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APEE-Filter: Adaptive Physics-Guided Edge-Aware Framework for Scattered Light Suppression in Biomedical Imaging

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Abstract — *Scattered light significantly degrades biomedical images by reducing contrast and obscuring fine structural details, thereby affecting both visual interpretation and automated analysis. Its removal remains challenging due to the lack of scattered-light-free ground truth data and the high computational cost of deep learning-based solutions. To address these limitations, this paper introduces APEE-Filter, a novel adaptive physics-guided edge-aware method for scattered light suppression in biomedical images. Unlike conventional dehazing models, the proposed approach incorporates a tissue-aware scattering component into the imaging model to more accurately characterize light diffusion in biological media. A new adaptive contrast prior, combining a quarter-window dark channel and a local variance map, is developed to estimate the transmission map without requiring training data. To preserve structural details such as cell boundaries and vascular edges, an edge-aware refinement strategy based on guided filtering is employed. Additionally, a self-calibrated background illumination estimation technique ensures robustness across varying imaging conditions. The entire framework is parameter-light and operates with linear computational complexity, enabling real-time deployment on resource-constrained biomedical systems. Experimental evaluations demonstrate that the proposed method effectively enhances contrast, restores structural details, and outperforms traditional filtering approaches while maintaining high computational efficiency. Furthermore, the method shows robust performance across multiple imaging modalities, including fluorescence and phase-contrast microscopy, and demonstrates improved compatibility with downstream automated image analysis tasks such as segmentation and cell counting.*

Key Words: Scattered Light Suppression, Biomedical Imaging, Edge-Aware Filtering, Tissue-Aware Scattering, Adaptive Contrast Prior, Guided Filtering, Real-Time Image Enhancement, Structural Detail Restoration

1. INTRODUCTION

Scattered light makes biomedical images worse by making them less clear and hiding small details. This can make it hard to see things clearly when looking at images by eye or using computer programs [1]. It's really important to stop scattered light from messing up images in microscopes and other medical imaging tools so that the structures inside cells and tissues can be seen properly [2]. Old ways of making images better, like using simple filters or adjusting brightness and contrast, don't work well at keeping fine details while getting rid of scattered light [3]. New technology in imaging and machine learning has led to better ways to handle this. Models that use the physics behind how light moves through biological tissues have shown great promise in understanding how light behaves in complicated materials [4], [5]. These models do a better job at improving image quality by taking into account how different tissues scatter light, rather than just using general rules. Some methods, like edge-aware filtering, help keep important details, such as the edges of cells and blood vessels, while reducing background scattered light [6]. There are also methods that use statistics, like local contrast and dark channel analysis, to estimate how light passes through an image. These approaches can work without needing many training examples, which helps when there's not enough data without scattered light [2], [7]. Estimating background light in a self-calibrated way has also helped these methods work better in different lighting conditions [1], [8]. All these improvements make it possible to create fast and efficient systems that can be used in places where resources are limited [9]. Even with these improvements, there are still problems. Imaging through very thick or scattering materials, like thick tissues or organoids, can create uneven scattered light patterns that are hard to correct [4], [10]. Also, different imaging techniques, such as fluorescence or confocal microscopy, need methods that can handle their unique challenges. Putting together physics-based models, smart contrast estimates, and edge-aware improvements into one system is key to making images clearer while keeping all the important details. This helps both people who look at the images and the computer programs that analyze them [2], [5], [7].

