Is Structural Awareness the Key to Event Camera Data Cleansing for Enhancing Veracity?

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1 Introduction

Event cameras offer high dynamic range, microsecond temporal precision, and low power consumption, yet are sensitive to illumination changes and background irrelevant event points.

- Problem: Existing reference-free metrics (e.g., TSS, MESR) are density-biased and overlook structural fidelity, often rewarding over cleansing.
- Goal: Propose a structure-aware, reference-free metric that penalizes structural loss while recognizing genuine noise removal.

The main contributions of our research are as follows:

- TSEI: Structure-aware, reference-free event quality metric.
- AES: Adaptive Event Segmentation for density fairness.
- Density-normalized contrast: Z-score + sigmoid weighting.
- TSSM: Temporal Structural Similarity across windows.

2 Methodology

The Temporal Structural Event Index (TSEI) evaluates event data quality without reference frames by integrating three modules: Adaptive Event Segmentation (AES), Density-Normalized Contrast, and Temporal Structural Similarity (TSSM).

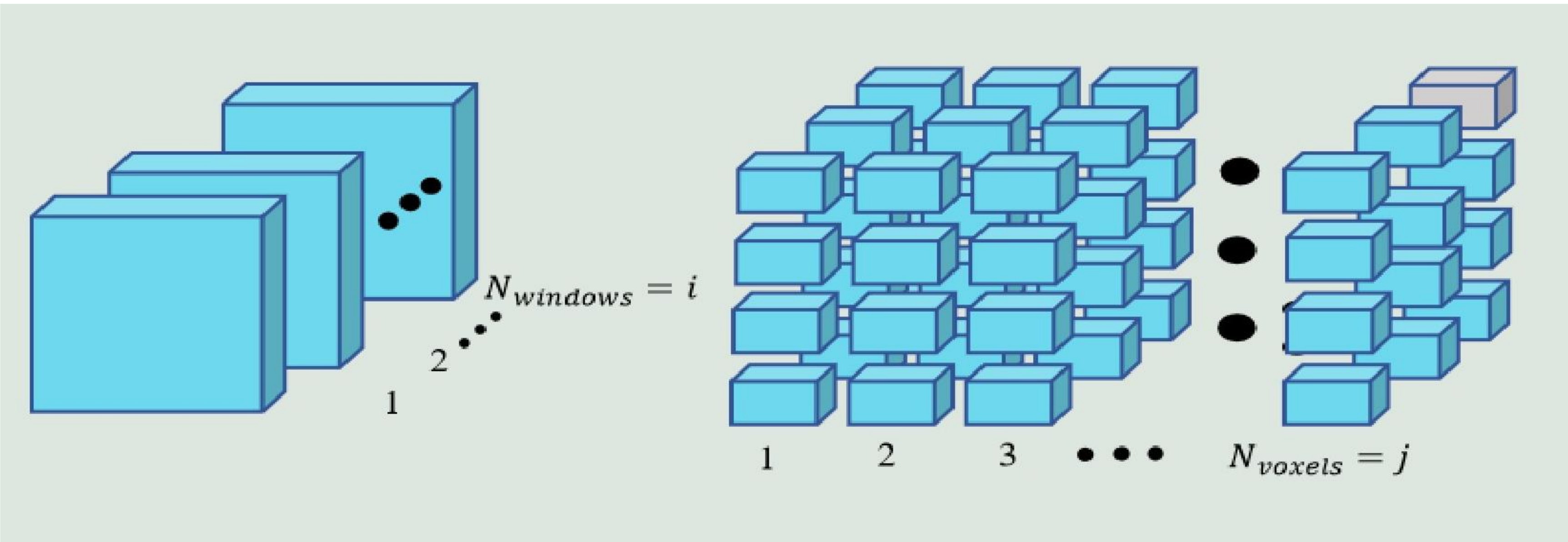

Fig. 1. Overview of the Adaptive Event Segmentation (AES) framework.

