A Systematic Literature Review of Transmission Estimation Improvements in Dark Channel Prior Digital Image Dehazing

Agus Izzuddin Agus Latif[1], Sirajdin Olagoke Adeshina[2], and Haidi Ibrahim[1]*

[1]School of Electrical and Electronic Engineering, Tuanku Syed Sirajuddin Engineering Campus, Universiti Sains Malaysia, 14300 Nibong Tebal, Pulau Pinang, Malaysia.

[2]School of Engineering, American University of Nigeria, Lamido Zubairu Way, Yola, Adamawa State, Nigeria.

*Corresponding Author's Email: haidi@usm.my

Article History: Received 27 March 2026; Revised 9 June 2026; Accepted 15 June 2026; Published 30 June 2026

Abstract

Image dehazing, the process of restoring visibility in images degraded by haze, fog, or smoke, is an essential task in computer vision with applications in autonomous driving, remote sensing, and safety-critical environments. Among various methods, the Dark Channel Prior (DCP) has gained widespread attention due to its simplicity and effectiveness in single-image dehazing. However, the original DCP method suffers from limitations such as halo artefacts, sky misestimation, and reduced accuracy in complex scenes. Over the past decade, numerous approaches have been proposed to improve the estimation of the transmission map, which is a critical step in DCP-based dehazing. This systematic literature review (SLR) provides a comprehensive overview of these advancements by analysing 33 selected studies, following PRISMA guidelines. The reviewed methods are categorised into twelve groups, including depth- and scene-adaptive methods, filtering-based refinements, transform-domain approaches, auxiliary image enhancements, physics-based models, statistical and mathematical modelling, feature-based and learning techniques, fusion and multi-scale strategies, region- and boundary-aware methods, colour-channel and prior-based enhancements, optimisation-based methods, and DCP operation improvements. The classification highlights the diversity of strategies used to enhance transmission estimation, ranging from simple filtering and colour-based modifications to complex physics-informed and optimisation-driven approaches. Analysis of the literature indicates that colour-channel and prior-based methods are the most frequently studied, likely due to their simplicity, flexibility, and effectiveness across diverse images. Future research may focus on hybrid approaches that integrate the strengths of multiple strategies, hardware-friendly implementations for real-time applications, and the exploration of richer image features, depth information, or polarisation cues to further improve transmission estimation in challenging environments.

Keywords: Dark Channel Prior, Digital Image Processing, Image Dehazing, Single Image Input, Systematic Literature Review

1.0 Introduction

Image dehazing, also known as image defogging, visibility restoration, or haze removal [1], is an important task in image processing. It aims to improve the clarity of images that are degraded by atmospheric conditions such as haze, fog, or smoke. These conditions reduce contrast and obscure important details, causing valuable visual information to become partially or completely hidden. As a result, image dehazing is essential for enhancing scene visibility and supporting accurate interpretation. This technique has many practical applications, including outdoor autonomous driving [2], where clear vision is required for safe navigation, and indoor fire scenarios [3], where removing smoke effects can assist rescue operations and hazard detection. The development of visibility restoration has evolved from traditional image enhancement methods such as histogram equalisation which improves contrast without physical modelling to physics-guided prior-based approaches, and more recently, data-driven deep learning networks. This evolution establishes a diverse research landscape where prior-based methods remain highly valued for their parameter transparency and predictability.

One of the most popular methods among these physics-guided, prior-based approaches for image dehazing is the dark channel prior (DCP), proposed by He et al. in 2011 [4]. This method operates on a single input colour image and is based on the observation that, in most non-sky regions of a haze-free image, at least one colour channel contains pixels with very low intensity values. The dark channel is computed by taking the minimum intensity across the red, green, and blue channels within a local patch, followed by a minimum operation over that patch. Using this prior, the transmission map is estimated by comparing the observed hazy image with the dark channel, assuming a constant atmospheric light. The atmospheric light is typically estimated by selecting the brightest pixels in the hazy image that correspond to the most haze-affected regions. After obtaining an initial transmission map, a refinement step is applied using the soft matting algorithm, which preserves edge information and improves the accuracy of object boundaries in the final dehazed image. To provide a clear direction for this study, the primary objectives of this systematic review are to categorise the extensive modifications designed to improve DCP transmission estimation, analyse their performance trade-offs, and outline promising future research.

Since then, many researchers have proposed various improvements to the DCP method to enhance its performance and robustness. These improvements aim to address limitations in the original formulation, particularly in challenging scenarios such as bright regions and dense haze. While existing review articles in the literature generally cover broad image dehazing models or overview deep learning trends, they frequently overlook the granular algorithmic modifications made to prior-based frameworks. A major research gap exists in systematically consolidating how the transmission maps, the most critical determinant of dehazing quality have been refined over the past decade. This systematic literature review (SLR) aims to provide a comprehensive overview of these developments by focusing on the improvements in transmission estimation, where more accurate or efficient approaches are introduced.

