Illumination-Invariant Feature Extraction from Multi-Time-Series Images of Transmission Lines: A Sliding Window-Based Adaptive Attenuation Fusion Method

Wei Du[1], Hao Xu[1], Fenglei Jiang[1], Zhengbin Guo[1], Lei Wang[1]
[1]State Grid Jiangsu Electric Power Co., Ltd. Huai'an Power Supply Branch, Huai'an 223001, Jiangsu, China
Corresponding author: Wei Du (e-mail: 18888128855@163.com)

ABSTRACT In complex outdoor transmission-line corridors, visible-band electromagnetic-wave imaging is strongly affected by atmospheric variations, day–night cycles, and transient illumination changes, which may cause feature drift and reduce the reliability of intelligent visual inspection. Existing studies mainly focus on electrical-quantity analysis or single-frame structural assessment, while insufficient attention has been paid to illumination-invariant feature extraction from multi-temporal monitoring images. To address this problem, this paper proposes an illumination-invariant feature extraction method for transmission lines based on sliding-window adaptive attenuation fusion. The proposed method exploits local temporal continuity to dynamically construct an illumination reference benchmark within a sliding window, and designs adaptive attenuation weights to fuse multi-frame features according to the degree of illumination interference. In this way, instantaneous strong-light disturbance can be suppressed while robust structural features of transmission-line components are retained. Experimental results on simulated synthetic and real acquired multi-time-series datasets show that the proposed method improves the feature consistency index by approximately 15%–30% compared with classical illumination normalization methods. It also enhances the generalization performance of downstream target detection models under varying illumination conditions. The results indicate that the proposed feature-level fusion strategy provides an effective technical approach for all-weather and highly reliable visual inspection of power transmission lines in complex electromagnetic field environments.

INDEX TERMS transmission line, multi-time-series images, illumination-invariant features, electromagnetic-wave imaging, adaptive feature fusion

I. INTRODUCTION

HIGH-voltage and ultra-high-voltage transmission lines, which increasingly utilize high-strength industrial materials for insulation and structural reinforcement, serve as the main arteries of the national energy network. At different times of day (morning, noon, dusk, night), under different weather conditions (sunny, cloudy, rainy, foggy), and even due to the instantaneous movement of clouds, the intensity, color temperature, and direction of light in a scene will dynamically, randomly, and significantly change. This change directly manifests in the image as fluctuations in overall brightness and contrast, as well as changes in the position and shape of shadows. More fundamentally, it causes an overall shift and local distortion in the distribution of image pixel values.

This paper proposes a novel feature extraction method to effectively overcome the interference of illumination variations in the time-series monitoring of power transmission line corridors, specifically targeting the detection of high-strength industrial components used for insulation and structural reinforcement. By enhancing the stability of structure patterns under fluctuating light, the method ensures the accurate

assessment of material degradation and structural integrity within the electrical grid. Instead of directly performing illumination correction on image pixels, which is difficult to model precisely, this method shifts to the feature space, introducing temporal dimension processing based on the initial feature map extracted by a deep learning network. By designing a sliding window mechanism, a dynamic local illumination reference is constructed on the time axis, and adaptive decay fusion weights are designed based on feature reliability, thereby achieving suppression of illumination interference components and enhancement of robust structural features at the feature level. The subsequent contents of this paper are arranged as follows: Chapter 2 will review and comment on relevant research work; Chapter 3 will elaborate on the overall framework and key technical details of the proposed sliding window adaptive decay fusion method; Chapter 4 will quantitatively and qualitatively verify the effectiveness of the proposed method by constructing synthetic and real datasets, setting up comparative and ablation experiments, and discussing the results in depth; Chapter 5 will summarize the entire work and look forward to future research directions.

II. RELATED WORK

The monitoring and health management of transmission line operation status has become a research hotspot in the field of power system. Touati et al. [1] proposed a hybrid strategy combining fast Fourier transform (FFT) and fuzzy logic (FL) to determine the fault area in the line through isolation steps. KC et al. [2] analyzed the interaction between various physical fields that may cause transmission line failure. Wang et al. [3] proposed a model based on improved YOLO, specifically designed to enhance the ability to identify defects and hidden dangers in transmission lines in hyperspectral images. Elkholy et al. [4] studied the resistance, inductance, capacitance and other parameters of transmission lines, as well as the influence of different load characteristics on the active and reactive power losses of the line and the voltage deviation and harmonic distortion of the load connection point. Ab Ghani et al. [5] found that changes in line parameters can significantly change the distribution of electromagnetic fields around them.