The main methods of our research are as follows:

- Adaptive Event Segmentation (AES). Given N events over spatial size X × Y and duration T, AES divides the stream into equal-event-count windows: layers.

prevents overly small segments.

event density

$$n = \max(n_{min}, \rho \log10(N)), \qquad \rho = \frac{N}{XYT}$$

- Density-Normalized Contrast. Each window i obtains a contrast score.

$$D_i = \frac{D_i' - \mu_D}{\sigma_D + \varepsilon}, \quad D_i' = w_i \sum_x I(x)^2, \quad w_i = \frac{1}{1 + e^{-\alpha_w(\rho_i - \beta_w)}},$$

event intensity

where W_i is a density weight with parameters α_w, β_w . This yields a density-invariant, structure-aware contrast measure.

- Temporal Structural Similarity (TSSM). Structural continuity between adjacent windows is measured by:

deviation

$$S(W_i, W_{i+1}) = \frac{(2\mu_i\mu_{i+1} + C_1)(2\sigma_{i,i+1} + C_2)}{(\mu_i^2 + \mu_{i+1}^2 + C_1)(\sigma_i^2 + \sigma_{i+1}^2 + C_2)},$$

mean

variance

A higher S implies stronger temporal consistency.

- Final Score Fusion (TSEI). Contrast and similarity are combined as:

$$E = \frac{1}{N}\sum_i(\alpha D_i + \beta S(W_i, W_{i+1})),$$

α, β control the balance between noise suppression and structure preservation. The final TSEI score E reflects both spatial fidelity and temporal stability of the cleansed event data.