This paper is organised into four sections. Section 1.0, which is this section, introduces the background of the research area. Section 2.0 explains this SLR methodology, which is conducted based on the Preferred Reporting Items for Systematic Reviews and Meta-Analyses (PRISMA) guidelines. Section 3.0 presents the review results and discussions. Finally, Section 4.0 concludes the paper.

2.0 Methodology

In this SLR, the literature search was conducted in March 2026 on ScienceDirect (https://www.sciencedirect.com). The selection process of the articles was conducted based on PRISMA, and the flowchart is shown in Figure 1. The search was done by utilising the keyword ("dark channel prior" AND "image dehazing" AND "single image"). The initial search returned 443 results. To manage this large number, the search was narrowed to include only "research articles", which reduced the total to 412 articles. Since this SLR focuses on digital image processing algorithms, the subject areas were further limited to "Computer Science" and "Engineering", resulting in 351 articles.

The title and abstract of the selected publications underwent initial screening through a manual review. During this stage, specific inclusion and exclusion criteria helped focus the search on traditional algorithmic frameworks. First, a publication was included only if its title or abstract clearly stated that the study was in the digital image processing field. Articles based on artificial intelligence or deep learning models were excluded. This decision aimed to separate deterministic, prior-based methodology changes from data-dependent neural networks. Second, the screening required that the proposed frameworks be specifically designed for land-based static images. As a result, works related to underwater optics or digital video processing were left out. This limitation was necessary because underwater conditions and temporal video characteristics introduce different physical scattering variables, which differ from the main single-image atmospheric scattering model. After completing this initial filtering step, a total of 137 articles were selected for full-text eligibility assessment.

Subsequently, a comprehensive full-text review was performed on the remaining publications to determine their final suitability for this SLR based on four stringent qualitative benchmarks. To ensure linguistic accessibility and global standardisation, the publication had to be written entirely in English. Substantively, the core theme of the publication had to be anchored strictly within digital image processing, focusing explicitly on the programmatic development of digital image processing algorithms. This criterion served to filter out peripheral studies that only applied dehazing as a pre-processing step rather than contributing a direct mathematical adjustment to the pipeline. Lastly, any secondary literature or prior review papers were excluded to ensure that the data extraction was driven purely by primary, empirical research. This multi-tiered filtration process effectively distilled the literature down, leaving a final cohort of 33 articles to be fully synthesised and evaluated within the systematic review.

