A Review of Illumination Estimation in Augmented Reality

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Abstract: Illumination estimation is a core component of augmented reality and the key to achieving illumination consistency in virtual-real fusion; its implementation directly governs the visual credibility of virtual objects in real scenes. Most existing studies address illumination estimation in a single dimension, and no prior survey has systematically categorized methods across the three dimensions of light intensity, shadow, and fog concentration. This survey follows three main threads—light intensity estimation, shadow estimation, and fog concentration estimation—to classify and summarize the technical routes and representative works within each dimension. Our review identifies three notable gaps: hierarchical adaptation of illumination modes, decoupled processing of shadow direction and intensity, and the rendering integration of multi-dimensional parameters. A systematic understanding of these advances and limitations provides a comprehensive technical reference for future research on illumination estimation in virtual-real fusion scenarios.

Keywords: Augmented Reality; Illumination Estimation; Light Intensity Estimation; Shadow Estimation; Fog Concentration Estimation

1. Introduction

The fundamental idea of augmented reality is to overlay computer-generated virtual information onto real scene images. The quality of virtual-real fusion depends substantially on the consistency between virtual objects and the real environment at the illumination level. Achieving such illumination consistency requires robust illumination estimation techniques.

Illumination estimation traces its origins to the color constancy problem, where early work treated dominant illuminant chromaticity estimation from a color-biased image as a typical regression task [1,2]. As AR application scenarios gradually moved from controlled indoor settings to complex outdoor open environments, the scope of illumination estimation expanded accordingly, incorporating light source direction, shadow morphology, ambient light intensity, and visibility degradation from atmospheric scattering [3]. The technical scope of illumination estimation has thus evolved beyond the chromaticity regression of a single light source into a multi-dimensional parameter estimation system spanning light intensity adaptation, shadow representation, and fog effect adaptation.

The rapid development of deep learning in recent years has transformed each sub-direction of illumination estimation, and a large body of work has emerged around different sub-tasks. Yet existing surveys largely confine their discussion to a single thread of illumination estimation, lacking systematic categorization and horizontal comparison across the three dimensions of light intensity, shadow, and fog concentration. This paper addresses that gap by organizing and summarizing the current research landscape of illumination estimation along these three dimensions.

2. Evolution of Illumination Estimation Techniques

The research history of illumination estimation traces a continuous evolutionary path: from a single global light source to multi-dimensional parameter decomposition, and from indoor controlled scenes to outdoor open scenes. Two main technical paradigms have emerged along this path: one grounded in statistical assumptions and shallow models, the other driven by deep learning and multi-task collaboration.

Early work took color constancy theory as its foundation, using low-level image statistics to infer the chromaticity parameters of the global light source. Representative approaches from this period include the Gray-World assumption and the White-Patch assumption, which estimate light source color from low-order image statistics [1]. The illumination estimation challenge launched by Ershov et al. [1] marked a key milestone: the competition tracks expanded from a single global light source to indoor scenes and dual-light-source scenes, reflecting the community's deepening understanding of illumination complexity. Subsequently, Büyükarıkan et al. [2] conducted a systematic comparison of convolutional architectures—VGG16, EfficientNet-B0, and ResNet50—on light source chromaticity estimation, establishing empirical evidence for model selection.

The emergence of intrinsic image decomposition shifted illumination estimation from estimating a single parameter to estimating a set of components. Illu-NASNet [4] adopts an unsupervised learning approach to simultaneously output four component types—albedo, normal, shadow shading, and illumination—from indoor video sequences, effectively decoupling illumination information from surface properties. Zhang Zhenfeng [5] enhanced this line of work with a dense spatio-temporal smoothness constraint to improve inter-frame coherence, and parameterized illumination using a mixed spherical Gaussian function. Zhu Yongjie [6] extended intrinsic decomposition from two layers to three, enabling scene-level relighting. Einabadi et al. [3] observed that the broader trend in deep illumination estimation points toward independent modeling of each component rather than joint estimation of the full scene parameter set.

The transition from indoor to outdoor settings represents a pivotal turning point for illumination estimation. Krawez et al. [7] proposed a real-time outdoor scheme that explicitly decomposes outdoor illumination into direct sunlight, diffuse skylight, and ground-reflected light; the solar direction is solved geometrically from geographic location and timestamp, while each component's brightness is estimated in real time from video frames. Wang Mingrui [8] incorporated the sky region's brightness channel into a convolutional neural network to improve regression accuracy for outdoor illumination parameters. Ma Fuyu [9], building on MobileNet and GhostNet, explored lightweight deployment on mobile devices. Zhang et al. [10] used a fully convolutional network to jointly regress solar direction and illumination intensity, applying model pruning and quantization to reduce the parameter footprint.

