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ISET-LFM: A Physics-based Simulation Framework and Dataset for LED Flicker in Automotive Imaging

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Abstract

LED flicker is a persistent artifact in imaging, where lights modulated via Pulse Width Modulation (PWM) above 90 Hz appear steady to humans but produce temporal intensity variations in captured video. While hardware mitigations like split-pixel architectures reduce flicker, they introduce a fundamental trade-off with motion blur. Progress in learned LED flicker mitigation (LFM) is currently hindered by a lack of public ground-truth datasets. We address this gap with ISET-LFM, an open-source physics-based simulation framework that models LED flicker in driving scenes. Built on the ISET ecosystem, our pipeline combines camera motion simulation with an analytical flicker model to generate realistic dual-exposure frame sequences alongside flicker-free ground truth. We provide a synthetic dataset of scene radiance, enabling benchmarking and training of LFM algorithms across diverse sensor and ISP architectures. The code and dataset are available at: `https://github.com/AyushJam/iset-lfm` *and* `https://purl.stanford.edu/wd776hn7919` *respectively.*

Introduction

Light Emitting Diodes (LEDs) are ubiquitous in automotive lighting and infrastructure. Driven by Pulse Width Modulation (PWM) to control brightness, they oscillate at frequencies imperceptible to humans ($\geq$ 90 Hz) but produce severe temporal artifacts in imaging, known as LED flicker [1, 2]. For Advanced Driver Assistance Systems (ADAS), this can lead to the misidentification of traffic signals or emergency vehicle strobes, posing significant safety risks. LED flicker is an important metric in the IEEE P2020 automotive imaging standard [3].

Modern HDR sensors typically use multi-exposure techniques, such as split-pixel architectures [4, 5], to capture the high dynamic range of driving scenes. However, fusing these exposures introduces a fundamental motion-flicker trade-off: long-exposure pixels may be flicker-free but suffer from motion blur, while short-exposure pixels remain sharp but exhibit intense flicker. Traditional fusion algorithms often fail to resolve these artifacts, leading to ghosting or mis-detected flickering edges. While deep learning-based fusion algorithms are possible, they need training data with flicker-free ground truth.

To overcome the inherent impossibility of capturing aligned flicker-free ground truth in real-world dynamic environments, we present ISET-LFM. This open-source physics-based simulation framework allows for the deterministic generation of flickered captures alongside flicker-free ground truth from identical spatio-temporal states. Leveraging ISET3D [6] and ISETCam [7], we model the entire imaging chain, from 3D scene dynamics to detailed sensor electronics.

Our contributions are as follows:

- A simulation pipeline integrating analytical PWM flicker with active camera transforms for realistic motion blur;
- A method for generating simultaneous dual-exposure captures with guaranteed flicker-free ground truth;
- A camera-agnostic synthetic radiance dataset (in EXR format) to enable LFM benchmarking across various sensor and Image Signal Processing (ISP) architectures without re-rendering.

Related Work

LED Flicker Mitigation (LFM) Methods

Current LFM approaches primarily utilize sensor-level hardware modifications to ensure temporal overlap between LED duty cycles and integration times. Techniques such as Lateral Overflow Integration Capacitors (LOFIC) [8] allow for longer integration without saturation, while chopped exposures [4] distribute sub-exposures to increase pulse capture probability. However, these methods can introduce significant motion blur, complex temporal aliasing, or reduced SNR.

The most prevalent approach to LFM in automotive HDR sensors is the aforementioned split-pixel architecture [5, 9, 10]. This design pairs a high-sensitivity Large Photodiode (LPD), which utilizes a short exposure time to maintain spatial sharpness, with a low-sensitivity Small Photodiode (SPD). To achieve high dynamic range, the SPD is operated with a longer exposure time, which also provides a flicker-free reference. Although this approach allows simultaneous multiple exposures, it still needs an exposure fusion algorithm that faces a fundamental motion-flicker trade-off: the SPD is flicker-free but blurred, while the LPD is sharp but flickers. Classical algorithms often struggle with this conflict, resulting in ghosting, residual flicker, or mis-detection of non-illuminant high-contrast edges. The complexity is further increased by the rolling shutter readout: interaction between the LED phase and the row-wise shutter timing produces horizontal banding artifacts where light sources appear partially dark or shifted in color. Although deep learning models work well for multi-exposure fusion tasks [11, 12, 13, 14], their application to LFM is limited by the lack of training data with flicker-free ground truth.