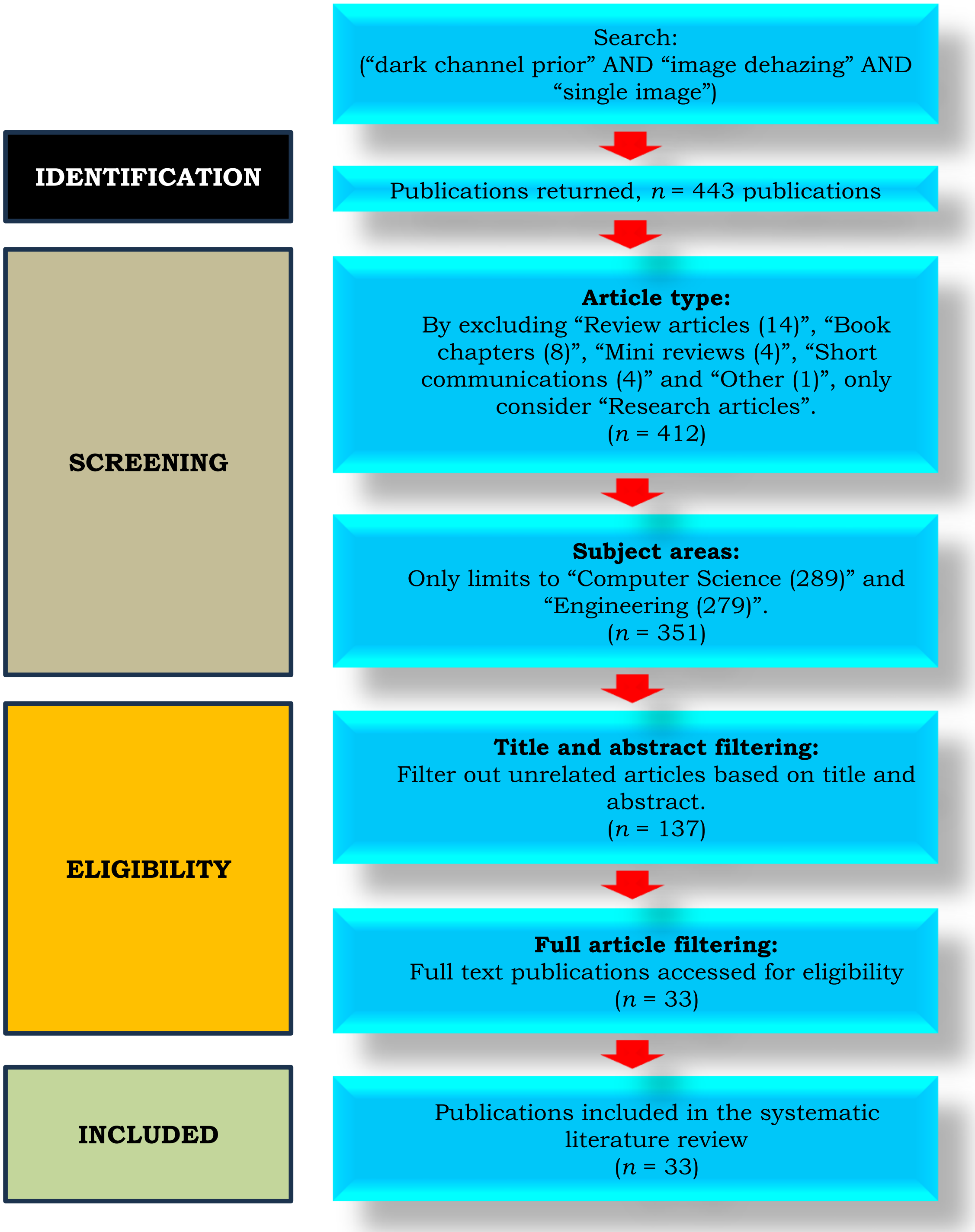

Figure 1: Flowchart showing the selection process for publications to be included in this systematic literature review

Following the final selection, a structured data extraction process was conducted before the classification stage. For each selected article, the primary transmission estimation approach and the key methodological contribution were identified through full-text analysis. Specifically, information describing the underlying transmission estimation strategy, the principal improvement over the conventional DCP framework, and the fundamental algorithmic concept was extracted. Based on these extracted characteristics, studies with similar methodological principles were grouped into common categories. This structured extraction process provided a consistent basis for the thematic classification and comparative discussion presented in this review.

3.0 Results and Discussions

Over the years, significant research has focused on improving transmission estimation in the Dark Channel Prior (DCP) framework to overcome its limitations, such as halo artefacts, sky misestimation, and computational inefficiency. These efforts have led to a diverse set of methods that can be categorised into twelve broad classifications, reflecting different strategies such as leveraging physical models, statistical formulations, image features, optimisation techniques, filtering refinements, and multi-scale or fusion approaches. Collectively, these classifications provide a structured view of the current landscape in DCP-based dehazing research, highlighting the variety of techniques developed to enhance accuracy, robustness, and computational efficiency.

The first classification is the depth- and scene-adaptive methods. The method improves DCP-based dehazing by adjusting transmission estimation according to scene depth or image information. By considering variations across the scene and guiding computation through information loss, these approaches can better handle heterogeneous regions and reduce errors in areas with complex depth structures. For example, Kim et al. [5] proposed a scene-depth adaptive method that incorporates information loss to optimise the transmission map, resulting in more accurate and visually consistent dehazing.

The second classification is the filtering-based refinement methods. These methods aim to improve coarse transmission estimates by smoothing boundaries and reducing artefacts while preserving structural details. Techniques such as guided filtering, boundary blurring, and edge-adaptive approaches allow for more accurate and visually pleasing transmission maps, particularly around edges and sky regions. For instance, Shi et al. [6] used a guided filter to refine the transmission, Wang et al. [7] applied a blurring filter at sky boundaries, and edge-based adaptive guided filtering adjusts window sizes based on edge type to further enhance refinement. Overall, filtering-based refinement methods are computationally efficient and relatively straightforward to implement, making them attractive for practical image enhancement applications. Their primary strength lies in improving edge preservation while suppressing halo artefacts without fundamentally changing the DCP framework. However, because these methods rely on an initially estimated transmission map, their effectiveness is constrained by the quality of the coarse estimate. Consequently, although they improve visual quality, they cannot fully compensate for errors introduced during the initial transmission estimation stage.

The third classification is the transform-domain methods. They enhance transmission estimation by operating in wavelet or frequency domains, which helps preserve important image information while reducing computational complexity. By separating low- and high-frequency components, these approaches can focus on relevant image structures for more accurate dehazing. For example, Wang and Feng [8] applied wavelet decomposition to the dark channel, and Liu et al. [9] used the open dark channel model (ODCM) on the low-frequency wavelet band to achieve efficient and reliable transmission estimation. Collectively, transform-domain methods offer an effective balance between estimation accuracy and computational efficiency by decomposing images into different frequency components and processing only the most informative features. This strategy can improve robustness against image noise while reducing the computational burden compared with pixel-domain processing, making these methods suitable for applications requiring faster execution. However, the transformation and reconstruction processes introduce additional implementation complexity, and inaccurate frequency decomposition may result in the loss of fine spatial details or the introduction of reconstruction artefacts. Consequently, although transform-domain approaches provide an efficient alternative to conventional DCP-based estimation, their performance depends heavily on the choice of transform and the effectiveness of feature separation.

