay limit.

$$\left| \frac{d \ln \hat{\sigma}}{dt} \right|_{\max} = \frac{\alpha_v f_s}{2} = 0,250 \text{ s}^{-1} \quad (14)$$

This asymmetry entails operational consequences that must be explicitly acknowledged. Following a high-energy event, the envelope requires time to contract again, and during this period, the detector's sensitivity to smaller events is reduced. The recovery times calculated from equation (14) are 2.77 seconds for a twofold energy decrease, 6.44 seconds for a fivefold decrease, and 9.21 seconds for a tenfold decrease. For volcanic monitoring, a desensitization period of less than ten seconds is acceptable; however, this characteristic must be taken into account for applications requiring the detection of small-scale aftershocks immediately following a main event.

Steady-State Signal Stability and Initialization Transients

The bottom panel of Figure 1 presents the normalized signal, with dashed lines marking the ± 3 limits. Following the warm-up period, the output exhibits a mean of 0.0026 and a standard deviation of 0.9925, indicating that the standardization objective was achieved with an error of less than 1%. A total of 99.989% of the samples fall within the ± 3 range, with a maximum excursion of only 3.195; this implies that the signal is not merely concentrated within the limits but also avoids extreme spikes that would saturate a threshold-based detector. Only 4 out of the 37,649 post-warm-up samples exceed these limits.

The excess kurtosis of -0.663 warrants specific explanation, as it could initially be misinterpreted as a loss of transient structure. Comparative analysis, however, reveals the opposite. The raw signal is leptokurtic, with an excess kurtosis of +2.472—not because its intrinsic distribution is heavy-tailed, but because the recording represents a scale mixture of segments following quasi-Gaussian distributions with varying variances. Theoretically, a scale mixture of Gaussian distributions always yields positive excess kurtosis; supporting evidence is found in a single local segment where the excess kurtosis is merely +0.134—effectively Gaussian. The reduction in excess kurtosis from +2.472 to -0.663 thus serves as direct quantitative proof that the algorithm successfully eliminated scale mixing, while the residual negative value reflects the quasi-sinusoidal nature of the harmonic tremor itself, given that a pure sinusoid has an excess kurtosis of -1.500.

The most striking observation in the bottom panel is the sharp spike during the initial seconds, reaching +10.978 at $t = 0.01$ seconds. This spike significantly exceeds the ± 3 limits and, without explanation, might be perceived as an algorithmic failure. Analysis indicates otherwise. The primary source is the slow convergence of the variance estimator: in the initial samples, the estimated standard deviation was 143.6 counts, whereas the steady-state value is approximately 9,774 counts—meaning the estimate was too low by a factor of 68.1. Since the normalized signal is the quotient derived from this estimate, an excessively small denominator results in a proportionally inflated quotient. Consequently, the spike is not an erroneous signal reading, but rather a direct

arithmetic consequence of an estimator that has not yet assimilated information regarding the signal's scale.

This phenomenon actually serves as positive evidence for the study's main claim. Offline normalization calculates the standard deviation based on the entire recording, meaning even the initial sample is normalized against the correct value; consequently, the offline scheme is structurally incapable of producing initialization transients. The presence of a spike at the start of the recording is an observable signature indicating that the estimator begins operation with no prior information and builds its knowledge solely from past samples. Conversely, the absence of a transient in a system claiming real-time operation would actually indicate a leakage of future information during initialization. The transient itself is brief and sharply defined: the standard deviation estimate reaches 90% of its steady-state value at 1.69 seconds—consistent with the designed 2.0-second time constant—while the contrast between 49 threshold violations in the first 10 seconds and only 4 violations in the subsequent 376 seconds confirms that the transient is perfectly isolated to the initial phase. The 10-second warm-up period proves to be conservative, with a margin of approximately six times the actual time to reach a steady state, and its operational cost is virtually negligible, as it is executed only once upon system startup or reset.

Consistency of Covariance Parameters in the Kalman Filter

The study's core claim—that statistical preconditioning enables downstream blocks to operate with fixed parameters—was directly tested using the Normalized Innovation Squared (NIS) test on a scalar Kalman estimator. The protocol was as follows: the measurement noise covariance matrix was calibrated once during a quiet segment (300–350 s) until the NIS expectation value equaled one; it was then locked and tested against a strong tremor segment (110–150 s). Consistency requires the NIS to remain close to unity across both segments.

With raw input, the covariance parameters established during quiet conditions became 17.1 times too small when tremor intensity increased—a condition defined as filter inconsistency that, in continuous operation, manifests as excessive state correction leading to divergence. With normalized input, the deviation was only 17%, representing a 14.6-fold improvement in consistency. Thus, treating the process and measurement noise covariance matrices as constants is valid for normalized input, whereas this approach is untenable for raw input. The reduction in dynamic range also eliminated the risk of numerical overflow: the squared value of the centered raw signal reached 5.549×10^9 —exceeding the 32-bit signed integer limit of 2.147×10^9 by a factor of 2.6—thereby necessitating a 64-bit accumulator for any downstream quadratic operations; following normalization, the maximum squared value was only 10.211, ensuring the entire computational chain remained safe even with 16-bit representation.

