IBIMA Publishing
Communications of International Proceedings
https://ibimapublishing.com/p-articles/46AI/2025/4632625/
Vol. 2025 (34), Article ID 4632625

Analysis of Lighting and Shape Features in Deepfake Identification*

Karol JEDRASIAK

WSB University, Dąbrowa Górnicza, Poland

Correspondence should be addressed to: Karol JEDRASIAK, kjedrasiak@wsb.edu.pl

* Presented at the 46th IBIMA International Conference, 26-27 November 2025, Ronda, Spain

Abstract

This study investigates interpretable photometric and geometric features for deepfake detection under realistic conditions. The dedicated DeepFake RealWorld (DFRW) dataset, comprising 46 371 clips generated by diffusion, reenactment, and face-swap models, was used to evaluate lighting and shape consistency. Key descriptors, including light direction mismatch ($\Delta\theta$), luminance deviation (ΔL), shading ratio (r_shade), shadow coherence (χ_shadow), and head-torso alignment, achieved $\Delta p \approx 0.20–0.23$ and PR up to 4.25. The results confirm that physically grounded descriptors of illumination and geometry enable reliable, explainable deepfake detection in forensic contexts.

Keywords: Deepfake detection, photometric and geometric features, forensic video analysis

Introduction

Advances in diffusion models (Ho et al., 2020; Poole et al., 2022) and neural rendering frameworks (Chan et al., 2022; Hong et al., 2023) have enabled photorealistic face synthesis, yet current systems still violate physical laws of illumination and geometry. Inconsistencies in lighting direction, shading, and three-dimensional alignment remain reliable indicators of manipulation (Wang et al., 2023; Guarnera et al., 2020). Deepfake generators often approximate light transport heuristically, resulting in incoherent brightness and shadow patterns (Durall et al., 2020; Kim et al., 2024). Meanwhile, CNN-based detectors lose reliability under compression or domain shifts (Verdoliva, 2020). This study investigates interpretable, physics-based features describing light–shape interaction, aiming for robustness across models and real-world degradations.

DFRW Dataset

The DeepFake RealWorld (DFRW) dataset used in this study includes 46 371 videos, with 4 186 authentic and 42 185 synthetic samples generated by recent diffusion, reenactment, and lip-sync models (2022–2024). Each clip underwent realistic distortions such as H.264/H.265 re-encodings (CRF 18–32), aspect-ratio changes, AR filters, and screen re-captures. The dataset covers 480p–1440p resolutions with diverse gender, age, and pose distribution. Metadata retain illumination and compression parameters, supporting detailed photometric validation. All labels were double-blind verified, making DFRW a reliable benchmark for evaluating physically interpretable deepfake features.

Methods

Two descriptor families were analyzed: photometric and geometric. Photometric features capture irregularities in facial lighting. Luminance disparity (ΔL) and shading ratio (r_shade) were derived using intrinsic image decomposition to separate illumination from reflectance (Barron and Malik, 2015). The angular difference of light vectors ($\Delta\theta$) was used to detect directional inconsistencies (Johnson and Farid, 2007), while shadow coherence (χ_shadow) measured contrast continuity along occlusion boundaries (Hu et al., 2021).

Cite this Article as: Karol JEDRASIAK, Vol. 2025 (34) "Analysis of Lighting and Shape Features in Deepfake Identification " Communications of International Proceedings, Vol. 2025 (34), Article ID 4632625, https://doi.org/10.5171/2025.4632625

Geometric descriptors, including 2D-to-3D reprojection error, facial symmetry deviation, and head–torso alignment, were applied to assess spatial coherence (Tewari et al., 2018; Deng et al., 2019). All features were extracted in the luminance domain and temporally aggregated. Anomaly thresholds were calibrated using real samples, and discriminative strength was quantified by Δp and PR, with false discovery rate (FDR) correction ensuring statistical reliability (Verdoliva, 2020).

Results

Photometric features reached $\Delta p \approx 0.20$ and $PR \approx 1.84$, while geometric ones achieved $\Delta p \approx 0.19$ and $PR \approx 2.45$. The most discriminative descriptors—Δθ, ΔL, r_shade, χ_shadow, and head–torso alignment—reached PR up to 4.25 for lighting inconsistency (Figure 1). These anomalies remained stable after compression and re-encoding, unlike colour or spectral cues (Verdoliva, 2020; Haliassos et al., 2022). The deviations reflect violations of physical illumination principles such as Lambertian reflectance and consistent light direction, showing that even advanced diffusion models fail to reproduce real photometric coherence. Physics-based descriptors thus offer measurable, interpretable evidence of deepfake manipulation.