The fourth classification is the auxiliary image and enhancement-based methods. These methods improve transmission estimation by leveraging modified versions of the original image to provide additional cues. These techniques help guide the computation of the transmission map and enhance accuracy in challenging regions. For instance, Gao et al. [10] used an adjusted negative image to support transmission estimation, while Qi et al. [11] introduced an airlight correction strategy to further refine the approximation and improve overall dehazing performance. From a methodological perspective, auxiliary image and enhancement-based methods improve transmission estimation by exploiting complementary information that is not directly available from the original image. Their main strength lies in enhancing estimation accuracy in challenging regions where conventional DCP assumptions are less reliable. However, these methods require additional image processing steps to generate auxiliary information, increasing algorithmic complexity and computational cost. Furthermore, their effectiveness depends on the quality of the generated auxiliary images or enhancement strategies, which may vary across different scene conditions and imaging environments.

The fifth classification is the physics-based and atmospheric scattering methods. They improve transmission estimation by incorporating underlying physical principles of light propagation and scattering. By grounding the estimation process in physics, these approaches produce more accurate and consistent transmission maps, particularly in complex scenes. For example, Zhang et al. [12] and Zhang et al. [13] leveraged polarisation information, Sun et al. [14] applied the atmospheric scattering model, and Hong et al. [15] restored latent images under multiple constant transmission values to enhance dehazing reliability. Physics-based methods generally provide physically meaningful transmission estimates and perform well under diverse atmospheric conditions because they are derived from established light scattering principles. However, they often require additional assumptions or specialised imaging conditions, such as polarisation information, which limits their applicability in general consumer imaging scenarios. Compared with filtering-based or prior-based approaches, they typically offer higher physical consistency at the expense of increased implementation complexity.

The sixth classification is the statistical and mathematical modelling methods. They enhance transmission estimation by replacing heuristic operations with analytical or probabilistic frameworks, improving robustness and precision. These approaches enable more reliable estimation across diverse image regions by incorporating statistical relationships or mathematical approximations. For example, Ge et al. [16] used a linear transformation, Wang et al. [17] proposed a variogram-based fast estimation, Tang et al. [18] applied a Taylor series expansion for local transmission, and Yuan et al. [19] modelled the distribution of channel-minimised values with a confidence ratio to guide estimation. In general, statistical and mathematical modelling methods provide a more rigorous theoretical foundation than heuristic-based approaches by explicitly modelling the relationships underlying transmission estimation. Their principal strengths include improved estimation robustness, greater adaptability to varying image characteristics, and reduced reliance on empirical assumptions. However, these methods often involve more sophisticated mathematical formulations, increasing implementation complexity and requiring careful parameter selection. Consequently, while they can achieve more reliable and accurate transmission estimation, their computational demands and modelling complexity may limit their suitability for real-time or resource-constrained applications.

The seventh classification is feature-based and learning methods. The methods improve transmission estimation by leveraging descriptive image features or machine learning models to capture complex haze characteristics. By incorporating information such as luminance, chromaticity, and texture, these approaches provide more adaptive and accurate predictions compared to purely heuristic methods. For instance, Ni et al. [20] utilised local property analysis to extract multiple image features, while Luan et al. [21] employed support vector regression trained on haze-related features to enhance prediction accuracy. Feature-based methods offer greater adaptability than handcrafted priors by modelling more complex image characteristics. They generally improve robustness in scenes where conventional DCP assumptions are violated. Nevertheless, their performance depends on feature quality and, for machine learning approaches, the representativeness of the training data. These methods therefore occupy a middle ground between traditional prior-based algorithms and modern deep learning techniques.

The eighth classification is the fusion and multi-scale approaches. They enhance transmission estimation by combining multiple estimates derived from different spatial levels or regions, improving robustness and consistency across the image. By integrating pixel-wise, patch-wise, or region-based information, these methods can better handle variations in depth and texture. For example, Riaz et al. [22] fused pixel-wise and patch-wise transmission using a reliability map, Zhao et al. [23] applied multi-scale fusion, and Gao et al. [24] utilised multi-region fusion to achieve more stable and accurate results. Overall, fusion and multi-scale approaches provide greater robustness by integrating complementary information from multiple spatial representations, resulting in more consistent transmission estimation across complex scenes. However, combining multiple estimates increases algorithmic complexity and computational cost compared with single-scale methods. As a result, these approaches offer improved estimation accuracy at the expense of reduced computational efficiency.