Automotive Datasets and Simulation

Existing large-scale driving datasets like BDD100K [15] or Waymo [16] provide vast RGB data but are unsuitable for LFM research. These are typically post-processed 8-bit videos where sensor artifacts are already either lost to compression or baked into pixel values, without any correspoding ground-truth radiance. Furthermore, these captures are fixed to the specific optics, sensors, and ISPs used during collection. LFM development requires access to raw scene radiance and sensor electronics to model PWM-shutter interactions.

While simulators like CARLA or AirSim support planning, they often simplify lights as steady-state emitters, ignoring PWM oscillation. Industrial tools (e.g., Ansys, rFPro) offer high fidelity flicker simulation but are proprietary black-box systems, hindering reproducible academic research. Prior research has explored general-purpose rendering engines for targeted LFM studies. Notably, Behmann et al. [17] utilized Blender to simulate flickering lights and generate ground-truth masks for detection. While effective for validating detection algorithms, such approaches typically do not account for detailed image sensor modeling, spectral light transport, or the complex multi-exposure fusion required by HDR sensors.

In the domain of vehicle lighting, research has traditionally focused on headlight detection and localization [18, 19]. However, in an LFM context, the challenge shifts from detection to signal restoration. If a light source is in its "OFF" phase during a short exposure capture, detection-based models may fail to register the object entirely.

Our work utilizes the ISETAuto dataset [20] as its primary foundation for scene assembly. These scenes were constructed using RoadRunner to integrate road descriptions from open-source standards, populating the environment with a rich collection of calibrated 3D assets including vehicles, pedestrians, cyclists, and vegetation. Each scene utilizes high-fidelity spectral power distributions for streetlights, vehicle lamps, and environmental sky maps to achieve realistic illumination and high dynamic range. We create scene spectral radiance from these three-dimensional scenes rendered with physically based rendering techniques (PBRT) [21] using ISET3D. By releasing these camera-agnostic radiance sequences, we enable researchers to develop LFM algorithms using a transparent simulator that accounts for motion blur, rolling-shutter banding, and variable PWM parameters. This framework also allows for the deterministic creation of safety-critical corner cases that are nearly impossible to capture consistently in the real world.

Methods

The ISET-LFM pipeline is built upon the scene assembly and sensor modeling foundations of the ISET ecosystem, utilizing PBRT to simulate light transport. The base image system simulation methods used in this work are detailed in previous publications [7, 22]. By utilizing high-quality assets, spectral light sources, and physically-defined materials, the ISET framework produces radiance and image data that has been validated for accuracy in several studies [23, 24, 25, 26]. Our four-stage pipeline (Fig. 1) integrates novel elements to simulate LED flicker and non-uniform motion blur.

HDR Scene Simulation and Motion Control (Stages I & II)

The simulation begins by constructing a 3D scene description for PBRT. We populate environment geometry with assets from ISETAuto, assigning each light source a specific spectral power distribution and radiant intensity. To simulate a dynamic environment, we define spatial states through camera transforms.

Ego-Motion and Active Transforms: Realistically simulating motion blur requires defining trajectories during the shutter interval. We implement a motion-aware rendering strategy by applying active transforms—moving the camera's spatial state during the exposure—to simulate ego-vehicle motion. For front-facing automotive cameras, a forward trajectory at user-defined velocities (e.g., 30 m/s) generates non-uniform radial motion blur that increases toward the periphery.

For the dual-exposure LFM strategy, we generate two PBRT scripts per frame. Since automotive LEDs typically operate above 90 Hz (period < 11.11 ms), we fix the long-exposure (SPD) duration to 11.11 ms to ensure integration over at least one full PWM cycle. The short-exposure (LPD) is typically set between 3–5 ms to maintain sharpness, though it remains prone to flicker. Note that while the long exposure integrates a full period, its absolute intensity may remain sensitive to the PWM parameters, resulting in intensity fluctuations known as *residual flicker*.

Light Source Control: We treat light sources (headlights, brake lights) as area lights with beam-angle controls adapted from ISETHDR [27]. This allows for directional modeling of illumination. The radiant intensity of these sources is treated as a time-varying parameter, modulated by the analytical flicker model in Stages II or IV.

Analytical Flicker Model (Stages II and IV)

We define a closed-form, piecewise linear model for radiant exposure Φ as a function of LED and camera parameters.

