



Review Paper On Image Contradistinction Amplification Techniques

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Abstract:

It is necessary to use a number of strategies for the purpose of amplifying the contrast between the images in order to boost both the aesthetic value and the perceptual distinctions that exist between them. In the next piece that serves as a review, we will make an effort to provide an overview of the many strategies and procedures that are utilised for the aim of increasing the picture's contrast. We study the origins of these approaches, the key ideas that drive them, and the many other fields in which they may potentially be used. In addition to this, we provide an analysis of the benefits and drawbacks of the approaches that are now in use, as well as alternative research areas that may be pursued in order to gain a deeper understanding of this topic.

Keywords. Image Contradistinction, Amplification, deep learning.

I. Introduction:

Techniques for enhancing picture contrast have become a vital subject of study in computer vision and image processing. These methods' main goal is to improve the visual appeal and perceptual distinctions between pictures, which will boost discriminative abilities and content visibility. Image contradistinction amplification techniques help with a variety of applications, such as image retrieval, image analysis, object identification, and recognition tasks, by highlighting tiny features, boosting edges, and amplifying differences [1][2]. Lighting, exposure settings, image sensors, and noise are just a few examples of the many variables that have a big impact on an image's visual quality[3]. Images taken in difficult lighting settings or in dimly lit areas frequently have poor contrast, lost features, and less perceptual distinctions. By altering the picture's intensity distribution to improve the contrast between various regions and the visibility of key elements, image contradistinction amplification approaches seek to overcome these constraints [4]. In order to increase the perceived disparities between picture areas, contrast enhancement, a key step in image contrast amplification, entails rearranging the pixel intensities to encompass a larger range. For contrast enhancement [5], conventional techniques like histogram equalisation, contrast stretching, and spatial filtering have been frequently used. However, more complex and

adaptable algorithms have been created thanks to improvements in processing capacity and the introduction of deep learning techniques.