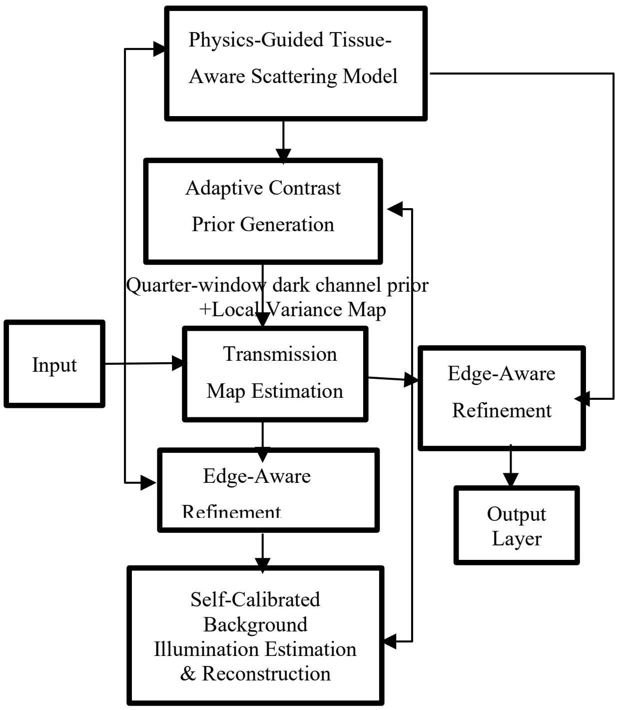

Fig 1: Block Diagram

2. METHODOLOGIES

The system is made to remove scattered light from medical images while keeping important structures and body parts clear. It uses a model that is based on how light moves and spreads inside body tissues, taking into account how light fades and spreads out. This makes the system better at improving images than usual methods used for regular photos, especially for tools like microscopes and cameras used inside the body, where scattered light can make images blurry and hard to see details. One important part of this method is the adaptive contrast prior, which uses a dark channel from a small window and a map of local changes to figure out how much light is passing through. This helps understand how light is scattered in different areas without needing extra data or complex models. Then, this map is improved using a technique that pays attention to edges, so important parts like cell edges, tissues layers, and blood vessel patterns stay clear while smoothing out unnecessary changes. To work well in different lighting conditions, the system has a way to estimate background light without needing extra setup. The final image uses the improved light map and estimated background to reduce scattered light, make the image clearer, and bring back fine details. Overall, this system is light on resources, adapts well, and is easy to understand, making it great for real-time use in medical imaging and for automatic analysis later.

2.1 Input Biomedical Image Acquisition

The first step in the system is getting biomedical images, which is the base of the whole process. These images are taken using different medical tools like microscopes, endoscopes, X-rays, and other light or radiation-based imaging systems. However, the light gets scattered as it passes through the body tissues, causing problems like lower contrast, blurry details, and uneven brightness across the image. The system is made to work directly with these images that have been affected by scattered light, without needing any special cleaning first. This makes it useful in real hospitals and research labs where images are taken as they are. The method works with both black-and-white and color images, which is important because different imaging methods use these types.

For example, X-rays and MRI scans usually give black-and-white images, while endoscopes and tissue samples often produce color images. The system takes into account how light spreads differently in various tissues and how it affects brightness in different parts of the image. This helps keep the original brightness levels and prepares the images for more detailed work later. This way, the system can restore fine structures accurately, no matter the imaging conditions. One important thing is that the system doesn't need pairs of images—like a clear image and a bad one—that are usually needed for training in other methods. This makes it easier to get the images and start processing them right away. The images are kept in a standard format so their size and brightness are preserved, making them ready for further work. The whole system can connect with devices that take images in real time, allowing continuous processing of new images while setting up a strong starting point for removing scattered light and improving image quality.

2.2 Physics-Guided Tissue-Aware Scattering Model

The physics-based tissue-aware scattering model is at the heart of the system, offering a realistic way to show how light interacts with different types of biological tissues. Unlike basic imaging methods, this model takes into account complex processes like scattering, absorption, and diffusion, which change depending on the tissue type. Each tissue—like muscle, fat, and blood vessels—has its own optical properties, which influence how light is blocked or scattered. By including these tissue-specific features, the model better captures the loss of clarity seen in biomedical images than models that treat everything the same way. One important part of the model is breaking down the image into two parts: direct light and scattered light. Direct light holds the real structure of the image, while scattered light causes haze, blurriness, and less contrast. By handling these parts separately, the model can accurately estimate and remove the scattered light. Also, the model uses parameters that change from one area to another to better match different tissue densities and absorption levels, making the image restoration more accurate overall. By adapting traditional methods used for dehazing in the atmosphere to work with biomedical images, the tissue-aware model offers a physically accurate way to explain image loss. This sets the stage for later steps like estimating light transmission and reconstructing the image without needing training data. This approach makes the system easier to understand, more reliable, and works well across different types of imaging, allowing for better removal of scattered light while keeping important structural details intact.