Definitions: As shown in Fig. 2, we define the irradiance at the sensor plane $I(t)$ from an LED that operates with period t_p, duty cycle D, and radiant intensity A during its ON-time $t_o = D \cdot t_p$. For a pixel with exposure duration t_e starting at phase offset $t_s \in [0, t_p)$, the radiant exposure is:

$$\Phi(t_s, t_e) = \int_{t_s}^{t_s+t_e} I(t)dt, \tag{1}$$

where t_s is the exposure start time relative to the latest rising edge of the LED pulse. Assuming t_s is a uniform random variable $t_s \sim \mathrm{U}[0, t_p)$, we define a flicker severity index (FSI) as in [1] by the formula:

$$\mathrm{FSI} = \frac{\Phi_{max} - \Phi_{min}}{\Phi_{max} + \Phi_{min}}, \tag{2}$$

where Φ_{max} and Φ_{min} are the maximum and minimum radiant exposure values observed in a sequence, respectively.

Spatio-Temporal Modeling: To simulate video, the phase t_s is updated recursively for each frame. For a frame rate $1/t_f$, the phase offset for frame $n+1$ is:

$$t_s^{(n+1)} = (t_s^{(n)} + t_f) \bmod t_p. \tag{3}$$

As illustrated in Fig. 3, short exposures ($t_e = 5$ ms) can result in absolute flicker (FSI $= 1$) where the shutter interval falls entirely within the LED's OFF period, while longer integration (11.11 ms) reduces FSI but leaves residual intensity variations. To simulate rolling-shutter artifacts on an $M \times N$ sensor, we apply a row-wise phase shift. For row i with sensor line delay t_d, the phase is:

$$t_s^{(i,n)} = (t_s^{(n)} + (i-1)t_d) \bmod t_p, \tag{4}$$

where $t_s^{(n)}$ is the offset for the first row. This formulation accurately replicates the horizontal banding artifacts characteristic of

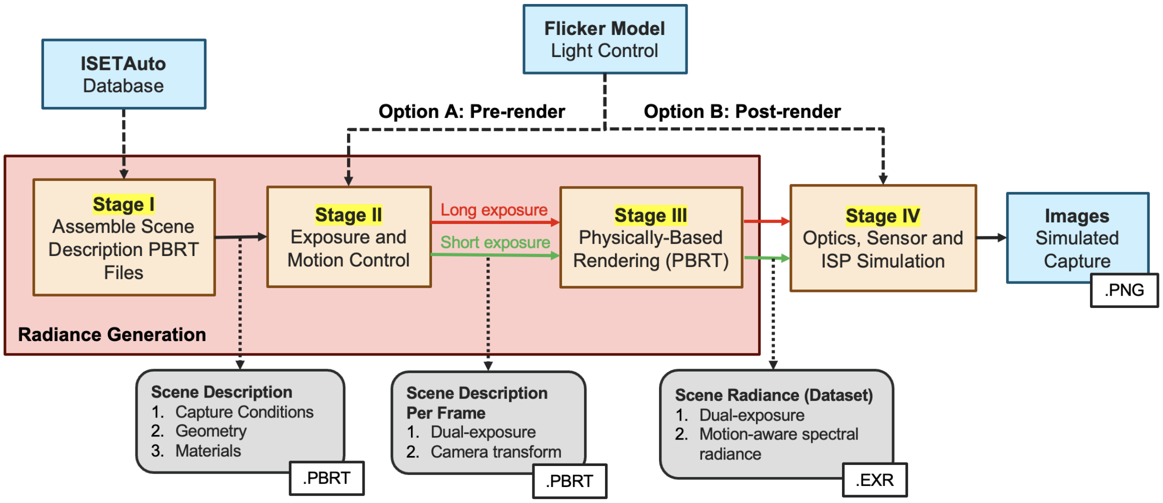

Figure 1. *The ISET-LFM Simulation Framework. Stages I–III utilize ISET3D and active camera transforms to generate dual-exposure spectral radiance maps (.EXR). The framework supports individual light modulation pre-rendering (Option A) or light-group weight modulation post-rendering (Option B). Stage IV utilizes ISETCam to process these maps through optics and a split-pixel sensor model to produce final flickered images.*

rolling-shutter cameras imaging high-frequency LEDs. The proposed flicker model was validated through laboratory experiments