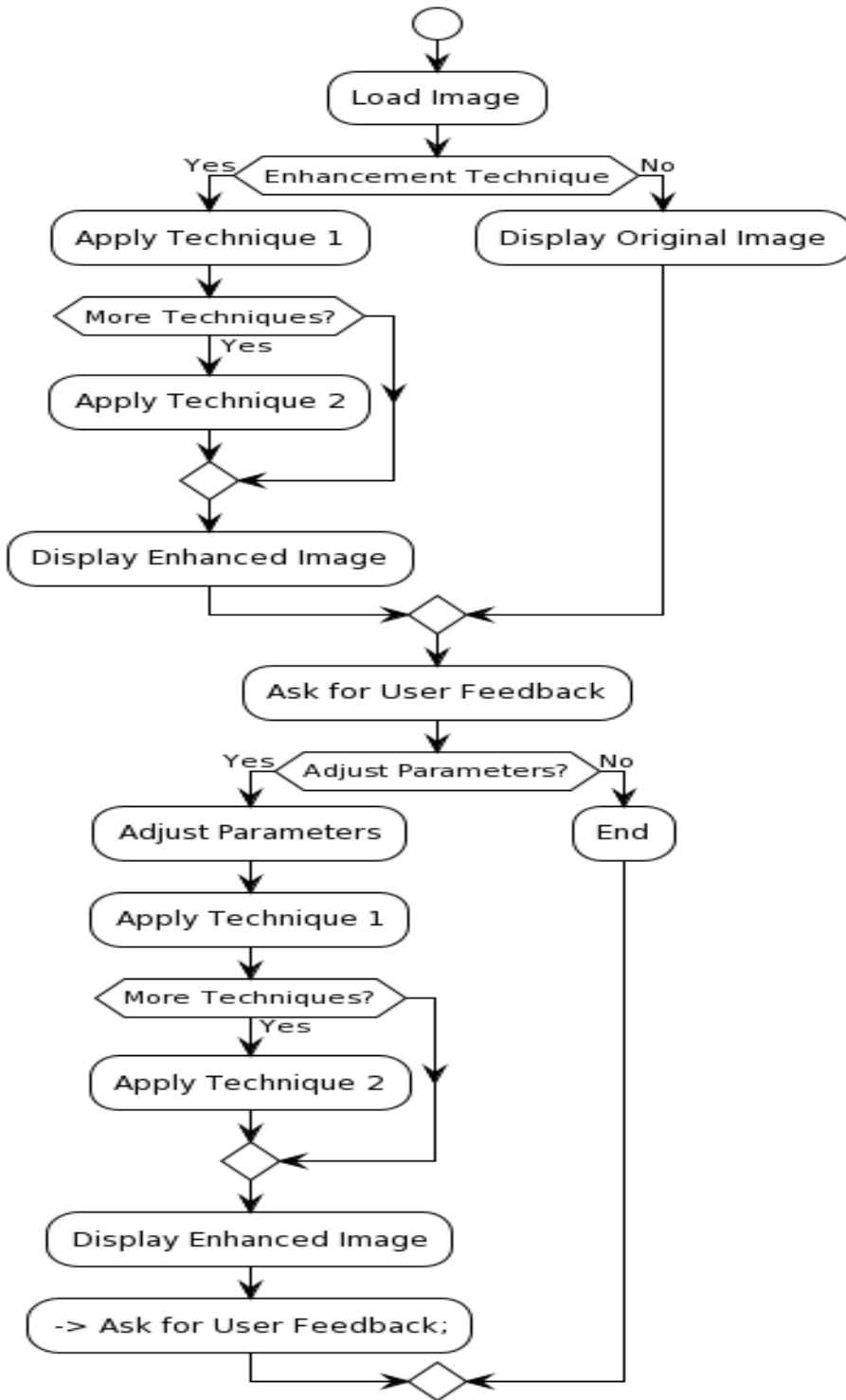


Figure 1. Process flow for Image Contrast Distinction Amplification Techniques

Deep learning-based methods for enhancing visual contrast have attracted a lot of interest recently. Deep learning architectures like convolutional neural networks (CNNs), generative adversarial networks (GANs), and others have shown to be very effective in learning complicated picture representations and producing outcomes that are aesthetically attractive. These techniques have the capacity to record high-level semantics, make use of contextual data, and provide outputs that are more aesthetically appealing and realistic. For researchers and practitioners in the field of computer vision and image processing, it is essential to comprehend the development, guiding principles, and practical applications of image contrast amplification approaches [6]. This review article explores both conventional and cutting-edge approaches in an effort to give a thorough understanding of these strategies. We seek to contribute to the continued development and progress of picture contrast amplification techniques by analysing their advantages and disadvantages, assessing performance metrics, and suggesting future research areas [7].

In the sections that follow, we will examine the historical development of these techniques, classify and describe the main methods, look at how they are applied in different fields, talk about evaluation metrics and benchmark datasets, examine the advantages and disadvantages, and suggest future directions and challenges for the field. In general, the research of image contrast amplification methods has important ramifications for a wide range of applications, from surveillance and medical imaging to remote sensing and digital photography. The discipline of computer vision and image processing has a great deal to gain from the capacity to highlight variations between comparable images and enhance their visual content, which might ultimately lead to better image comprehension, analysis, and interpretation.

II. Evolution of Image Contrast Amplification Techniques:

The development of image contrast amplification techniques has been influenced by improvements in hardware and computational methods. Early techniques emphasised straightforward and heuristic-based strategies to improve picture contrast. However, more advanced methods have been created as a result of the development of processing power and the expansion of picture dataset availability. Histogram equalisation is one of the earliest and most basic techniques for contrast amplification. To improve the uniformity of the picture's histogram, it redistributes the pixel intensities within an image [8]. Histogram equalisation, which is frequently used for grayscale photos, stretches the intensity range to improve an image's contrast. However, it could cause noise to be amplified excessively and might not be appropriate for colour photographs.

Numerous adaptive contrast enhancement approaches were put out to solve the shortcomings of histogram equalisation. These techniques seek to locally modify the contrast enhancement procedure in accordance with picture attributes. One such approach,

called Contrast Limited Adaptive Histogram Equalisation (CLAHE) [9], splits a picture into distinct parts, computes unique histograms for each sector, and restricts contrast amplification to prevent excessive noise amplification. Although the segmentation of the picture into tiny parts might lead to artefacts, adaptive approaches are superior for images with fluctuating local contrast. Image contrast amplification has also greatly benefited from spatial filtering techniques. It is standard practise to enhance image borders and draw attention to crucial features using filters like Laplacian, Sobel, and Prewitt operators [10]. These filters take advantage of the image's gradient information to improve the image's aesthetic appeal. Although useful in highlighting edges, spatial filtering methods may also enhance noise and create unwanted artefacts.