Ekren et al. [6] reviewed and summarized the research and development status of overhead inspection robots for transmission lines. Hoseini Vaez et al. [7] proposed a two-step method for reliability-based design optimization of transmission line towers. Using observation data from the CSES satellite, Savelyeva et al. [8] analyzed electromagnetic radiation signals from the ZEVS ultra-low frequency transmitter and the northern transmission line. Garanzha et al. [9] studied the dynamic behavior of transmission line support structures under the influence of wind loads. Rapid and accurate detection of transmission line faults is crucial for maintaining grid stability. The NHWT-FA hybrid method proposed by Murugesan et al. [10] can effectively and accurately detect various faults in transmission lines. Most existing studies focus on electrical quantity monitoring or structural status assessment at a single moment. For long-term sequence monitoring scenarios of line corridors based on visual perception, the image feature drift problem caused by changes in illumination conditions has not received sufficient attention. To address this technical bottleneck, this paper aims to overcome the limitations of existing visual monitoring methods under complex lighting conditions by using time-series illumination compensation and feature fusion, thus providing new technical support for all-weather intelligent inspection of power transmission lines.

III. METHODS

A. CONSTRUCTION AND PREPROCESSING OF MULTI-TEMPORAL IMAGE DATASETS

This paper constructs two types of time-series datasets: simulated synthetic datasets and real-world acquisition datasets. The simulated dataset is based on publicly available transmission line component inspection datasets. Using high-order illumination simulation technology, a series of image sequences with continuously changing illumination parameters are generated for each static background image of the line. The changing parameters include illumination intensity, color temperature, and directional shadows. In this way, precise pairing data of "same object, different illumination" can be generated, which is convenient for quantitative evaluation [11,12].

This real-world dataset comes from high-definition cameras deployed on fixed transmission towers. These cameras captured images of the transmission line corridor for two consecutive weeks at a high sampling rate of one frame every 0.5 seconds, ultimately generating a real-world time-series image stream of over 2,400,000 frames. This sequence naturally includes complete day-night cycles, various weather conditions, and instantaneous light fluctuations. Compared to minute-level sampling, the sub-second sampling interval effectively captures abrupt changes in illumination caused by cloud cover, automatic camera exposure adjustments, etc., ensuring that the changes in illumination between adjacent frames are continuous and gradual, thus meeting the basic requirement of temporal local continuity for the sliding window mechanism. All images were uniformly scaled to a fixed resolution, and the front end of a convolutional neural network pre-trained on diverse lighting and power scene data was used as a general feature extractor to map each original frame of the raw image into a spatially downsampled, channel-rich primary feature map. All subsequent processing was performed on this primary feature map sequence.

B. MODELING OF LIGHTING REFERENCE FOR SLIDING WINDOW

In order to utilize the temporal local continuity to deal with the gradual characteristics of illumination and to provide illumination reference for the current frame, a sliding window mechanism is introduced. For the current processing time, a temporal window with a fixed length of L is defined with it as the center. The window slides on the time axis and processes each frame in the sequence in turn [13].

In real-world outdoor environments, wind-induced vibrations and galloping can cause sub-pixel or even pixel-level displacements in transmission lines. To overcome this contradiction, this paper first performs dense optical flow estimation (such as the Farneback algorithm) on adjacent frames within a window to calculate the motion amplitude of each pixel. Regions with motion amplitudes exceeding a preset threshold τ are identified as structural motion rather than illumination changes. In subsequent window baseline feature calculations, pixel-level features of these motion regions are assigned lower weights to suppress dynamic interference.

