Appendix

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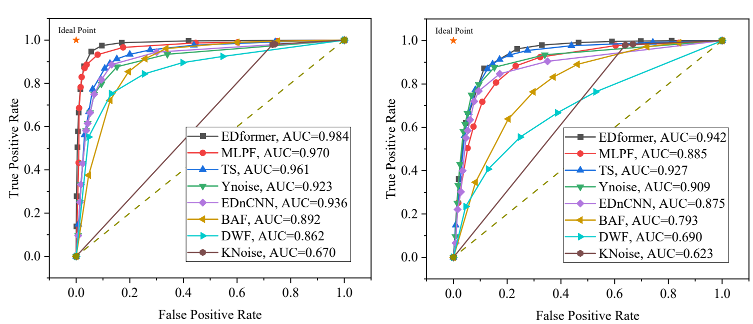
A Appendix Content

This document provides additional contents for

- The results of ROC corresponding to AUC tests in the experimental section.
- The limitation of MESR in evaluating event over-denoising.
- A detailed introduction to our proposed ED24 dataset.
- The complete probability density distribution of BA noise under different illumination conditions for the DAVIS346 event camera.

B Supplementary ROC Results

Fig. 1 presents the results of ROC corresponding to AUC tests in the experimental section. The denoising comparison video for the DND21 dataset [1] and zebrafish blood vessels is provided as supplementary material with the filename 'Comparison.mp4'.

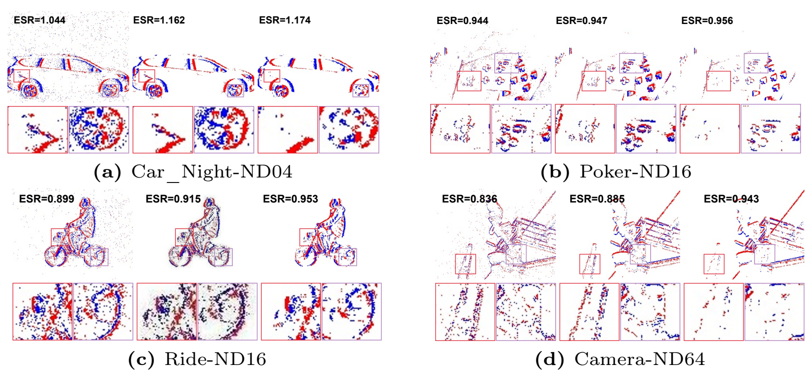


(a) Hotel-bar 5Hz/pixel **(b)** Driving 5Hz/pixel

Fig. 1: ROC results of different denoising algorithms at 5Hz/pixel noise rate

C The limitation of MESR

By adjusting the classification threshold θ, we were able to intentionally control the degree to which the model denoises the event sequence. For example, when setting the classification probability threshold to $\theta = 0.8$, events with a classification probability greater than 0.8 are considered non-noise, allowing the model to preserve the texture details of the original event sequence effectively. When setting $\theta = 0.95$, some texture details that closely resemble noise are removed, leading to over-denoising. As shown in Fig. 2, we found that ESR score may not accurately reflect the denoising accuracy of the model. Even if the denoising model removes events that are not noise, the ESR score may still be higher. We attribute this to the fact that ESR score only consider the global contrast of an image of warped events. However, when aiming to retain intricate texture details that bear resemblance to BA noise, there might be a trade-off resulting in a reduction of ESR scores. Therefore, we believe that evaluating the event denoising performance solely through image quality assessment may not accurately measure the accuracy of event denoising.



(a) Car_Night-ND04 **(b)** Poker-ND16

(c) Ride-ND16 **(d)** Camera-ND64

Fig. 2: (a)-(d) are four different scenarios in the E-MLB dataset. The left of each subfigure is the raw data, the middle is moderately denoised result, and the right is over-denoising result, which boosts ESR score but may inadvertently filter out valid events as noise.

D ED24 dataset

In Tab. 1, we present the contents of our ED24 dataset. Our focus has been on incorporating diverse rotations and translations of event camera, along with a varied set of moving objects, into the dataset. Additionally, we introduced BA noise at 21 different levels, adjusting attenuator voltages from 1.5V to 3.5V for each scene, aiming to ensure robust data generalization. Furthermore, we offer a demo video titled 'ED24_demo.mp4', featuring visualizations of BA noise

Table 1: The contents of ED24 datasets

Dataset	ED24
Train	Bicycle_01, Bicycle_02, Bicycle_03, Car_01, Car_02, Car_03, Car_04, Car_05, Car_06, Car_07, Car_08, Car_09, Car_10, Charger_01, Crossing_01, Crossing_02, Drop_01, Drop_02, Drop_03, Fence_01, Fire_01, Fist_01, Floor_01, Hand_01, Headset_01, Headset_02, House_01, House_02, House_03, House_04, House_05, Jump_01, Keyboard_01, Key_01, Knife_01, Knife_02, Knife_03, Leg_01, Library_01, Library_02, Library_03, make_datasets.py, Mirror_01, Monitor_01, Motor_01, Paper_01, Paper_02, Pedestrain_01, Pedestrain_02, Pedestrain_03, Pedestrain_04, Pedestrain_05, Pedestrain_06, Pedestrain_07, Pedestrain_08, Pedestrain_09, Pedestrain_10, Pedestrain_11, Pedestrain_12, Phone_01, PingPong_01, PingPong_02, PingPong_03, Revolving_01, Roll_01, Roll_02, Roll_03, Roll_04, Roll_05, Running_01, Running_02, Shoes_01, Sign_01, Sign_02, Sign_03, Sign_04, Sign_05, Sign_06, Sign_07, Stairs_01, Strike_01, Throw_01, Throw_02, Throw_03, Throw_04, Throw_05, Toy_01, Toy_02, Toy_03, Tree_01, Tree_02, Tree_03, Tree_04, Umbrella_01, Walk_01, Walk_02, Walk_03, Wall_01, Wall_02, Wave_01, Wave_02

corresponding to attenuator voltages of 0.0V, 2.0V, and 3.0V across 100 scenes in the ED24 dataset. Each frame of the video captures a snapshot of the complete sequence of events at 100ms intervals.