The ninth classification is the region-based and boundary-aware methods. These methods improve transmission estimation by explicitly handling spatial segmentation and enforcing boundary constraints, particularly in challenging areas such as sky regions and depth discontinuities. By incorporating edge detection, local contrast, and boundary consistency, these approaches reduce artefacts and enhance structural accuracy. For instance, Zhu et al. [25] used Canny edge detection to identify sky regions, He et al. [26] improved boundary consistency through patch similarity, and Liao et al. [27] incorporated boundary constraints with local contrast to produce more reliable transmission estimates. From a practical perspective, region-based and boundary-aware methods are particularly effective at preserving structural details and reducing artefacts around object boundaries and sky regions, where conventional DCP often performs poorly. However, their performance depends on accurate region segmentation and boundary detection, which can be sensitive to complex scene content or inaccurate edge localisation. Consequently, these methods improve visual consistency but may incur additional computational overhead due to the required segmentation and boundary analysis.

The tenth classification is the colour-channel and prior-based enhancement methods that improve transmission estimation by extending the original DCP formulation with additional colour information or modified priors. These approaches increase robustness under varying imaging conditions by exploiting alternative colour representations and channel relationships. For example, Sahu et al. [28] introduced a new colour channel, Dwivedi and Chakraborty [29] computed transmission from three colour layers, Gautam et al. [30] proposed the Weighted Median Channel Prior with a scale-invariant technique, Lv et al. [31] developed a hardware-friendly DCP, and He et al. [32] utilised the HSI colour model to enhance estimation accuracy. In general, colour-channel and prior-based enhancement methods improve the adaptability of DCP by reducing the dependence on the original dark channel assumption and incorporating additional image characteristics. These approaches generally maintain relatively low computational complexity while improving robustness under diverse colour distributions and illumination conditions. However, their performance remains dependent on the suitability of the selected colour representation or prior, which may limit generalisation across different types of haze and complex scenes.

The eleventh classification is the optimisation-based methods. They enhance transmission estimation by formulating the problem as an optimisation task, enabling improved accuracy, edge preservation, and smoothness of the transmission map. These approaches iteratively refine the estimate based on defined objective functions or constraints. For instance, Gao et al. [33] proposed an adaptive boundary-limited local gradient optimisation, Singh and Parihar [34] combined structure-aware smoothing with variational optimisation, and Ashwini et al. [35] applied the Jaya optimisation algorithm for efficient and effective convergence. From an optimisation perspective, these methods provide a systematic framework for improving transmission estimation by balancing multiple constraints, resulting in accurate and structurally consistent transmission maps. However, the iterative nature of optimisation algorithms often increases computational complexity and processing time compared with direct estimation approaches. Therefore, while optimisation-based methods offer high accuracy and flexibility, their practical deployment may be limited in real-time applications or systems with restricted computational resources.

The twelfth classification is the DCP operation improvement methods. These methods focus on modifying or replacing the traditional minimum operation used in the dark channel computation to reduce artefacts and improve robustness. By introducing alternative selection or estimation strategies, these approaches address issues such as halo effects and instability near edges. For example, Wu et al. [36] replaced minimum filtering with a mode-like selection strategy, Dai et al. [37] proposed a statistically constrained estimation, and Sahu et al. [28] improved the operation through colour channel modification to achieve more stable transmission results. These methods offer a relatively simple and computationally efficient solution by improving the core DCP operation without requiring major modifications to the overall framework. However, their effectiveness remains constrained by the inherent assumptions of DCP, limiting their ability to address complex haze conditions that require deeper scene understanding.

Table 1 provides an overview of the classification framework established from the reviewed transmission estimation methods. The distribution of categories indicates that improvements to DCP-based transmission estimation have evolved through several complementary research directions rather than a single dominant strategy. While colour-channel and prior-based enhancement methods represent the most frequently investigated category within the reviewed studies, this trend suggests that researchers continue to favour approaches that improve the original DCP formulation while preserving its simplicity and computational efficiency.

Table 1: Classification of DCP transmission estimation methods

Category	Key Strategy/Description	Citations
Depth-/Scene-Adaptive & Information-Guided	Adjust transmission based on scene depth or image information loss to handle heterogeneity and improve accuracy.	[5]
Filtering-Based Refinement	Use guided, blurring, or edge-adaptive filters to smooth transmission, preserve edges, and reduce artefacts.	[6], [7]
Transform-Domain Methods	Apply wavelet or frequency-domain decomposition to improve estimation and reduce computational complexity.	[8], [9]
Auxiliary Image / Enhancement-Based	Use adjusted or enhanced versions of the image (negative image, airlight correction) to refine transmission estimation.	[10], [11]
Physics-Based / Atmospheric Scattering	Incorporate physical principles like polarisation or scattering to produce physically consistent transmission.	[12], [13], [14], [15]
Statistical / Mathematical Modelling	Use analytical/statistical frameworks (linear transform, variogram, Taylor expansion, distribution modelling) to replace heuristics.	[16], [17], [18], [19]
Feature-Based / Learning Methods	Employ local image features or machine learning models (SVM, local property analysis) to predict transmission.	[20], [21]
Fusion & Multi-Scale Approaches	Combine multiple estimates (pixel/patch, multi-scale, multi-region) for robust and consistent transmission maps.	[22], [23], [24]
Region-Based / Boundary-Aware	Handle sky and depth discontinuities via boundary constraints, edge detection, and patch similarity.	[25], [26], [27]
Colour-Channel & Prior-Based Enhancements	Modify DCP using additional colour channels, multiple layers, priors, or HSI information for improved performance.	[26], [28], [29], [30], [31]
Optimisation-Based Methods	Formulate transmission estimation as an optimisation problem for higher accuracy and edge preservation.	[33], [34], [35]
DCP Operation Improvement	Replace or enhance the minimum operation in DCP to reduce artefacts and improve stability.	[28],[36], [37]