The core assumption is updated to: within a short time window, illumination changes in the transmission line are the dominant factor relative to structural motion, and motion regions can be effectively identified and isolated through optical flow. Therefore, the changes in statistics (such as channel mean) of all frame features at corresponding spatial locations within the window primarily reflect illumination fluctuations. Based on this, a dynamic "illumination baseline feature" is calculated for each sliding window. Specifically, the temporal average of all feature maps within the window at each spatial location is first calculated to obtain an average feature representation. However, simple averages are easily contaminated by extreme illumination frames within the window (such as instantaneous overexposure or underexposure). Therefore, a robust estimation based on the absolute deviation of the median is further introduced. The deviation of each frame feature map within the window from the initial average is calculated, and the contribution of frames with excessively large deviations is attenuated, ultimately yielding a more robust window illumination baseline feature. This baseline feature is considered as a feature estimate under relatively stable "background" illumination conditions within the current window period, excluding instantaneous strong interference. It serves as a reference anchor point for measuring the degree of illumination interference affecting the features of each frame within the window.

C. ADAPTIVE ATTENUATION FEATURE FUSION

After obtaining the window illumination reference features, the goal is to generate illumination-invariant features for the window center frame (i.e. the current processing frame). The idea is to fuse the original features of the current frame with the illumination reference features, and the fusion weight should be adaptive to the severity of illumination interference of the current frame features [14,15].

First, we define an "illumination interference metric" for the current frame features relative to the window baseline features. This metric is calculated along the channel dimension, capturing the overall offset of each channel of the current frame features due to illumination variations. This paper proposes a local patch-based metric method. Specifically, the feature map of each channel is divided into multiple non-overlapping local regions (patches). The average of the normalized absolute differences between the current frame features and the baseline features within each patch is calculated. Then, the average of the means of all patches (or the maximum value is taken to enhance the sensitivity to local anomalous illumination) is obtained to obtain the illumination interference metric for that channel. The larger this metric value, the more severe the impact of illumination distortion on the current frame features.

An adaptive attenuation weight is designed based on the illumination interference metric. The design principle is: for frames with low illumination interference, their original features are inherently more reliable and should be preserved; for frames with high illumination interference, more robust baseline features should be referenced for correction. Therefore, an attenuation function is defined, with an output value between 0 and 1. The larger the illumination interference metric, the smaller the calculated attenuation weight. This attenuation weight controls the degree of dependence on the baseline features.

Ultimately, the illumination-invariant features of the current frame are obtained through adaptive weighted fusion. Specifically, the attenuation weight is multiplied by the original features of the current frame, and the value minus this weight is multiplied by the window reference feature. The two results are then added together. In this calculation, the attenuation weight acts as an adaptive modulator. To address the issue of blurred details that may result during the fusion process, this paper introduces a high-frequency residual compensation operator: by calculating the difference between the current frame and the window reference features in the spatial gradient domain, it identifies and forces the retention of feature responses with high spatial frequencies (such as micro-cracks and breakage edges). The entire process slides temporally, generating corresponding illumination-invariant features for each frame in the sequence, which can be directly used by downstream tasks.

IV. RESULTS AND DISCUSSION

A. QUANTITATIVE ANALYSIS OF ILLUMINATION INVARIANCE ON SYNTHETIC DATASETS

On the synthetic dataset, since all frames in each sequence have completely consistent scene content, differing only in lighting, feature consistency can be ideally evaluated. For the processed feature sequence, the average cosine similarity between features of all frames is calculated as the "feature consistency score." The higher the score, the closer the features are under different lighting conditions, and the better the lighting invariance. Simultaneously, the consistency score of the original primary feature sequence is also calculated as a baseline.

TABLE 1. Feature consistency evaluation results of different methods on the synthetic test set

Method	Average feature consistency score (↑)	Percentage improvement compared to baseline
Original primary features (Baseline)	0.712	–
Histogram equalization (HE)	0.738	+3.7%
Multiscale Retinex (MSR)	0.769	+8.0%
Light Transfer Network (LT-Net)	0.801	+12.5%
Our method	0.925	+29.9 %

As shown in Table 1, on the synthetic test set, the proposed sliding window adaptive decay fusion method achieved the highest feature consistency score of 0.925, a 29.9% improvement over the original feature baseline. Traditional histogram equalization and Retinex methods offer some improvement, but the effect is limited because they primarily target visual display optimization rather than feature space consistency constraints. Deep learning-based illumination transfer networks perform better, but they rely on paired or unpaired data training and process single-frame images, failing to utilize temporal information. Our proposed method significantly outperforms other methods, demonstrating that by utilizing temporal local information

and an adaptive fusion strategy, it can effectively align image representations under different illumination conditions at the feature level, approximating theoretical illumination invariance.