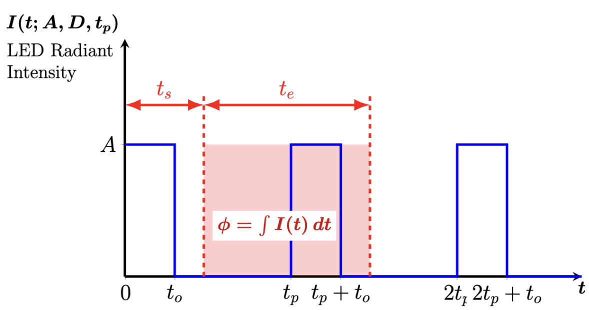

Figure 2. *Analytical model of LED radiant intensity $I(t)$ and resulting pixel radiant exposure Φ. The LED operates with period t_p, radiant intensity A during ON-time t_o. Camera exposure t_e begins at phase offset t_s; the shaded area represents the total irradiance integrated over t_e.*

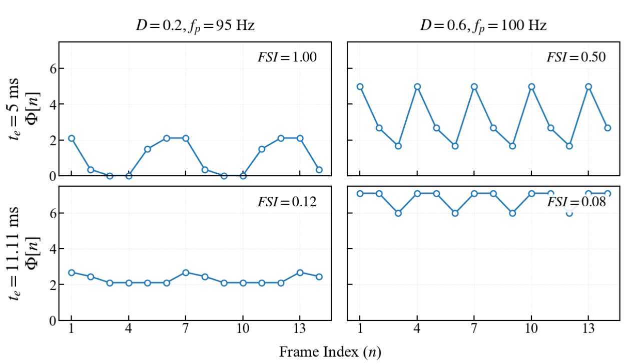

Figure 3. *Simulated temporal flicker $\Phi[n]$ at 30 FPS for $t_e = 5$ ms (top) and $t_e = 11.11$ ms (bottom). Short exposures exhibit high flicker ($\mathrm{FSI} = 1$ for $D = 0.2$), while integration over a full PWM period (11.11 ms) ensures non-zero Φ (low FSI) but leaves residual flicker.*

using a controlled LED lightbox.

Implementation Strategies: To maintain computational efficiency, the simulator supports two strategies:

- **Option A (Pre-render Light Control):** Φ is pre-calculated per LED per frame and used to modulate source power in the PBRT scene description. This allows for independent control of unsynchronized light sources.
- **Option B (Post-render Light Control):** We utilize light-group decomposition [27] to render four separate radiance maps (L_j) for headlights, streetlights, skymap, and "other" lights, respectively. These maps can be linearly combined to reconstruct the full scene radiance $L_{total} = \sum_{j=1}^{4} w_j L_j$. The flicker model is then applied as a weight to the specific light-group's radiance per frame. This enables rapid dataset scaling by varying D and t_p without re-rendering.

Image Systems Simulation (Stage IV)

The spectral radiance from Stage III is processed through ISETCam to simulate optics, sensor electronics, and ISP.

Sensor Architecture: We use ISETCam's implementation of a split-pixel sensor model based on a three-capture architecture [5]. The Large Photodiode (LPD) is read twice with dual conversion gains (High: HCG and Low: LCG) during a short exposure. The Small Photodiode (SPD) utilizes a long exposure (11.11 ms) and lower sensitivity to capture bright, flicker-free signals without saturation [28]. Because the sensor simulator in ISETCam generates both LPD and SPD readings for every input pass, we select the two LPD readings from the short-exposure radiance pass and the SPD reading from the long-exposure radiance pass.

Exposure Fusion: Data from the three captures (LPD-HCG, LPD-LCG, and SPD) are integrated into a single HDR image using the input-referring algorithm as in ref. [27]. The LPD signal is prioritized for spatial sharpness; if LPD pixels saturate, the algorithm falls back to the SPD signal. While this baseline fusion method is relatively simple, it effectively illustrates the propagation of LPD flicker artifacts into final HDR outputs.