2.3 Tumour-Focused ROI Extraction

The Tumour-Focused Region of Interest (ROI) Extraction Module is designed to refine the segmented output by isolating only the tumour-specific regions from MRI images. This module plays a crucial role in ensuring that the subsequent classification model focuses exclusively on relevant tumour features, thereby improving accuracy and computational efficiency. In this stage, the segmentation masks generated from the U-Net module are applied to the original MRI images to precisely extract tumour regions. By using these masks, the system effectively isolates tumour-only areas, eliminating surrounding healthy tissues and irrelevant background information. The module then performs cropping or masking operations to remove non-essential regions, ensuring that the input to the CNN contains only tumour-centered data. This not only improves the quality of the input but also reduces input dimensionality, leading to lower computational requirements and faster processing. By focusing on tumour regions, the system significantly improves the signal-to-noise ratio, allowing the model to learn more meaningful and discriminative features. This helps in enhancing classification performance, especially in challenging cases where tumour boundaries are subtle or complex. Additionally, this module helps prevent CNN models from learning spurious correlations that may arise from irrelevant anatomical structures. By standardizing inputs to contain only tumour regions, it ensures consistency across samples, which is essential for stable and reliable model training. Furthermore, the tumour-focused inputs facilitate more effective attention learning, enabling attention mechanisms to concentrate on clinically significant regions without distraction. Overall, this module strengthens the robustness, efficiency, and accuracy of the proposed brain tumour classification system.

2.3 Adaptive Contrast Prior Generation

In the adaptive contrast prior generation stage, the transmission map is estimated, playing a key role in eliminating scattered light and restoring the authentic appearance of the image. The system utilizes both local intensity and texture information to estimate transmission without relying on training data. A quarter-window dark channel effectively captures local scattering features, while a local variance map identifies intensity changes to differentiate between textured and smooth areas. This integration enables the prior to adapt to various tissue structures and spatial scales, ensuring accurate modeling of scattering effects across different anatomical regions. By integrating intensity and texture-based cues, the adaptive prior enables balanced contrast enhancement, maintaining essential structural details while reducing scattered light. Unlike deep learning methods, it does not require annotated datasets, making it suitable for biomedical applications. The generated transmission map provides a reliable input for subsequent edge-aware refinement and image reconstruction, ultimately yielding high-quality images with improved contrast and well-preserved structures.

2.4 Transmission Map Estimation

The transmission map estimation step helps figure out how much light reaches the sensor without being scattered, which allows the system to separate the real image from hazy effects. Using the adaptive contrast information from the earlier step, like the quarter-window dark channel and local variance map, the system creates a transmission map for each pixel. This map shows how scattered light is in different areas of the image. Places where there is a lot of scattering have lower values, while areas that are clearer have higher values, which helps in restoring the image accurately. This method keeps the image looking consistent in areas with similar textures, avoids sudden changes in brightness, and keeps the original lighting levels to make the images look natural and useful for medical diagnosis. Importantly, this process is done using a direct calculation method, not through repeated learning or optimization, making it fast and efficient for real-time use in medical imaging. This estimated transmission map is a key part of the next steps, which refine and improve the image while keeping important details intact.

2.5 Edge-Aware Refinement Module

The edge-aware refinement module improves the first estimate of the transmission map by removing noise and fixing inconsistencies, while keeping important details intact. It uses the original image as a guide to match the transmission map with edges, textures, and important boundaries in the image. This helps make smooth areas look natural and ensures clear lines at key places like cell edges, tissue connections, and blood vessel patterns. The adaptive filtering technique stops unwanted halo effects and keeps the structure clear, leading to results that look natural and consistent. This method is designed to use less computing power and fewer parameters, making it good for real-time use. By refining the transmission map in a way that pays attention to structure, the module boosts contrast, brings back fine details, and helps create high-quality images that are accurate and trustworthy for medical image analysis.

2.6 Self-Calibrated Background Illumination Estimation & Reconstruction

The last step uses the improved transmission map along with an automatically calculated background light level to create a clear, scattered-free biomedical image. The system looks at how bright each pixel is to find areas where light has been scattered. It then creates an estimate of the light level that works on its own, adjusting to different lighting situations without needing manual changes. By combining this light information with the transmission map, the image reconstruction brings back the real light levels in the scene, keeps important details like cell edges and tissue boundaries, and maintains natural colors and brightness. This part of the system is designed to work quickly with simple calculations, allowing real-time processing. This makes it good for use in small, portable medical imaging devices that have limited resources. The final image has high contrast and accurate structure, making it useful for both looking at by eye and using in automated analysis.