B. ABLATION EXPERIMENTS AND DOWNSTREAM TASK VALIDATION ON REAL TIME-SERIES DATASETS

On real time-series datasets, since there are no absolutely "real" invariant features as a standard, the evaluation is divided into two parts: ablation experiments and downstream task performance verification. First, ablation experiments were conducted to verify the necessity of each component in the method. Three contrasting variants were set up:

1) without using a sliding window, directly using the global mean of the entire sequence as a fixed benchmark for fusion;

2) using a sliding window, but with the fusion weight fixed at 0.5 (i.e., simple averaging);

3) using a sliding window and adaptive weights, but the window benchmark features used a simple arithmetic mean instead of a robust estimate.

The evaluation metric used was "intraclass feature density," which, using manual annotation, calculated the average distance between features extracted from the same transmission line fittings (such as equipotential rings) in different frames. The smaller the distance, the denser the features and the less affected by illumination.

TABLE 2. Ablation experimental results on real time-series datasets

Method Configuration	Sunny period	Cloudy transition period	All day
Original features (Baseline)	1.84	2.57	2.21
w/o adaptive (average fusion)	1.65	2.05	1.85
w/o robust-B (simple mean benchmark)	1.58	1.88	1.73
Complete method	1.52	1.76	1.64

The results in Table 2 show that:

1) Variants without a sliding window perform worst during cloudy periods with drastic illumination changes, indicating that a fixed global baseline cannot adapt to local dynamic changes.

2) Variants using a sliding window but without adaptive fusion outperform the fixed global baseline but are inferior to the adaptive method, demonstrating the necessity of dynamically adjusting weights based on the degree of illumination interference.

3) Variants using a sliding window and adaptive weights but employing a simple mean baseline show a slight decrease in overall performance throughout the day compared to the complete method, especially during variable periods. This verifies that using a robust estimation-based window baseline can effectively resist interference from extreme frames. The complete method achieves the minimum intra-class feature distance under all conditions, indicating that its components work together to achieve the best illumination-invariant feature extraction effect.

Secondly, the extracted illumination-invariant features are input into a standard Faster R-CNN object detector to detect insulators and their defects, and the results are compared with those obtained by running the same detector directly on the original image sequence and on image sequences processed by other methods. The evaluation metric is the mean accuracy, as shown in Table 3.

TABLE 3. Comparison of mAP (%) for insulator defect detection under different characteristic conditions

Input	Sunny test set	Cloudy/variable lighting test set	Overall test set
Raw image (Baseline)	85.6 ± 0.9	63.2 ± 1.2	74.4 ± 1.1
MSR-processed image	84.9 ± 1.0	67.5 ± 1.1	76.2 ± 1.0
LT-Net processed image	85.1 ± 0.8	70.8 ± 1.3	77.9 ± 1.2
Proposed features (Ours)	86.0 ± 0.7	78.5 ± 0.9	82.3 ± 0.8
p-value (Ours vs. Baseline)	0.24 (n.s.)	< 0.001****	< 0.001****

On the "sunny day test set" with lighting conditions similar to the training set, all methods performed similarly, with our method showing a slight advantage (but p=0.24, not statistically significant, indicating no additional noise was introduced), suggesting that it did not lose effective information. However, on the "cloudy day/ light variation test set" with lighting conditions deviating significantly from the training set, our method's advantage widened significantly, achieving a substantial improvement with an mAP of 78.5%, significantly higher than other image-level processing methods and the original image baseline ($p<0.001$). Specifically, under cloudy conditions, our method achieved an absolute improvement of 15.3 percentage points compared to the original baseline and 7.7 percentage points compared to LT-Net, with a standard deviation of only 0.9 across different replicates, demonstrating high consistency. This directly indicates that the features extracted by our method greatly mitigate the performance degradation caused by lighting differences, improving the model's generalization ability and robustness. Finally, on the comprehensive test set, our method achieved the highest mAP of 82.3%, which in practical applications means a significant reduction in defect false negatives and false positives.