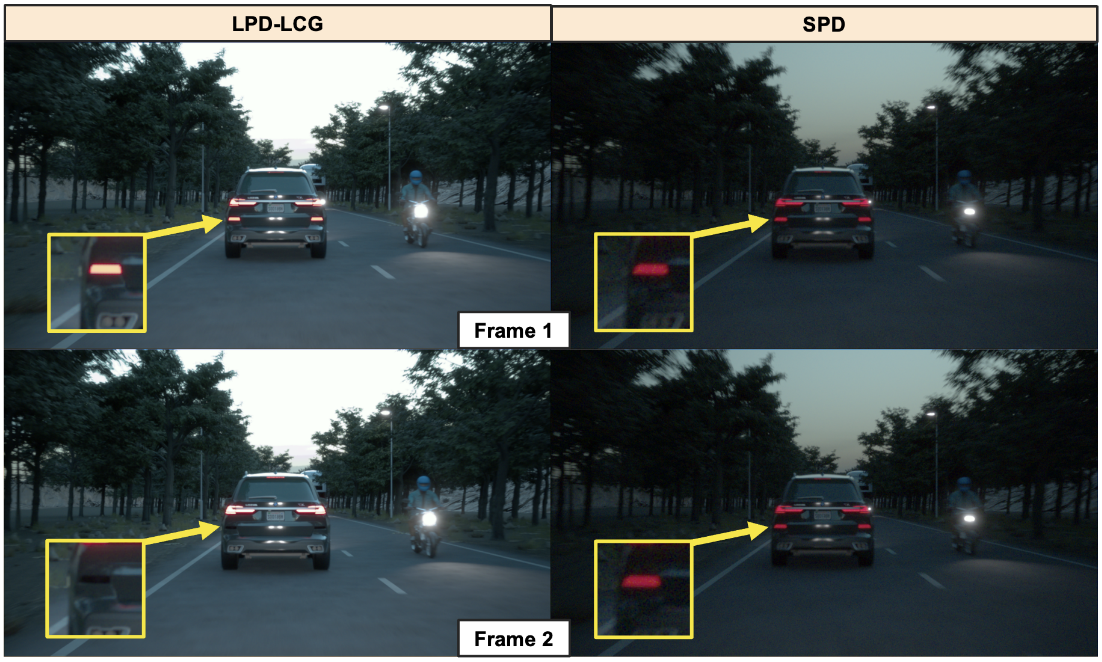

Figure 4. Two-frame sequence showing temporal flicker (60 fps, 60 m/s; this velocity was chosen to clearly illustrate motion blur artifacts). Short-exposure LPD (5 ms) is relatively sharp but exhibits flickering tail lights (arrows). Long-exposure SPD (11.11 ms) ensures steady intensity but introduces significant motion blur.

Experiments

Simulations were rendered at 1920×1080 resolution on an NVIDIA RTX 3090 Ti. We isolate two primary phenomena: temporal intensity oscillations and spatial rolling-shutter banding.

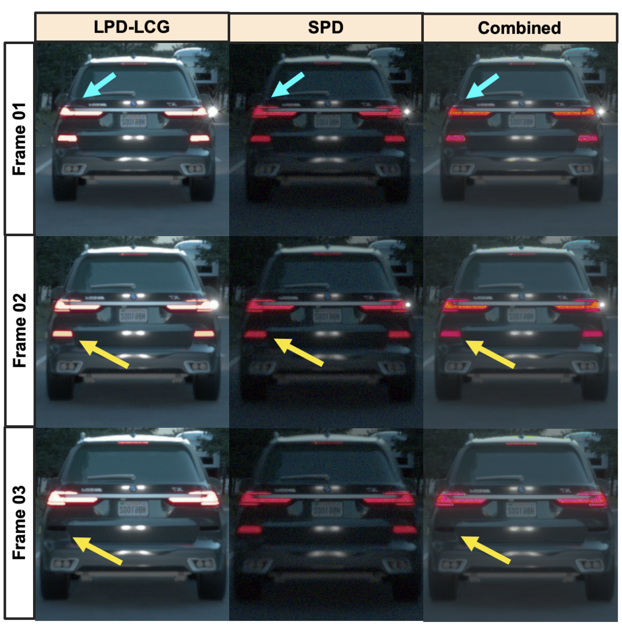

Figure 5. Failure modes in HDR fusion. Frame 01 (LPD) captures flickered brake lights (cyan arrows) while Frame 03 (LPD) captures a flickered "OFF" state for auxiliary lamps (yellow arrows). The simple fusion algorithm discussed in the text prioritizes the sharp LPD signal, propagating the flicker artifact into the final HDR output.

Simulating Temporal Flicker

We simulated vehicle tail lights with $D \in [0.1, 0.5]$ and $f \in [90, 110]$ Hz. To isolate temporal effects, we assumed a 60 fps camera using a global shutter, within a vehicle moving at 60 m/s. The simulation follows the pre-render light control strategy (Option A). As shown in Fig. 4, the 5 ms LPD captures maintain relative sharpness but exhibit inconsistent intensity across frames (flicker). Conversely, the 11.11 ms SPD capture remains steady but suffers from significant non-uniform motion blur, particularly at the periphery (Fig. 6). The resulting HDR fusion propagates these LPD flicker artifacts, causing active light sources to appear extinguished in certain frames (Fig. 5).