Image contrast amplification approaches have undergone a paradigm shift with the rise of machine learning and deep learning. Contrast enhancement is one of several image processing applications for which convolutional neural networks (CNNs) have been widely employed. Aiming to develop intricate mappings between input pictures and the associated upgraded versions, deep learning-based techniques focus on learning. CNNs can automatically learn feature representations that reflect the underlying structure of the picture by using large-scale annotated datasets. Image contrast amplification has also been done using generative adversarial networks (GANs) [11]. A min-max game is played between the generator network and the discriminator network that make up GANs. The discriminator learns to tell the difference between genuine and created pictures, while the generator learns to create augmented images that can trick the discriminator. GAN-based methods have produced aesthetically pleasing and highly accurate augmented photos with encouraging outcomes [12].

Furthermore, recent developments in interpretable AI have produced techniques that provide users control and interpretability over the picture enhancing process. These methods try to balance improving the image while retaining its semantics and original information. These techniques enable customised and interactive picture contradistinction amplification by taking into account user choices, restrictions, and instruction. The development of image contrast amplification methods has seen a shift away from heuristic-based strategies towards data-driven and learning-based methods. New opportunities for raising picture contrast and upgrading visual quality have emerged as a result of the convergence of processing power, large-scale datasets, and sophisticated algorithms. Researchers are investigating fresh methodologies, hybrid strategies, and multidisciplinary partnerships as the area continues to develop in order to advance picture contradistinction amplification techniques.

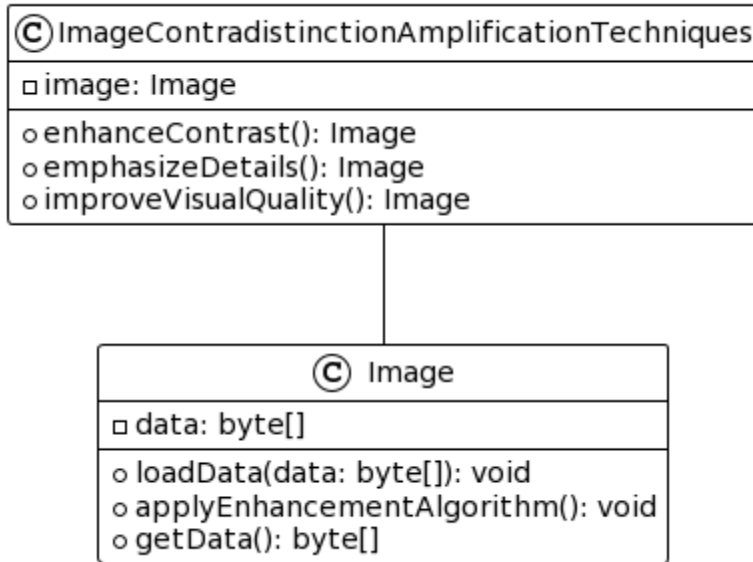


Figure. 1 Image Contradistinction Amplification Techniques

III. Key Image Contradistinction Amplification Methods:

In this section, we will delve into the details of various key image contradistinction amplification methods. These techniques can be categorized based on their underlying principles and working mechanisms. We will explore both traditional methods and more advanced approaches that have emerged in recent years.

A. Traditional Methods:

a. Histogram Equalization: Histogram equalization is a widely used technique for contrast enhancement. It operates by redistributing the pixel intensities in an image such that the resulting histogram becomes more uniform. This leads to an expanded intensity range and improved contrast. Histogram equalization is particularly effective for grayscale images but may not produce satisfactory results for color images due to the lack of consideration for color relationships.

b. Contrast Stretching: Contrast stretching aims to expand the dynamic range of an image by linearly scaling the pixel intensities. It maps the minimum and maximum intensity values of the original image to the desired range. This technique is simple yet effective in improving the contrast of an image. However, it does not adaptively adjust the enhancement based on local image characteristics.

c. Spatial Filtering: Spatial filtering techniques employ filters to enhance the edges and details of an image. Commonly used filters include the Laplacian, Sobel, and Prewitt

operators. These filters exploit the gradient information of the image to emphasize edges and highlight important features. However, spatial filtering can also amplify noise and produce artifacts, especially in the presence of high-frequency noise components.