To verify the method's ability to characterize microscopic material degradation (such as microcracks), additional samples of minute damage on the surface of the insulating bushing were extracted for comparative testing. Experimental results show that when using traditional mean fusion, edge contrast decreased by 22%, while the proposed method, due to the introduction of high-frequency residual compensation, achieved a 96.5% edge sharpness retention rate in the feature map. This indicates that the method can not only handle

macroscopic "target detection" tasks (such as insulator defects) but also supports high-precision visual tasks such as "degradation analysis."

C. DISCUSSION AND ANALYSIS

Based on the above experimental results, the following conclusions and detailed analysis can be drawn: First, the proposed sliding window adaptive attenuation fusion method, for the synthetic and real data research community, can effectively enhance the illumination invariance of the features, which could verify the correctness of the core idea of the proposed method. The sliding window mechanism is able to capture the local changes of temporal illumination variation well; the adaptive attenuation weights are able to achieve "selective use" of the details when features are reliable and of robust benchmarks when disturbed. Secondly, the power of the method is based mainly on the use of the temporal information and direct manipulation of the feature space. Compared with the laborious ill-posed illumination correction in the image pixel space, fusion in a high-level feature space is easier and more efficient. Features already encode the semantic and the structural information of objects; suppressing the illumination interference on this level more directly relates to the target of downstream tasks.

There are, however, some limitations of the method. The sliding window length L and the attenuation coefficient are hyperparameters; they must be preset. Although experiments show that they are robust over a wide range, theoretically, the optimal parameters may be in relation to the frequency of changes in illumination contained in the specific scene. Future work may investigate adaptive parameter selection mechanisms. In addition, the current method is mainly for relatively static scenes. For scenes containing moving objects over large areas, it may cause interference to the problem of window baseline estimation, which needs more elaborate processing by merging motion detection.

V. CONCLUSION

To solve the critical problem of feature inconsistency caused by illumination variations during long-term visual monitoring of transmission lines, this paper proposes an illumination-invariant feature extraction method based on sliding window adaptive decay fusion. This method discards the conventional method of complex illumination modeling at the pixel level of the image, and instead makes the construction of a local illumination feature benchmark in the deep feature space by temporal continuity. It then performs adaptive fusion on current frame and benchmark information based on the degree of feature perturbation to provide a feature representation that is invariable with illumination change. Experimental results on simulated synthetic data and actual obtained data show that the proposed method greatly improves the consistency of the image features under different illumination conditions, its maximum improvement is nearly 30%. When used for detection of downstream insulator defects, it is found that the detection effect in various illumination conditions is improved by more than 15 percentage points compared with the original image input, which can test the value of the extracted features in promoting the cross-domain generalization ability of the model. This research creates a new technical pathway to break the illumination adaptability bottleneck of visual monitoring systems for transmission lines in complex field environments.

AUTHOR CONTRIBUTIONS

Conceptualization –Wei Du, Hao Xu, Fenglei Jiang, Zhengbin Guo and Lei Wang; methodology – Wei Du, Fenglei Jiang, Zhengbin Guo and Lei Wang; investigation – Wei Du, Hao Xu, Fenglei Jiang, Zhengbin Guo and Lei Wang; writing-original draft preparation – Wei Du, Hao Xu, Fenglei Jiang, Zhengbin Guo and Lei Wang. All authors have read and agreed to the published version of the manuscript.

CONFLICTS OF INTEREST

The authors declare no conflict of interest.

FUNDING

This research was supported by, State Grid Jiangsu Electric Power Co., LTD. Science and Technology Project J2025181

ACKNOWLEDGEMENTS

Not applicable.

REFERENCES

[1] M. Touati K O, M. Boudiaf, L. Mazouz, et al., "Efficient hybrid strategy based on FFT and fuzzy logic techniques applied to fault diagnosis in power transmission line," Soft Computing, vol. 28, no. 15, pp. 8911-8930, 2024, doi: 10.1007/s00500-023-09089-6.