3 Experimental Results

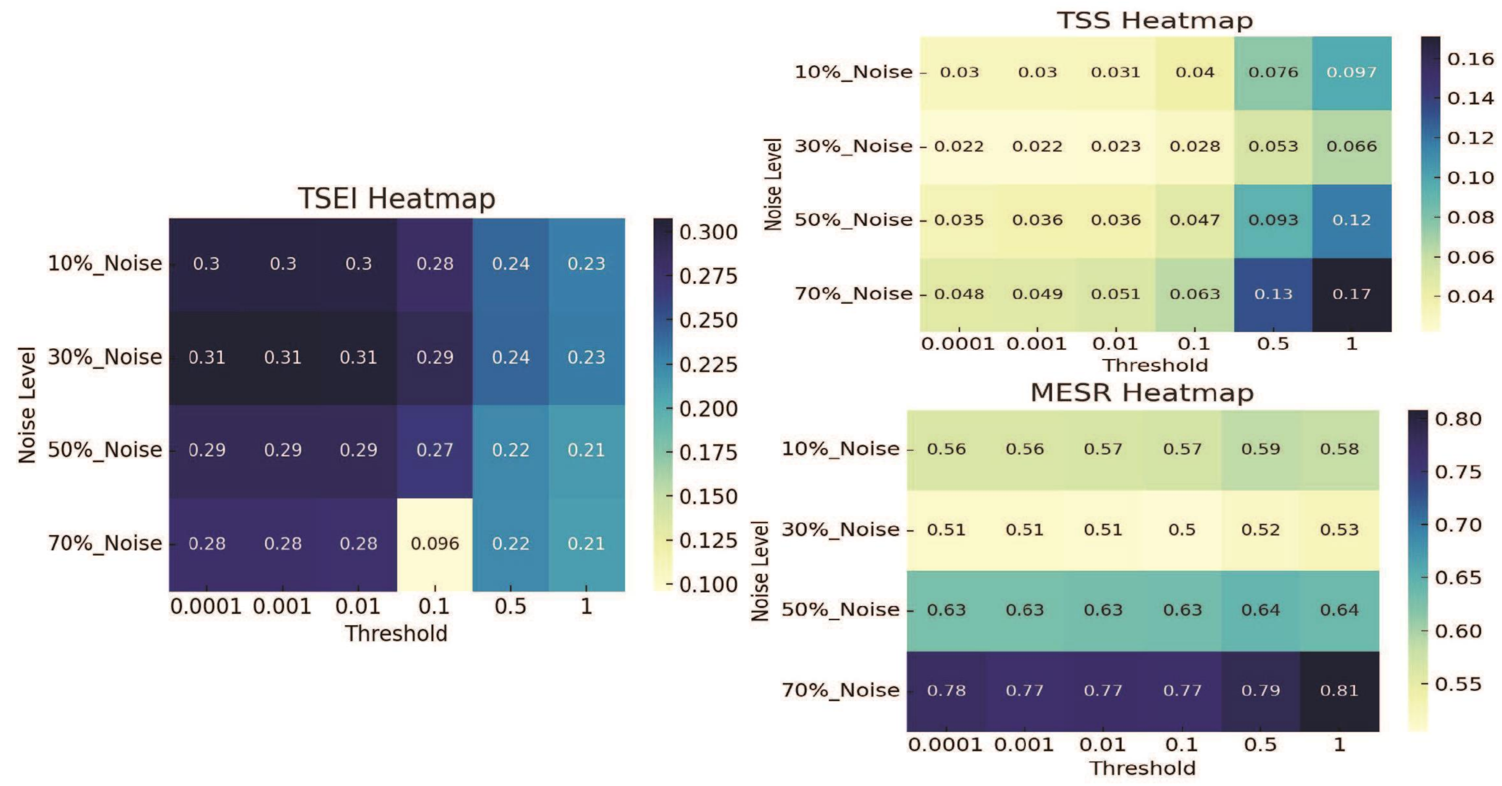

Fig. 2. TSEI, MESR, and TSS heatmaps across noise–threshold grids.

- Fig. 2 shows that TSEI heatmap reveals distinct low-value regions in high-noise/high-threshold conditions, marking structural collapse zones that MESR and TSS fail to capture.

Dataset name		Cleansing Method			
		AW-GATCN	BAF	DWF	TS
Caltech101	ΔMESR	0.1886	0.1056	0.1421	**0.4769**
	ΔTSEI (Our)	**0.019**	-0.0275	-0.0218	-0.1371
Cifar10	ΔMESR	**0.0072**	-0.0618	-0.0651	-0.3282
	ΔTSEI (Our)	0.0593	0.0755	0.0427	**0.1025**
D-END	ΔMESR	0.024	**0.1343**	0.1293	0.1183
	ΔTSEI (Our)	**0.0514**	0.0444	0.0447	0.033
N-CARS	ΔMESR	**0.2725**	0.0096	0.0358	0.0235
	ΔTSEI (Our)	**0.1866**	0.0116	0.0516	0.0023
N-END	ΔMESR	0.7729	**0.1872**	0.1863	0.0458
	ΔTSEI (Our)	0.0237	0.0053	0.0074	**0.0326**

Table.1. Comparison of metrics improvements across different cleansing methods and datasets.

Dataset Name	Cleansing Method(accuracy%)			
	AW-GATCN	BAF	DWF	TS
Caltech101	**74.07**	50.87	50.33	36.49
Cifar10	60.05	65.7	55.56	**71.69**
D-END	**85.73**	80.43	82.61	75.06
N-CARS	**90.18**	66.67	71.88	49.79
N-END	**75.47**	63.33	64.76	73.06

Table. 2. Classification accuracy (%) across datasets and cleansing methods.