Currently, our ED24 dataset is exclusively utilized for training denoising models. In the future, we will contemplate incorporating other event camera data to further enrich our dataset. Subsequently, this expansion will encompass a test dataset suitable for evaluating the denoising performance of models.

E BA noise statistics

In this section, we present a visualization of the variations in the probability density distribution of the BA noise captured by the DAVIS346 event camera, which conducted by systematically adjusting the attenuator voltage across the range from 0.0V to 4.0V. The results of BA noise statistical modeling are depicted in Fig. 3. It can be observed that as the attenuator voltage increases, corresponding to a decrease in scene brightness, the leakage current noise in the low-frequency range gradually decreases. Simultaneously, the proportion of dark current noise in the mid-frequency range gradually increases, eventually dominating, while the hot pixel noise in the high-frequency range persists. Under low-light conditions, the overall distribution of the BA noise approximates a logarithmic Gaussian distribution. However, if not under extremely bright or dark conditions (for example, attenuator voltage ranging from 1.0V to 2.0V, corresponding illuminance from 9.01 lux to 0.82 lux), the overall BA noise does not strictly adhere to a specific distribution. It is challenging to accurately model it using traditional mathematical methods. Therefore, it is necessary to directly use real-world BA noise to create a denoising dataset for training denoising models.

References

1. Guo, S., Delbruck, T.: Low cost and latency event camera background activity denoising. IEEE TPAMI **45**(1), 785–795 (2023). https://doi.org/10.1109/TPAMI.2022.3152999

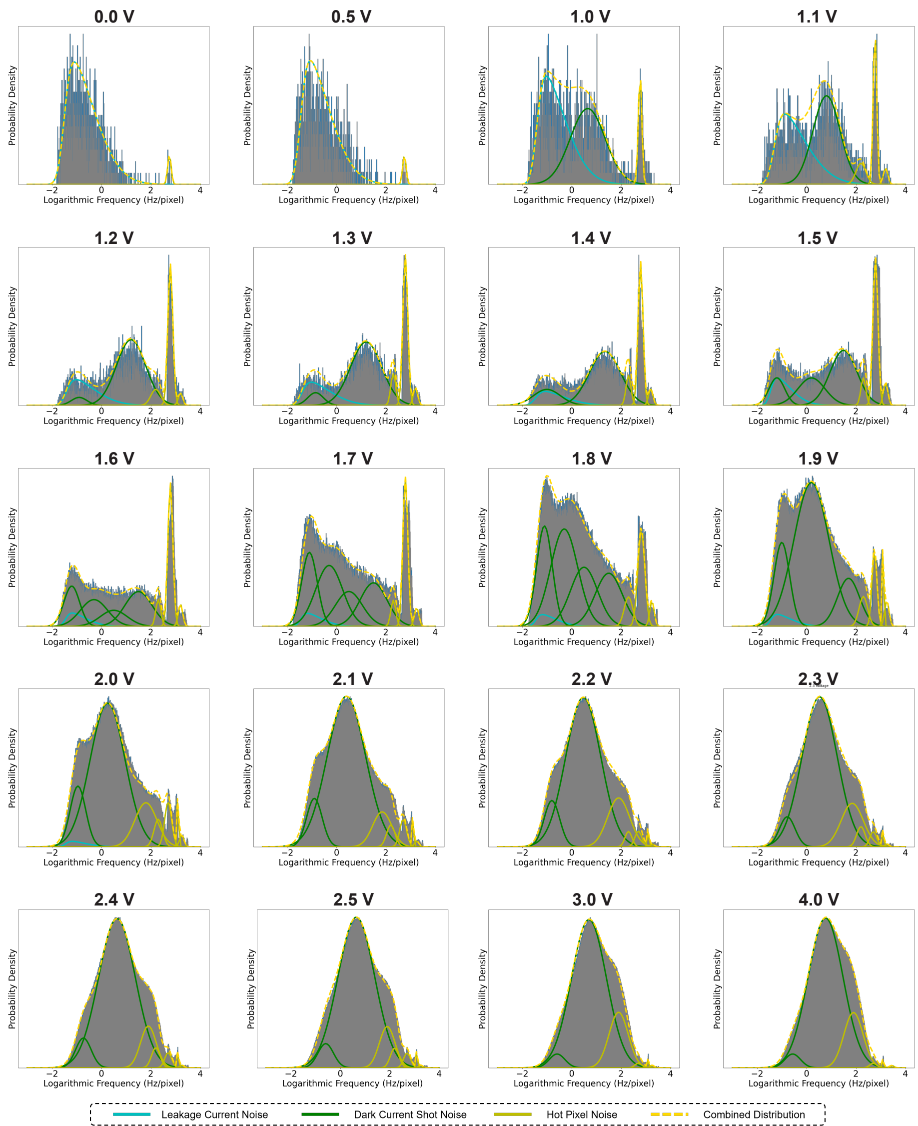


Fig. 3: Statistical results of BA noise at different illumination conditions