Figure 6. Motion-flicker trade-off in fusion. The algorithm attempts to merge sharp LPD data with the elongated motion trail of the SPD, resulting in a non-physical comet artifact. This distortion can degrade downstream perception accuracy.

Simulating Spatial (Rolling Shutter) Flicker

To simulate rolling-shutter artifacts without the prohibitive cost of per-row rendering, we utilized post-render modulation (Option B). To isolate spatial banding from motion-induced distortions, we performed this specific simulation using a static scene and used a standard single-exposure sensor model. We synchronized all vehicle LEDs at $D = 0.20$ and $f = 105$ Hz. We recombined the four light groups for each row by applying a row-wise weight Φ_i (eq. 4) and passed the radiance maps through ISETCam. Finally, we constructed the rolling-shutter image by selecting and concatenating the corresponding rows from the resulting captures. As the phase offset t_s varies, this band can completely occlude critical features like tail lights or motorcycles (Fig. 7), demonstrating a failure mode for downstream ADAS perception.

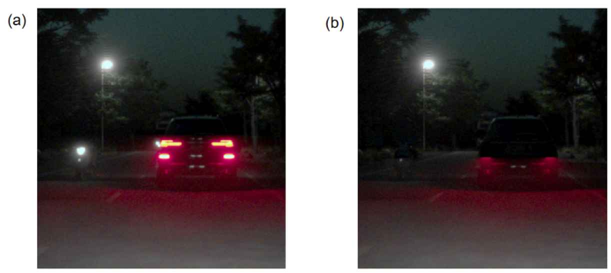

Figure 7. Rolling-shutter banding for a synchronized LED group (all vehicle lights at $f = 105$ Hz, $D = 0.20$). (a) Phase offset causes dark banding above tail lights. (b) A different phase results in total source occlusion, rendering the motorcycle invisible to the camera.

Dataset Generation and Accessibility

To support learning-based LFM, we release the first open-source synthetic dataset (Fig. 8) with ground-truth flicker-free radiance. We utilize Option B (post-render control) to scale the dataset efficiently. We provide 200 automotive scenes from the ISETAuto database, decomposed into four light groups: headlights, streetlights, environmental skymap, and other lights.

For each light group in each scene, we provide the following.

- **Three-frame Sequences:** Captured at 60 fps.
- **Dual-Exposure Radiance Pairs:** Simultaneous short (3–5 ms) and long (11.11 ms) exposure EXR maps with realistic motion blur ($v \in [20, 50]$ m/s).
- **Metadata and Ground Truth:** Depth maps, rendering parameters, and flicker-free ground truth, which is generated by setting constant modulation weights across frames.

The camera-agnostic nature of this data allows researchers to apply custom sensor models or ISPs to investigate LFM robustness across diverse hardware. The complete ISET-LFM radiance dataset is available via the Stanford Digital Repository [29].

Discussion and Conclusion

The ISET-LFM framework addresses a need in automotive imaging by providing a transparent, physically accurate pipeline for LED flicker simulation. While our current model assumes static environments relative to high-speed ego-motion and synchronized light groups for efficiency, it successfully replicates the complex motion-flicker trade-off that degrades current ADAS pipelines.

Our experiments demonstrate that standard HDR fusion propagates flicker artifacts (Fig. 5) or introduces geometric distortions (Fig. 6). Furthermore, rolling-shutter banding can lead to total source occlusion (Fig. 7), posing severe risks to object detection and tracking. By providing simultaneous dual-exposure pairs and ground-truth radiance, ISET-LFM enables the development of deep learning models capable of restoring sharp, flicker-free signals. Future work will expand the dataset to include complex urban infrastructure, such as traffic signals and message signs.

Acknowledgments

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Figure 8. Dataset Diversity and Dual-Exposure Capture Analysis. Representative scenes from the ISET-LFM dataset illustrating the motion-flicker trade-off across varying environments. Top row (LPD): short-exposure (3–5 ms) and bottom row (SPD): long-exposure (11.11 ms), with ego-velocities (v) labeled for each scenario. These examples, generated via Option B, represent the separate radiance components provided in the dataset prior to HDR fusion.

References

[1] B. M. Deegan, "LED flicker: Root cause, impact and measurement for automotive imaging applications," *Electronic Imaging*, vol. 30, pp. 1–6, 2018.

[2] B. M. Deegan, "LED flicker measurement: Challenges, considerations, and updates from IEEE P2020 working group," *Electronic Imaging*, vol. 32, pp. 1–6, 2020.

[3] IEEE Working Group, "IEEE P2020 automotive imaging white paper," 2018.