The above review shows that illumination estimation has matured into a three-dimensional parameter estimation system that spans light intensity adaptation, shadow representation, and fog effect adaptation. The following sections examine existing research along each of these three dimensions.

3. Light Intensity Estimation Methods

Light intensity estimation addresses the problem of extracting the overall brightness baseline and light source intensity parameters from images, providing a quantitative reference for shading and rendering virtual objects. Existing methods fall broadly into two categories: light source chromaticity estimation within the color constancy framework, and outdoor light intensity parameter regression.

On the color constancy side, light source chromaticity estimation has undergone a thorough transformation from statistical methods to deep networks. Zhao et al. [11] proposed ReCC-GAN, which first isolates the reflection component via a Retinex module to reduce interference from scene brightness and then applies a generative adversarial network for global light source chromaticity estimation. Yu Lianjiang et al. [12] introduced a singular value decomposition loss function into cosine spherical distribution regression to quantify differences between two parameterized light sources, markedly improving estimation accuracy. Domislović et al. [13] designed a lightweight convolutional network with only about 42,000 parameters that estimates local light source chromaticity on a per-patch basis, breaking the uniform illumination assumption of earlier methods. Ai [14] further integrated deep-learning illumination estimation into a complete mobile augmented reality system, validating the end-to-end deployment of illumination estimation on resource-constrained mobile devices.

Outdoor light intensity parameter regression has seen particularly active research in recent years. Feng et al. [15] proposed a multi-illumination estimation strategy: Gamma correction produces a series of differently exposed images, which are then fused via Laplacian multi-scale fusion into an enhanced result, indirectly yielding a multi-level representation of scene illumination intensity. Singh et al. [16] combined multi-scale guided filtering with multi-objective optimization to correct brightness while preserving image naturalness. Zhao et al. [17] proposed a non-regularization self-supervised Retinex approach with parameterized illumination estimation, which decouples illumination estimation from reliance on paired training data while retaining a parametric illumination map for low-light enhancement. Shen et al. [18] introduced an attention gate mechanism into the illumination distribution estimation network, improving performance under low-light conditions through feature attention and detail reconstruction modules. Zhao et al. [19] constructed both forward and reverse initial illumination maps, combining them with adaptive Gamma correction and multi-scale exposure fusion to handle diverse exposure conditions with a single model. These results indicate that illumination intensity estimation from images has reached considerable maturity; however, the explicit distinction and layered treatment of different illumination modes—sunny versus overcast—remains unresolved.

4. Shadow Estimation Methods

Shadow estimation addresses the direction, intensity, and edge transition characteristics of shadows in a scene—properties essential for ground anchoring and spatial embedding of virtual objects. Existing methods can be grouped into three technical routes based on how shadow information is acquired: intrinsic decomposition, independent detection, and geometric computation.

On the intrinsic decomposition route, shadows emerge as a natural byproduct of image decomposition. The shading component from Illu-NASNet[4] directly encodes the degree of shadow shading at each pixel. Cao Tianchi et al. [20] first split the input image into specular and diffuse reflection maps, then further separate the diffuse map into albedo and shadow maps, obtaining independent shadow information through this stepwise decomposition. Zhu Yongjie ’ s [6] three-layer decomposition framework treats shadows as an explicit intermediate-layer output, supporting scene-level relighting and shadow editing. This route benefits from jointly optimizing shadows and albedo within a single framework, yielding strong physical interpretability.

The independent detection route treats shadows as a standalone visual target. Xiao Zhipeng [21] uses bright channel and brightness ratio characteristics for adaptive threshold segmentation of shadow regions, identifies pixels with extremely low brightness ratios within these regions to fit a straight line, and recovers the light source direction through projection modeling. This method avoids complex image segmentation and performs well in simple outdoor scenes; however, under complex backgrounds such as grassland or mountains, texture interference degrades direction estimation accuracy. Wen et al. [22] designed a multi-task generative adversarial network that unifies detail extraction and illumination estimation, jointly optimizing shadow region localization and indirect illumination estimation.

The geometric computation route exploits the physical relationship between solar position and geographic information to derive shadow direction. Krawez et al. [7] compute the theoretical solar azimuth from the scene’s latitude, longitude, and current time to predict shadow projection direction. This approach ensures physically deterministic direction estimates but cannot capture the real-time effects of cloud cover or atmospheric scattering on shadow intensity. Wang et al. [23], in uncalibrated photometric stereo reconstruction, estimate illumination direction using a weight-shared convolutional structure with self-attention, then recover surface normals under uncertain illumination through PCA whitening and Huber robust regression, achieving joint inference of illumination direction and surface geometry. This approach strikes a reasonable balance between directional accuracy and environmental adaptability. Overall, each of these three routes has distinct strengths, but a unified framework that simultaneously guarantees directional precision and dynamic intensity response remains absent.