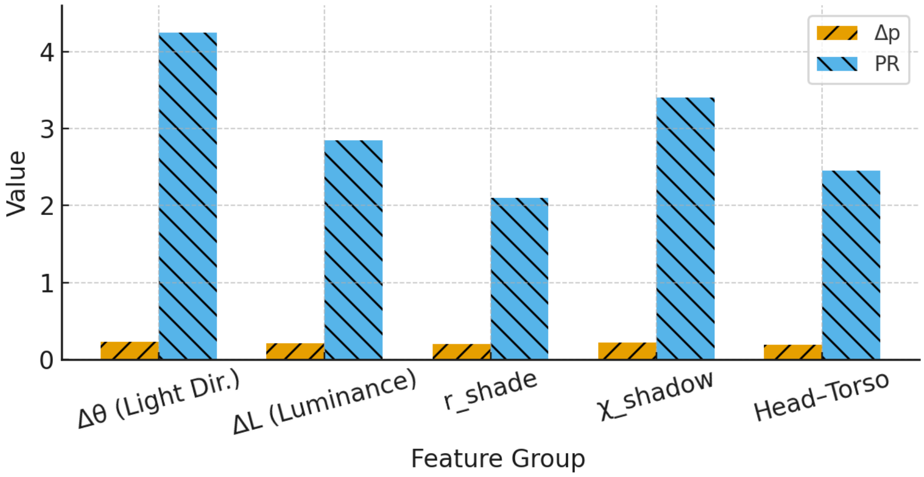

Fig. 1. Comparative effectiveness of lighting and shape descriptors (Δp and PR on DFRW dataset).

Discussion and Conclusions

Lighting and shape coherence metrics offer robust, interpretable cues for deepfake detection, remaining stable across compression levels and model architectures. The DFRW dataset enables realistic benchmarking, and the resulting atlas (Δθ, ΔL, r_shade, χ_shadow, head–torso) can complement deep models as an explainable forensic layer (Wang et al., 2023; Verdoliva, 2020; Haliassos et al., 2022). Achieving PR up to 4.25 demonstrates that lighting inconsistencies occur over four times more frequently in fake videos than in real ones, representing a strong and interpretable forensic marker. These physically grounded cues are both explainable and statistically discriminative, providing practical tools for verifying video authenticity in journalism, law enforcement, and digital forensics.

Acknowledgments

This research was conducted within the project "Analysis of Features and Patterns of the Most Popular Deepfakes and Analysis of Existing Deepfake Datasets" funded by the Metropolis GZM under the Metropolitan Fund for Supporting Science Program

References

- Barron, J. and Malik, J. (2015) 'Shape, Illumination, and Reflectance from Shading', IEEE Transactions on Pattern Analysis and Machine Intelligence (TPAMI), 37(8), pp. 1670–1687.
- Chan, E., Monteiro, M., Wiles, O. and Zisserman, A. (2022) 'EG3D: Efficient Geometry-Aware 3D Generative Adversarial Networks', Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).

- Deng, J., Cheng, S., Xue, N., Zhou, Y. and Zafeiriou, S. (2019) '3D Face Alignment in the Wild', Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).
- Durall, R., Keuper, M., Pfreundt, F. and Keuper, J. (2020) 'Watch Your Up-Convolution: CNNs Fail to Reproduce Spectral Distributions', Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition Workshops (CVPRW).
- Guarnera, L., Giudice, O. and Battiato, S. (2020) 'DeepFake Detection by Analyzing Convolutional Traces', IEEE Access, 8, pp. 165085–165098.
- Haliassos, A., Vougioukas, K., Petridis, S. and Pantic, M. (2022) 'Lips Don't Lie: A Generalisable and Robust Approach to Face Forgery Detection', Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).
- Ho, J., Jain, A. and Abbeel, P. (2020) 'Denoising Diffusion Probabilistic Models', Advances in Neural Information Processing Systems (NeurIPS).
- Hong, Y., Li, J., Sun, Y. and Zhang, J. (2023) 'Depth-Aware Generative Modeling of 3D Faces', Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV).
- Hu, X., Zhao, Y., Wang, F. and Xu, J. (2021) 'Shadow Consistency for Deepfake Detection', Proceedings of the IEEE/CVF International Conference on Computer Vision (ICCV).
- Johnson, M. and Farid, H. (2007) 'Exposing Digital Forgeries through Specular Highlights on the Eye', IEEE Transactions on Information Forensics and Security (TIFS), 2(3), pp. 450–461.
- Kim, S., Park, J., Han, D. and Lee, K. (2024) 'Physical Consistency of Illumination in AI-Generated Images', Proceedings of the IEEE/CVF Winter Conference on Applications of Computer Vision (WACV).
- Poole, B., Jain, A., Barron, J. and Mildenhall, B. (2022) 'DreamFusion: Text-to-3D Using 2D Diffusion', arXiv preprint arXiv:2209.14988.
- Tewari, A., Zollhöfer, M., Kim, H. and Theobalt, C. (2018) 'High-Fidelity Monocular Face Reconstruction Based on Shape and Appearance', Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).
- Verdoliva, L. (2020) 'Media Forensics and DeepFakes: An Overview', IEEE Journal of Selected Topics in Signal Processing, 14(5), pp. 910–932.
- Wang, H., Chen, X., Liu, S., Zhu, M. and Hu, R. (2023) 'Illumination-Aware Deepfake Detection', Proceedings of the IEEE/CVF Conference on Computer Vision and Pattern Recognition (CVPR).