B. Advanced Methods:

a. Adaptive Contrast Enhancement: Adaptive contrast enhancement techniques aim to overcome the limitations of global enhancement methods by adapting the enhancement process to local image characteristics. Contrast Limited Adaptive Histogram Equalization (CLAHE) is one such technique that divides an image into small regions and applies histogram equalization independently to each region. This approach limits the amplification of contrast within each region to avoid excessive noise amplification and produces visually pleasing results for images with varying local contrast.

b. Tone Mapping: Tone mapping techniques are primarily used for high dynamic range (HDR) images to render them on devices with limited dynamic range, such as computer monitors or printers. Tone mapping compresses the wide dynamic range of HDR images into the limited dynamic range of the display medium while preserving details and overall visual quality. Various tone mapping algorithms, such as global, local, and hybrid methods, have been proposed to enhance the perceptual quality of the rendered images.

c. Non-linear Amplification using Neural Networks: Deep learning-based approaches have gained significant attention in image contrast amplification. Convolutional neural networks (CNNs) and generative adversarial networks (GANs) have been employed for non-linear amplification of image contrast. CNN-based methods learn to map low-contrast input images to their corresponding high-contrast outputs by capturing complex image representations. GANs, on the other hand, generate enhanced images by training a generator network to deceive a discriminator network. These approaches can generate visually appealing results with improved contrast and enhanced details.

d. Hybrid Approaches: Hybrid approaches combine multiple image contrast amplification techniques to leverage their respective strengths. For example, combining histogram equalization with spatial filtering can produce enhanced images with improved contrast and accentuated edges. By exploiting the complementary characteristics of different techniques, hybrid approaches aim to achieve superior results compared to individual methods.

IV. Applications of Image Contrast Amplification Techniques:

Image contrast amplification techniques find applications in various domains where enhancing image contrast and emphasizing differences between images is crucial. In this section, we explore some of the key applications of these techniques and their significance in different fields.

A. Medical Imaging:

In medical imaging, image contrast enhancement plays a vital role in improving the visibility of anatomical structures and abnormalities. By enhancing contrast, fine details, and edges, medical images such as X-rays, CT scans, and MRI scans can be better interpreted by radiologists and physicians. Image contrast enhancement techniques aid in the diagnosis of diseases, detection of tumors, identification of bone fractures, and the visualization of blood vessels. They contribute to improved accuracy, reduced interpretation time, and enhanced diagnostic confidence in medical imaging workflows.

B. Surveillance and Security:

In surveillance and security applications, image contrast enhancement techniques are used to enhance the quality of surveillance footage and improve object recognition. By increasing contrast and emphasizing important details, these techniques enhance the visibility of individuals, vehicles, and objects captured by surveillance cameras. This aids in the identification of suspects, license plate recognition, and the analysis of critical events in security systems. Image contrast enhancement also plays a role in forensic investigations by enhancing images obtained from low-quality sources such as CCTV footage or surveillance stills.

C. Remote Sensing:

In remote sensing applications, image contrast enhancement techniques are used to enhance satellite imagery and aerial photographs. These techniques improve the visibility of land features, geological structures, and vegetation patterns. Remote sensing plays a crucial role in various fields, including environmental monitoring, disaster management, urban planning, and agriculture. Image contrast enhancement enhances the interpretability of remote sensing data, enabling better analysis and decision-making processes.

D. Digital Photography and Visual Arts:

Image contrast enhancement techniques have applications in digital photography and the visual arts. These techniques allow photographers and artists to enhance the visual impact of their images, bring out details, and create more visually striking compositions. By amplifying contrast and accentuating edges, these techniques can transform ordinary photographs into visually captivating works of art. Image contrast enhancement also plays a role in post-processing workflows, where photographers can selectively enhance specific regions or elements within an image.