5. Fog Concentration Estimation Methods

Fog concentration estimation addresses scene visibility degradation from atmospheric scattering. The estimated parameters can be used to adjust the transparency, contrast, and edge blur of virtual objects. This line of research originates primarily from image dehazing, where a notable recent trend has been the shift from discrete classification to continuous parameter regression.

For fog concentration parameterization, Wang Lanlan et al. [24] built a fog concentration estimation model using saturation and chromaticity information, applying fuzzy clustering to partition image regions into light-fog and heavy-fog zones and designing zone-specific atmospheric light veil estimation models. Guo Hong [25] combined the dark channel prior with pseudo-edge details to build a fog concentration grading model for real-time monitoring of fog concentration variation in videos. Li Zichen [26] introduced texture restoration enhancement, employing long-range and short-range feature modules to capture both global and local information for per-pixel fog concentration regression, thereby advancing estimation from discrete classification to continuous regression. Xu Chaojie [27], targeting waterway channel applications, introduced and refined a fog-aware density estimator, screened the feature subset most correlated with fog concentration through correlation coefficient analysis, and developed a method capable of rapid operation.

In complex real-world environments, Li Chunming et al. [28] identified dark channel, saturation-brightness, and chromaticity as the three most critical fog-related features and built a surrogate model with optical thickness as the objective function. Their work explicitly highlights that fog-induced image quality degradation severely impairs battlefield reconnaissance and identification. Li Jiling et al. [29] addressed the high dust-fog imaging conditions of underground coal mines, training a fog concentration estimation model with brightness, saturation, and gradient features, while incorporating dynamic atmospheric scattering coefficients to accurately estimate transmittance and atmospheric light values. Gong et al. [30] used cascaded channel and spatial attention modules to extract illumination features, then applied a multi-scale light adjustment module for per-pixel illumination correction across different receptive fields. These works collectively demonstrate a solid methodological foundation for treating fog concentration as a continuous estimable parameter. A critical limitation, however, is that most existing methods target image restoration rather than rendering control: they have yet to convert concentration parameters into real-time visibility control quantities capable of driving virtual-real fusion rendering. This gap is the key bottleneck constraining the transition of fog concentration estimation from image dehazing to augmented reality applications.

6. Limitations and Future Directions

Despite considerable progress in illumination estimation across light intensity, shadow, and fog concentration, current research exhibits several limitations when evaluated against the practical demands of outdoor virtual-reality fusion.

6.1 Hierarchical Adaptation of Illumination Modes

Current outdoor light intensity estimation predominantly relies on a unified end-to-end regression framework, processing clear-sky direct sunlight and overcast diffuse skylight—two substantially different illumination conditions—with the same model. The resulting differences in brightness distribution and contrast between these modes are significant, and when the scene's illumination mode changes, single-model estimates exhibit noticeable fluctuations. The root cause is the absence of a preceding illumination state classification step and a corresponding hierarchical regression mechanism.

6.2 Decoupling of Shadow Direction and Intensity Response

Geometric computation and visual estimation have followed largely independent paths for shadow information acquisition. Geometric methods provide direction estimates with clear physical grounding but lack the capacity to perceive real-time changes in environmental lighting. Visual methods capture real-time environmental information, yet direction estimation is prone to inaccuracy under complex outdoor textures. These two approaches have yet to realize complementary advantages within a unified estimation framework.

6.3 Fragmented Rendering Integration of Multi-Dimensional Parameters

Although light intensity, shadow, and fog concentration have each accumulated substantial work along their respective research threads, they currently serve disjoint downstream tasks: light source chromaticity for automatic white balance, shadow detection for image editing, and fog concentration for image dehazing. These threads remain disconnected, let alone integrated into a unified parameter estimation and output pipeline for virtual-real fusion rendering.

Several directions merit exploration in future work. First, illumination state discrimination should be established as a preprocessing step for light intensity estimation, with separate regression models for clear-sky and overcast conditions, to improve estimation stability in complex outdoor scenes. Second, fusing geometric computation with visual perception—using geometric results to provide prior directional constraints and visual results to supply real-time intensity correction—can simultaneously improve directional accuracy and dynamic response. Third, a unified multi-dimensional illumination parameter framework for AR rendering should be developed, integrating the estimation results of all three parameter categories into the rendering pipeline and connecting the full chain from scene perception to rendering control.

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