[4] T. Lule, "Challenges of HDR imaging in automotive environment," *AutoSens, Brussels*, 2017.

[5] J. Solhusvik, T. Willassent, S. Mikkelsen, M. Wilhelmsen, S. Manabe, D. Mao, Z. He, K. Mabuchi, and T. Hasegawa, "1280× 960 2.8 μm HDR CIS with DCG and split-pixel combined," in *Proceedings of the International Image Sensor Workshop (IISW), Snowbird, UT, USA*, pp. 23–27, 2019.

[6] Z. Liu, M. Shen, J. Zhang, S. Liu, H. Blasinski, T. Lian, and B. Wandell, "A system for generating complex physically accurate sensor images for automotive applications," *arXiv preprint arXiv:1902.04258*, 2019.

[7] J. E. Farrell, P. B. Catrysse, and B. A. Wandell, "Digital camera simulation," *Applied optics*, vol. 51, no. 4, pp. A80–A90, 2012.

[8] M. Oh, S. Nicholes, M. Suryadevara, L. Lin, H.-C. Chang, D. Tekleab, M. Guidash, S. Amanullah, S. Velichko, M. Innocent, *et al.*, "3.0 μm backside illuminated, lateral overflow, high dynamic range, LED flicker mitigation image sensor," in *Proc. Int. Image Sensor Workshop*, pp. 262–265, 2019.

[9] M. Innocent, A. Rodriguez, D. Guruaribam, M. Rahman, M. Sulfridge, S. Borthakur, B. Gravelle, T. Goto, N. Dougherty, B. Desjardin, *et al.*, "Pixel with nested photo diodes and 120 dB single exposure dynamic range," in *International Image Sensor Workshop*, pp. 95–98, 2019.

[10] T. Willassen, J. Solhusvik, R. Johansson, S. Yaghmai, H. Rhodes, S. Manabe, D. Mao, Z. Lin, D. Yang, O. Cellek, *et al.*, "A 1280× 1080 4.2 μm split-diode pixel HDR sensor in 110 nm BSI cmos process," in *Proceedings of the International Image Sensor Workshop, Vaals, The Netherlands*, pp. 8–11, 2015.

[11] Q. Yan, D. Gong, Q. Shi, A. v. d. Hengel, C. Shen, I. Reid, and Y. Zhang, "Attention-guided network for ghost-free high dynamic range imaging," in *Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition*, pp. 1751–1760, 2019.

[12] Z. Liu, Y. Wang, B. Zeng, and S. Liu, "Ghost-free high dynamic range imaging with context-aware transformer," in *European Conference on computer vision*, pp. 344–360, Springer, 2022.

[13] N. K. Kalantari, R. Ramamoorthi, *et al.*, "Deep high dynamic range imaging of dynamic scenes.," *ACM Trans. Graph.*, vol. 36, no. 4, pp. 144–1, 2017.

[14] K. Ram Prabhakar, V. Sai Srikar, and R. Venkatesh Babu, "Deepfuse: A deep unsupervised approach for exposure fusion with extreme exposure image pairs," in *Proceedings of the IEEE international conference on computer vision*, pp. 4714–4722, 2017.

[15] F. Yu, H. Chen, X. Wang, W. Xian, Y. Chen, F. Liu, V. Madhavan, and T. Darrell, "BDD100k: A diverse driving dataset for heterogeneous multitask learning," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 2636–2645, 2020.

[16] P. Sun, H. Kretzschmar, X. Dotiwalla, A. Chouard, V. Patnaik, P. Tsui, J. Guo, Y. Zhou, Y. Chai, B. Caine, *et al.*, "Scalability in perception for autonomous driving: Waymo open dataset," in *Proceedings of the IEEE/CVF conference on computer vision and pattern recognition*, pp. 2446–2454, 2020.

[17] N. Behmann, H. Blume, G. Schewior, and S. Hesselbarth, "Selective LED flicker detection and mitigation algorithm for non-hdr video sequences," in *2018 IEEE 8th International Conference on Consumer Electronics-Berlin (ICCE-Berlin)*, pp. 1–5, IEEE, 2018.

[18] T.-A. Pham and M. Yoo, "Nighttime vehicle detection and tracking with occlusion handling by pairing headlights and taillights," *Applied Sciences*, vol. 10, no. 11, p. 3986, 2020.

[19] S. Zhou, J. Li, Z. Shen, and L. Ying, "A night time application for a real-time vehicle detection algorithm based on computer vision," *Research Journal of Applied Sciences, Engineering and Technology*, vol. 5, no. 10, pp. 3037–3043, 2013.