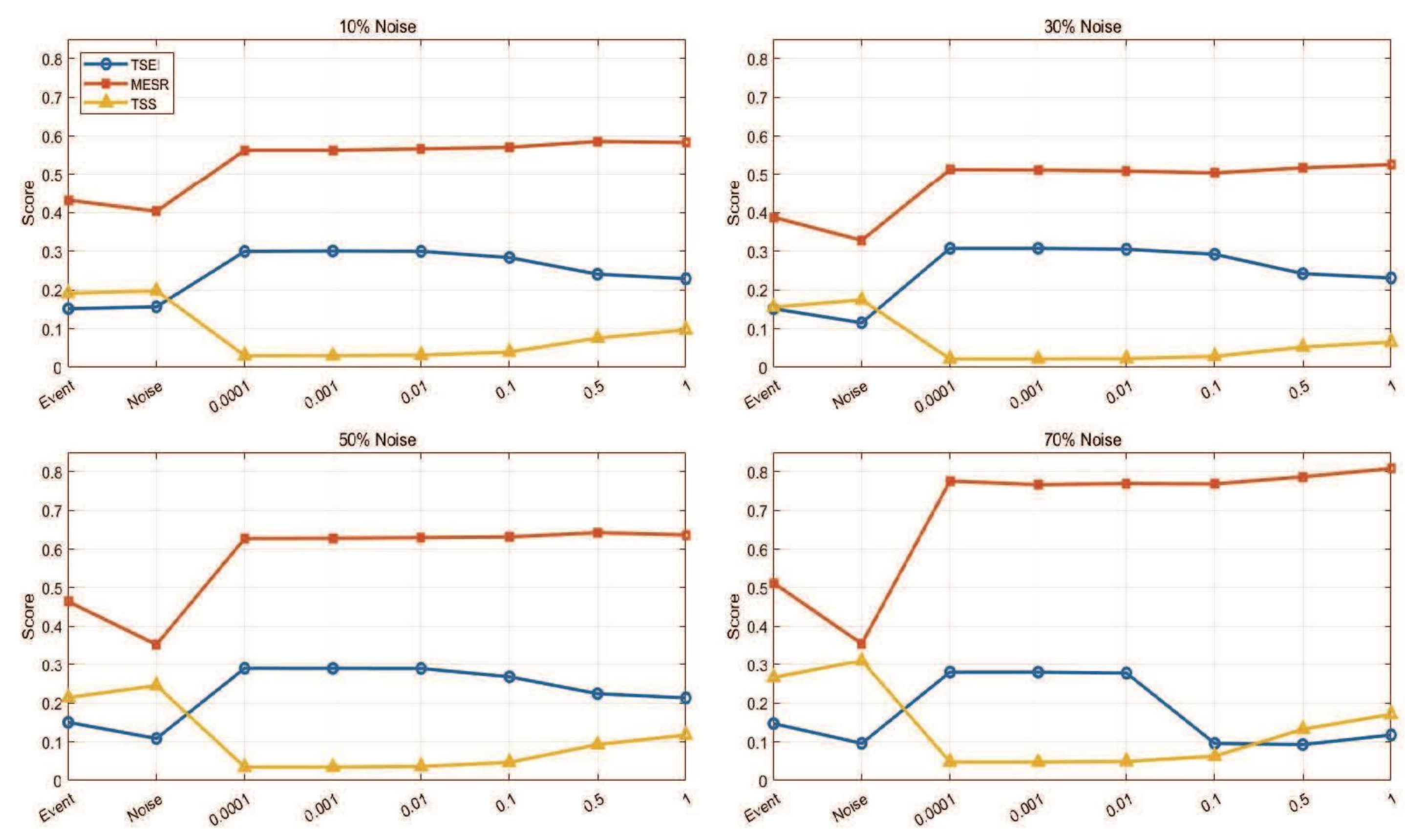

Fig. 3. TSEI vs.Hausdorff distance under varying cleansing strengths.

Unlike contrast-based metrics that increase monotonically, TSEI exhibits a clear turning point— rising during effective denoising and decreasing when structural content is lost. This aligns with Hausdorff-distance trends, validating that TSEI quantitatively tracks geometric degradation. The consistent inverse relationship between TSEI and Hausdorff distance confirms that it faithfully encodes both perceptual and geometric fidelity.

4 Conclusions

- Proposed TSEI, a lightweight reference-free metric for event data quality.
- Models temporal–spatial continuity of event structures.
- Detects geometric degradation and over-cleansing missed by traditional metrics.

For More Information

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