The classification also reveals a gradual shift from direct modifications of handcrafted priors towards more adaptive and theoretically driven approaches. Physics-based, statistical modelling, and optimisation-based methods attempt to improve the reliability of transmission estimation by introducing stronger mathematical formulations or additional constraints. Meanwhile, fusion, multi-scale, feature-based, and region-aware approaches demonstrate increasing efforts to incorporate more contextual image information to address the limitations of pixel-level estimation.

A comparison across categories highlights a common trade-off between accuracy, robustness, and computational complexity. Methods based on prior modification, filtering refinement, and DCP operation improvement generally maintain lower implementation complexity and are more suitable for practical applications with limited computational resources. In contrast, approaches involving optimisation, fusion, or mathematical modelling often achieve more reliable transmission estimation but require greater computational effort due to iterative procedures, additional information sources, or complex formulations.

Furthermore, the classification suggests an emerging trend towards hybrid transmission estimation frameworks that combine multiple strategies rather than relying on a single assumption. By integrating physical knowledge, image features, and adaptive optimisation mechanisms, future methods may achieve a better balance between interpretability, robustness, and efficiency. This observation highlights the importance of developing transmission estimation approaches that can generalise across diverse environmental conditions while remaining computationally feasible for real-world deployment.

Overall, the reviewed methods demonstrate that DCP transmission estimation has evolved through diverse strategies aimed at improving accuracy, robustness, and computational efficiency. The twelve classifications reveal a trade-off between simple and efficient approaches, such as prior-based and filtering methods, and more complex strategies, such as optimisation and hybrid frameworks, which provide enhanced adaptability. Future research should focus on integrating complementary approaches to achieve reliable transmission estimation while maintaining practical applicability.

4.0 Conclusion

This SLR provides an overview of the methods developed to improve transmission estimation in the DCP framework. The reviewed approaches were grouped into twelve categories, ranging from relatively simple filtering and colour-channel enhancements to more complex physics-based, statistical modelling, and optimisation-based strategies. Among the reviewed studies, colour-channel and prior-based methods represent the most frequently investigated category, likely due to their ability to enhance the original DCP formulation while maintaining relatively low computational complexity. In contrast, physics-based and statistical modelling approaches provide stronger theoretical foundations and improved adaptability but generally involve greater modelling complexity. From a practical perspective, lightweight approaches such as filtering refinement and colour-channel modifications are suitable for resource-constrained applications, including embedded vision systems and consumer surveillance cameras. Meanwhile, more sophisticated approaches involving physical constraints, optimisation, or multi-source information fusion may provide advantages in applications requiring reliable visibility restoration, such as autonomous vehicles, intelligent transportation systems, and outdoor monitoring under adverse weather conditions. Future research should focus on developing hybrid transmission estimation frameworks that integrate complementary strategies while reducing their individual limitations. Combining physical models with adaptive learning, fusion strategies, or richer image information such as depth and polarisation cues may improve robustness in complex scenes. In addition, hardware-efficient implementations, including FPGA-compatible and real-time processing solutions, remain important for practical deployment. Developing methods that achieve a better balance between estimation accuracy, computational efficiency, and generalisation across diverse environmental conditions will be essential for advancing DCP-based dehazing towards reliable real-world image restoration systems.

Acknowledgement
The authors would like to acknowledge Universiti Sains Malaysia for providing access to the ScienceDirect database and other academic resources that supported the literature retrieval process for this systematic literature review. No external funding was received for this study.

Author Contributions
Agus Izzuddin Agus Latif: Conceptualisation, Formal Analysis, Investigation, Writing-Original Draft Preparation; **Sirajdin Olagoke Adeshina**: Formal Analysis, Writing-Review & Editing; **Haidi Ibrahim**: Conceptualisation, Formal Analysis, Investigation, Writing-Reviewing and Editing, Supervision.

Conflicts of Interest
The manuscript has not been published elsewhere and is not under consideration by any other journal. All authors have reviewed and approved the manuscript, consent to its submission, and declare that there are no conflicts of interest.

References
[1] D. Ngo, S. Lee, T. M. Ngo, G.-D. Lee, and B. Kang, “Visibility restoration: A systematic review and meta-analysis,” *Sensors*, vol. 21, no. 8, 2021, Art. no. 2625, doi: 10.3390/s21082625.