[20] Z. Liu, J. Farrell, and B. A. Wandell, "ISETAuto: Detecting vehicles with depth and radiance information," *IEEE Access*, vol. 9, pp. 41799–41808, 2021.

[21] M. Pharr, W. Jakob, and G. Humphreys, *Physically Based Rendering: From Theory to Implementation*. San Mateo, CA, USA: Morgan Kaufmann, 3rd ed., 2016.

[22] Z. Liu, T. Lian, J. Farrell, and B. Wandell, "Soft prototyping camera designs for car detection based on a convolutional neural network," in *Proceedings of the IEEE/CVF International Conference on Computer Vision Workshops*, pp. 0–0, 2019.

[23] Z. Lyu, K. Kripakaran, M. Furth, E. Tang, B. Wandell, and J. Farrell, "Validation of image systems simulation technology using a cornell box," *arXiv preprint arXiv:2105.04106*, 2021.

[24] T. Goossens, Z. Lyu, J. Ko, G. C. Wan, J. Farrell, and B. Wandell, "Ray-transfer functions for camera simulation of 3D scenes with hidden lens design," *Optics Express*, vol. 30, no. 13, pp. 24031–24047, 2022.

[25] J. Farrell, M. Okincha, and M. Parmar, "Sensor calibration and simulation," in *Digital Photography IV*, vol. 6817, pp. 249–257, SPIE, 2008.

[26] J. Chen, K. Venkataraman, D. Bakin, B. Rodricks, R. Gravelle, P. Rao, and Y. Ni, "Digital camera imaging system simulation," *IEEE Transactions on Electron Devices*, vol. 56, no. 11, pp. 2496–2505, 2009.

[27] Z. Liu, D. Shah, and B. A. Wandell, "ISETHDR: A physics-based synthetic radiance dataset for high dynamic range driving scenes," *IEEE Sensors Journal*, 2025.

[28] S. K. Nayar and T. Mitsunaga, "High dynamic range imaging: Spatially varying pixel exposures," in *Proceedings IEEE Conference on Computer Vision and Pattern Recognition. CVPR 2000 (Cat. No. PR00662)*, vol. 1, pp. 472–479, IEEE, 2000.

[29] A. Jamdar, "ISET-LFM: A Physics-based Synthetic Radiance Dataset for LED Flicker Mitigation in Automotive Imaging." Stanford Digital Repository, 2026. Available at `https://purl.stanford.edu/wd776hn7919`.

Author Biography

Ayush Jamdar received the B.Tech. degree in Electrical Engineering from the Indian Institute of Technology Madras (2024). He joined the University of California San Diego in 2024, where he is pursuing an M.S. in Electrical and Computer Engineering. At UCSD, he serves as a student researcher at the Computational Imaging Systems Lab (CISL). During the summer of 2025, he was a Camera Systems Intern at Omnivision Technologies and a Research Affiliate at Stanford's VISTA Lab, where he developed the simulation framework and dataset presented in this work.

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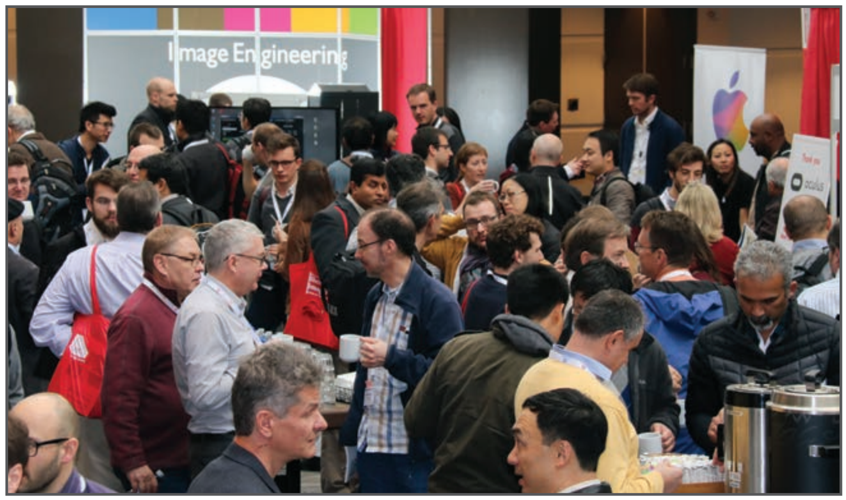

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