Table 6. Consistency test of static covariance parameters in the Kalman estimator

Input estimator	Calibrated R	NIS (calm)	NIS (tremors)	Ratio	Status
Raw counts	1.901×10^7	1.000	17.099	17.10×	inconsistent
Normalized $z[n]$	0.807	1.000	1.173	1.17×	consistent

STA/LTA Detector

Testing of the STA/LTA detector yielded findings that require qualification; these are presented here openly due to their implications for the architectural design. Detector contrast—measured as the ratio of the peak value to the median value—was recorded at 3.917 for raw counts, rising to 4.691 at the Stage 1 output, but dropping to 3.822 at the Stage 2 output. Stage 1 thus improved contrast by 19.8% by eliminating unidirectional bias, whereas Stage 2 actually reduced it to a level slightly below that of the raw signal. The cause is structural: STA/LTA operates by comparing short-term energy against long-term energy, while Stage 2 divides the signal by a running energy estimator functionally equivalent to the LTA component; consequently, the Z-score normalization partially negates the very contrast intended to be measured. These findings do not undermine the proposed architecture but rather determine the appropriate tap points for the respective downstream blocks. Since the design is two-stage, both outputs are available simultaneously; the recommended architecture therefore involves tapping the STA/LTA at the Stage

1 output and the Kalman Filter at the Stage 2 output. This highlights the functional rationale for employing a two-stage separation rather than combining the processes into a single operation.

Table 7. Recapitulation of signal statistical characteristic transformations

Metric	Raw signal	Normalized	Improvement
Average	-7,292.4 counts	0.0026	Bias eliminated
Dynamic ratio σ (10 s)	10.42×	1.52×	85.4%
Local standard deviation CV	0.4980	0.0764	84.7%
Excess kurtosis	+2.472	-0.663	Mixed scale erased
Excursion range	$\pm 67,219$ counts	± 3.195	Limited
NIS Consistency	17.10×	1.17×	14.6×

Table 7 summarizes the overall transformation. The three objectives stated in the Introduction were achieved with measurable results: unidirectional bias was eliminated with an accuracy of 0.070%, scale variability was reduced by 85%, and the seismic signal frequency band was preserved with attenuation below 0.04 dB. The combination of these three factors satisfies the prerequisites for the Kalman Filter block to operate using a constant measurement noise covariance matrix.

CONCLUSION

This study formulates, analyzes, and validates a two-stage adaptive normalization architecture based on the Exponential Moving Average (EMA) as a statistical preconditioning block for raw volcanic seismic counts. Testing was conducted on actual vertical-channel recordings from the Leker station (Mount Semeru) spanning 386.48 seconds at a 100 Hz sampling rate. The adaptive DC offset removal stage successfully locked onto the bias component with a deviation of only 7.72 counts from the true value—equivalent to 0.070% of the signal's standard deviation—without requiring access to global statistics. The accompanying residual ripple of 564.08 counts was oscillatory in nature, did not accumulate into a bias, and matched the magnitude predicted by the transfer function's analytical model. The spectral-separation-based criterion for selecting the adaptation constant proved effective: the effective cutoff frequency of 0.0796 Hz lay approximately eighteen times below the fundamental frequency of harmonic tremor, resulting in a passband attenuation of only -0.035 dB.

The dynamic-variance-based standardization stage reduced the dynamic ratio from 10.42 to 1.52 and the local standard deviation's coefficient of variation from 0.4980 to 0.0764; the output exhibited a mean of 0.0026 and a standard deviation of 0.9925, with 99.989% of samples falling within the ± 3 range. The shift in excess kurtosis from +2.472 to -0.663 provides quantitative evidence that scale mixing was eliminated. The initialization transient observed during the first second was identified as a direct consequence of the estimator starting from a state of zero prior information, effectively serving as an observable signature of the system's causality. The Normalized Innovation Squared test demonstrated that static covariance parameters remained consistent for the normalized input—yielding a ratio of 1.17 compared to 17.10 for the raw input—representing a 14.6-fold improvement. The algorithm requires 8 bytes of state memory and 0.0104% processor utilization on a 48 MHz ARM Cortex-M4F, whereas static normalization of the same recording requires 151.0 kB and cannot be implemented on that platform.

Four limitations must be noted. First, testing was conducted using a single recording from one station; thus, generalizability across stations and event types remains untested. Second, the consistency test utilized a random-walk scalar estimator as a proxy, while integration with a full seismic state-space model remains a task for future work. Third, envelope response asymmetry results in reduced sensitivity to small events for a duration of 2.77 to 9.21 seconds following the conclusion of a large event. Fourth, the cycle budget per sample was derived from architectural specifications rather than direct hardware measurements. Based on these findings and limitations, four development directions are recommended: cross-station validation across the Mount Semeru network and across seismo-volcanic event types; implementation and direct hardware measurement on the Cortex-M4F using the DWT cycle counter; development of asymmetric adaptation constants to shorten the post-event desensitization period, accompanied by stability analysis; and full integration with a seismic state-space Kalman Filter block, along with an end-to-end detection performance evaluation.

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