[2] H. Huang, G. T. S. Ho, M. W. Geda, M. Li, and Y. M. Tang, “Dehaze-attention: Enhancing image dehazing with a multi-scale, attention-based deep learning framework,” *Scientific Reports,* vol. 15, 2025, Art. no. 44191, doi: 10.1038/s41598-025-27959-x.

[3] C. Wang, J. Hu, X. Luo, M.-P. Kwan, W. Chen, and H. Wang, “Color-dense illumination adjustment network for removing haze and smoke from fire scenario images,” *Sensors,* vol. 22, no. 3, 2022, Art. no. 911, doi: 10.3390/s22030911.

[4] K. He, J. Sun, and X. Tang, “Single image haze removal using dark channel prior,” *IEEE Transactions on Pattern Analysis and Machine Intelligence,* vol. 33, no. 12, pp. 2341–2353, 2011, doi: 10.1109/TPAMI.2010.168.

[5] J.-H. Kim, W.-D. Jang, J.-Y. Sim, and C.-S. Kim, "Optimized contrast enhancement for real-time image and video dehazing," *Journal of Visual Communication & Image Representation*, vol. 24, pp. 410−425, 2013, doi: 10.1016/j.jvcir.2013.02.004.

[6] Z. Shi, J. Long, W. Tang, and C. Zhang, "Single image dehazing in inhomogeneous atmosphere," *Optik*, vol. 125, pp. 3868−3875, 2014, doi: 10.1016/j.ijleo.2014.01.170.

[7] W. Wang, X. Yuan, X. Wu, and Y. Liu, "Dehazing for images with large sky region," *Neurocomputing,* vol. 238, pp. 365−376, 2017, doi: 10.1016/j.neucom.2017.01.075.

[8] Z. Wang, and Y. Feng, "Fast single haze image enhancement," *Computers and Electrical Engineering,* vol. 40, pp. 785−795, 2014, doi: 10.1016/j.compeleceng.2013.06.009.

[9] Q. Liu, X. Gao, L. He, and W. Lu, "Haze removal for a single visible remote sensing image," *Signal Processing,* vol. 137, pp. 33−43, 2017, doi: 10.1016/j.sigpro.2017.01.036.

[10] Y. Gao, H.-M. Hu, S. Wang, and B. Li, "A fast image dehazing algorithm based on negative correction," *Signal Processing,* vol. 103, pp. 380−398, 2014, doi: 10.1016/j.sigpro.2014.02.016.

[11] M. Qi, Q. Hao, Q. Guan, J. Kong, and Y. Zhang, "Image dehazing based on structure preserving," *Optik*, vol. 126, pp. 3400−3406, 2015, doi: 10.1016/j.ijleo.2015.07.114.

[12] W. Zhang, J. Liang, H. Ju, L. Ren, E. Qu, and Z. Wu, "A robust haze-removal scheme in polarimetric dehazing imaging based on automatic identification of sky region," *Optics & Laser Technology,* vol. 86, pp. 145−151, 2016, doi: 10.1016/j.optlastec.2016.07.015.

[13] W. Zhang, J. Liang, and L. Ren, "Haze-removal polarimetric imaging schemes with the consideration of airlight's circular polarization effect," *Optik,* vol. 182, pp. 1099−1105, 2019, doi: 10.1016/j.ijleo.2019.01.048.

[14] W. Sun, H. Wang, C. Sun, B. Guo, W. Jia, and M. Sun, "Fast single image haze removal via local atmospheric light veil estimation," *Computers and Electrical Engineering,* vol. 46, pp. 371−383, 2015, doi: 10.1016/j.compeleceng.2015.02.009.

[15] S. Hong, M. Kim, and M. G. Kang, "Single image dehazing via atmospheric scattering model-based image fusion," *Signal Processing,* vol. 178, 2021, Art. no. 107798, doi: 10.1016/j.sigpro.2020.107798.

[16] G. Ge, Z. Wei, and J. Zhao, "Fast single-image dehazing using linear transformation," *Optik,* vol. 126, pp. 3245−3252, 2015, doi: 10.1016/j.ijleo.2015.07.138.

[17] J.-B. Wang, N. He, L.-L. Zhang, and K. Lu, "Single image dehazing with a physical model and dark channel prior," *Neurocomputing,* vol, 149, pp. 718−728, 2015, doi: 10.1016/j.neucom.2014.08.005.

[18] Q. Tang, J. Yang, X. He, W. Jia, Q. Zhang, and H. Liu, "Nighttime image dehazing based on Retinex and dark channel prior using Taylor series expansion," *Computer Vision and Image Understanding,* vol. 202, 2021, Art. no. 103086, doi: 10.1016/j.cviu.2020.103086.

[19] F. Yuan, Y. Zhou, X. Xia, X. Qian, and J. Huang, "A confidence prior for image dehazing," *Pattern Recognition,* vol. 119, 2021, Art. no. 108076, doi: 10.1016/j.patcog.2021.108076.