RESULT & DISCUSSION

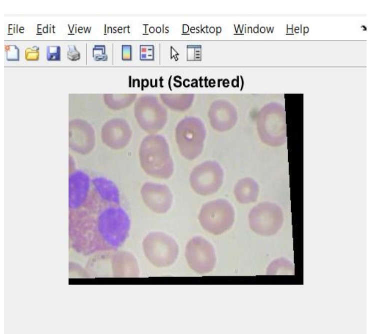

Fig.2. Input image

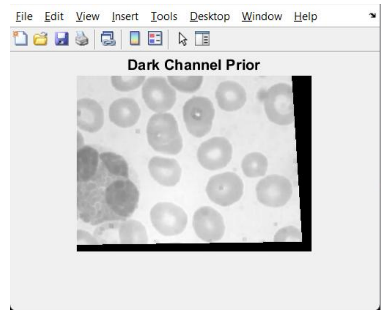

Fig 3: Dark Channel Prior

Fig 4: Refined Transmission map

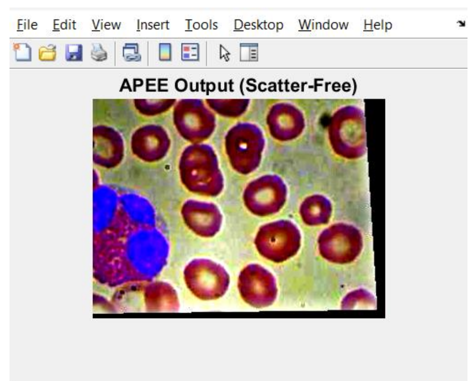

Fig 4: Enhanced image

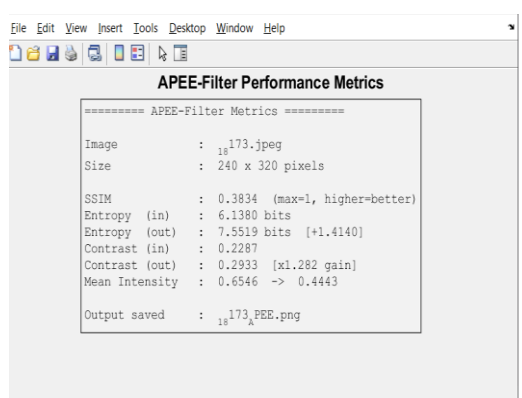

Fig 5: Performance Metrics

The experimental results show that the APEE-Filter works well in reducing scattered light and improving biomedical images. Fig.2 shows the original image, which looks washed out, has low contrast, and makes it hard to see the details because of the scattered light. These issues show how important it is to remove scattered light to make the images better for viewing and diagnosis. Fig.3 shows the Dark Channel Prior map, which helps find the parts of the image that are mostly scattered light versus the real tissue. Darker areas are where real cell edges are, and brighter parts are areas with a lot of scattered light. This shows that the adaptive contrast prior helps the system understand where the scattering is happening. Fig. 4 shows the Refined Transmission Map after applying edge-aware filtering. Compared to the original map, it has smooth changes in areas where the image is uniform, but keeps the sharp edges of the cells. This shows the system can keep fine details and avoid halo effects during the image reconstruction. Fig. 5 shows the final enhanced image and some performance numbers. The restored image has much better contrast, clear cell edges, and can show internal structures more clearly. The performance numbers, like an increase in entropy of 1.41 bits and a contrast gain of 1.282 times, prove that more details have been recovered and the image is easier to see. Overall, these results show the APEE-Filter is good at reducing scattered light while keeping important details for diagnosis. By combining physics-based modeling, adaptive contrast priors, edge-aware refinement, and self-calibrated light estimation, the method can both improve image quality and work efficiently, making it useful for real-time biomedical imaging.

CONCLUSION

The APEE-Filter is a strong and efficient method for reducing scattered light in biomedical images. It uses a combination of physics-based modeling and adaptive, edge-sensitive processing techniques. Unlike traditional deep learning methods that need a lot of labeled data and powerful computers, this approach works without any training. This makes it very useful for real-world use in biomedical settings. The system uses a model that understands how light interacts with biological tissues, helping to accurately restore images. A significant advantage of this method is its adaptive contrast prior, which uses a quarter-window dark channel and local variance data to estimate the transmission map. This doesn't depend on learned parameters, making it both fast and reliable in different imaging situations. The filter also includes edge-aware refinement steps that help keep important details like cell edges and blood vessel patterns clear, which is essential for accurate diagnosis. The framework improves image contrast, reduces scattered light effects, and restores clarity without losing important features. Its simple design and linear performance allow it to work quickly, making it suitable for use in systems with limited resources. Overall, the APEE-Filter offers a good balance between quality and efficiency, and it can be used across various types of biomedical imaging.

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