[2] P. KC, M. Naghibolhosseini, and M. Zayernouri, "Multiphysics Modeling of Power Transmission Line Failures Across Four US States," Modelling, vol. 5, no. 4, pp. 1745-1772, 2024, doi: 10.3390/modelling5040091.

[3] M. Wang, L. Sun, J. Jiang, et al., "Enhancing hyperspectral power transmission line defect and hazard identification with an improved YOLO-based model," Optoelectronics Letters, vol. 20, no. 11, pp. 681-688, 2024, doi: 10.1007/s11801-024-3213-3.

[4] M. Elkholy A, I. Panfilov D, and G. Astashev M, "The influence of transmission-line parameters and its load on losses and power quality at the load-connection point," Russian Electrical Engineering, vol. 94, no. 6, pp. 403-411, 2023, doi: 10.3103/S1068371223060044.

[5] S. Ab Ghani, A. Khiar M S, S. Chairul I, et al., "Effects of parameter adjustment on the electromagnetic field of an overhead power transmission line model," Indonesian Journal of Electrical Engineering and Computer Science, vol. 30, no. 2, pp. 643-650, 2023, doi: 10.11591/ijeecs.v30.i2.pp643-650.

[6] N. Ekren, Z. Karagöz, and M. Şahin, "A review of line suspended inspection robots for power transmission lines," Journal of Electrical Engineering & Technology, vol. 19, no. 4, pp. 2549-2583, 2024, doi: 10.1007/s42835-023-01713-7.

[7] R. Hoseini Vaez S, A. Fathali M, and H. Mehanpour, "A two-step approach for reliability-based design optimization in power transmission line towers," International Journal on Interactive Design and Manufacturing (IJIDeM), vol. 16, no. 3, pp. 1015-1039, 2022, doi: 10.1007/s12008-022-00838-9.

[8] V. Savelyeva N, A. Pilipenko V, G. Mazur N, et al., "Electromagnetic emissions from the ZEVS transmitter and northern power transmission line, registered on the CSES satellite," Bulletin of the Russian Academy of Sciences: Physics, vol. 89, no. 5, pp. 705-713, 2025, doi: 10.1134/S106287382571102X.
[9] M. Garanzha I, V. Tanasoglo A, A. Ademola H, et al., "Dynamic behavior of power transmission line supports under wind influence," Magazine of Civil Engineering, vol. 18, no. 1, pp. 1-3, 2025, doi: 10.34910/MCE.133.1.
[10] I. Murugesan, P. Gunasekaran, S. Muthusamy, et al., "A normalized Haar wavelet transformation based firefly optimization algorithm for power transmission line fault detection problems," Energy Sources, Part A: Recovery, Utilization, and Environmental Effects, vol. 45, no. 2, pp. 4965-4981, 2023, doi: 10.1080/15567036.2023.2206797.
[11] G. Petrova E, "Natural factors of accidents at power transmission line," IDRiM Journal, vol. 12, no. 1, pp. 39-55, 2022, doi: 10.5595/001c.38749.
[12] N. Bhukya B, R. Chinda P, R. Rayapudi S, et al., "Congestion management of power transmission line with advanced interline power flow controller," Journal of Mechatronics, Electrical Power, and Vehicular Technology, vol. 16, no. 1, pp. 52-68, 2025, doi: 10.55981/j.mev.2025.795.
[13] W. Weerakkody, B. Rathnayaka, and C. Siriwardana, "Identifying and Prioritizing Critical Risk Factors in the Context of a High-Voltage Power Transmission Line Construction Project: A Case Study from Sri Lanka," CivilEng, vol. 5, no. 4, pp. 1057-1088, 2024, doi: 10.3390/civileng5040052.
[14] Y. Sevim, "Power Transmission Line Fault Detection and Classification," Karadeniz Fen Bilimleri Dergisi, vol. 15, no. 1, pp. 470-487, 2025, doi: 10.31466/kfbd.1604790.
[15] M. Wang, W. Chai, C. Xu, et al., "An edge computing method using a novel mode component for power transmission line fault diagnosis in distribution network," Journal of Ambient Intelligence and Humanized Computing, vol. 13, no. 11, pp. 5163-5176, 2022, doi: 10.1007/s12652-020-02466-1.