[20] W. Ni, X. Gao, and Y. Wang, "Single satellite image dehazing via linear intensity transformation and local property analysis," *Neurocomputing,* vol. 175, pp. 25−39, 2016, doi: 10.1016/j.neucom.2015.10.010.

[21] Z. Luan, Y. Shang, X. Zhou, Z. Shao, G. Guo, and X. Liu, "Fast single image dehazing based on a regression model," *Neurocomputing,* vol. 245, pp. 10−22, 2017, doi: 10.1016/j.neucom.2017.03.024.

[22] I. Riaz, T. Yu, Y. Rehman, and H. Shin, "Single image dehazing via reliability guided fusion," *Journal of Visual Communication & Image Representation,* vol 40, pp. 85−97, 2016, doi: 10.1016/j.jvcir.2016.06.011.

[23] D. Zhao, L. Xu, Y. Yan, J. Chen, and L.-Y. Duan, "Multi-scale optimal fusion model for single image dehazing," *Signal Processing: Image Communication,* vol. 74, pp. 253−265, 2019, doi: 10.1016/j.image.2019.02.004.

[24] Y. Gao, Q. Li, and J. Li, "Single image dehazing via a dual-fusion method," *Image and Vision Computing,* vol. 94, 2020, Art. no. 103868, doi: 10.1016/j.imavis.2019.103868.

[25] Y. Zhu, G. Tang, X. Zhang, J. Jiang, and Q. Tian, "Haze removal method for natural restoration of images with sky," *Neurocomputing,* vol. 275, pg. 499−510, 2018, doi: 10.1016/j.neucom.2017.08.055.

[26] L.-Y. He, L. Kun, J.-Z. Zhao, and D.-Y. Bi, "Visibility restoration of single foggy images under local surface analysis," *Neurocomputing,* vol. 341, pp. 212−226, 2019, doi: 10.1016/j.neucom.2019.01.001.

[27] B. Liao, P. Yin, C. Xiao, "Efficient image dehazing using boundary conditions and local contrast," *Computers & Graphics,* vol. 70, pg. 242−250, 2018, doi: 10.1016/j.cag.2017.07.016.

[28] G. Sahu, A. Seal, O. Krejcar, and A. Yazidi, "Single image dehazing using a new color channel," *Journal of Visual Communication & Image Representation,* vol. 74, 2021, Art. no. 103008, doi: 10.1016/j.jvcir.2020.103008.

[29] P. Dwivedi, and S. Chakraborty, "Single image dehazing using extended local dark channel prior," *Image and Vision Computing,* vol. 136, 2023, Art. no. 104747, doi: 10.1016/j.imavis.2023.104747.

[30] S. Gautam, T. K. Gandhi, and B. K. Panigrahi, "WMCP-EM: An integrated dehazing framework for visibility restoration in single image," *Computer Vision and Image Understanding,* vol. 229, 2023, Art. no. 103648, doi: 10.1016/j.cviu.2023.103648.

[31] T. Lv, W. Mao, Z. Li, G. Du, X. Wang, W. Ni, and D. Zhang, "An efficient dehazing accelerator by fusing dark channel prior and guided filter," *Microelectronics Journal,* vol. 164, 2025, Art. no. 106782, doi: 10.1016/j.mejo.2025.106782.

[32] L.-Y. He, J.-Z. Zhao, and D.-Y. Bi, "Effective haze removal under mixed domain and retract neighborhood," *Neurocomputing,* vol. 293, pp. 29−40, 2018, doi: 10.1016/j.neucom.2018.02.089.

[33] Y. Gao, Y. Su, Q. Li, H. Li, and J. Li, "Single image dehazing via self-constructing image fusion," *Signal Processing,* vol. 167, 2020, Art. no. 107284, doi: 10.1016/j.sigpro.2019.107284.

[34] K. Singh, and A. S. Parihar, "Variational oprimization based single image dehazing," *Journal of Visual Communication & Image Representation,* vol. 79, 2021, Art. no. 103241, doi: 10.1016/j.jvcir.2021.103241.

[35] K. Ashwini, H. Nenavath, and R. K. Jatoth, "Image and video dehazing based on transmission estimation and refinement using Jaya algorithm," *Optik,* vol. 265, 2022, Art. no. 169565, doi: 10.1016/j.ijleo.2022.169565.

[36] M. Wu, C. Zhang, Z. Jiao, and G. Zhang, "Improvement of dehazing algorithm based on dark channel priori theory," *Optik,* vol. 206, 2020, Art. no. 164174, doi: 10.1016/j.ijleo.2020.164174.

[37] C. Dai, M. Lin, X. Wu, and D. Zhang, "Single hazy image restoration using robust atmospheric scattering model," *Signal Processing,* vol. 166, 2020, Art. no. 107257, doi: 10.1016/j.sigpro.2019.107257.