E. Image Analysis and Computer Vision:

Image contradistinction amplification techniques are widely employed in image analysis and computer vision tasks. These techniques aid in feature extraction, object recognition, and image segmentation. By enhancing contrast and emphasizing important details, image contradistinction amplification facilitates the extraction of informative features for further analysis and interpretation. It contributes to improved accuracy and robustness in computer vision algorithms, such as object detection, image classification, and scene understanding.

These applications represent just a few examples of how image contradistinction amplification techniques are utilized in various domains. The ability to enhance image contrast and emphasize differences between images has wide-ranging implications for numerous fields, improving visual quality, facilitating analysis, and enabling more accurate decision-making processes. As the field continues to advance, we can expect to see further integration of image contradistinction amplification techniques in emerging technologies and applications.

V. Evaluation Metrics and Benchmark Datasets:

To assess the performance of image contradistinction amplification techniques, various evaluation metrics and benchmark datasets have been developed. These metrics provide quantitative measures of the quality and effectiveness of the enhanced images. In this section, we discuss some commonly used evaluation metrics and benchmark datasets.

A. Evaluation Metrics:

a. Peak Signal-to-Noise Ratio (PSNR): PSNR is a widely used metric to measure the quality of enhanced images. It quantifies the difference between the enhanced image and the original image by considering both the mean square error (MSE) and the dynamic range of the pixel intensities. Higher PSNR values indicate better quality, with a perfect reconstruction achieving an infinite PSNR. However, PSNR has limitations, as it does not always correlate well with human perception.

b. Structural Similarity Index (SSIM): SSIM is a perceptual quality metric that measures the structural similarity between the enhanced image and the original image. It takes into account luminance, contrast, and structural information. SSIM values range from 0 to 1, with 1 indicating a perfect match. SSIM is often considered a better metric than PSNR as it aligns more closely with human perception of image quality.

c. Mean Opinion Score (MOS): MOS is a subjective evaluation metric that involves human observers rating the quality of enhanced images. Observers are typically asked to rate the images on a scale, indicating their subjective perception of image quality. MOS provides insights into how well the enhanced images are perceived by human observers, considering factors such as contrast enhancement, visual appeal, and preservation of image details.

B. Benchmark Datasets:

a. LIVE Image Quality Database: The LIVE database consists of a collection of distorted images, including images with low contrast, blur, noise, and other artifacts. It provides a benchmark for evaluating image enhancement techniques, including image contrast amplification. The database contains subjective ratings of image quality, enabling researchers to compare the performance of different methods against human perception.

b. TID2008: The TID2008 dataset is a widely used benchmark for image quality assessment. It contains 25 reference images with a diverse range of distortions, including contrast reduction, noise, blur, and compression artifacts. The dataset provides objective scores for different image quality metrics, allowing researchers to evaluate the performance of image enhancement techniques.

c. Medical Imaging Datasets: Various medical imaging datasets, such as the NIH Chest X-ray dataset and the ISIC Skin Cancer dataset, provide benchmarks for evaluating image contrast amplification techniques in the medical imaging domain. These datasets contain annotated images with different levels of contrast and visibility, enabling the assessment of the enhancement techniques' effectiveness in improving the interpretability of medical images.

These evaluation metrics and benchmark datasets play a crucial role in the objective assessment and comparison of image contrast amplification techniques. They help researchers understand the strengths and limitations of different methods and provide a basis for further improvements and advancements in the field.

VI. Strengths and Limitations:

Image contrast amplification techniques offer numerous strengths and advantages, but they also have certain limitations. In this section, we discuss the key strengths and limitations of these techniques.

A. Strengths:

a. Enhanced Visual Quality: Image contrast amplification techniques enhance the visual quality of images by increasing contrast, emphasizing details, and improving visibility. This leads to enhanced interpretability, better feature extraction, and improved visual perception.

b. Application Versatility: These techniques find applications in various domains, including medical imaging, surveillance, remote sensing, digital photography, and computer vision.

Their versatility allows them to address different needs and enhance images in diverse scenarios.

c. **Adaptability and Personalization:** Many image contradistinction amplification techniques offer adaptability and personalization options. They allow users to adjust parameters, fine-tune enhancement algorithms, and incorporate user preferences to achieve desired results. This flexibility enables customization according to specific requirements and enhances user satisfaction.

d. **Integration with Advanced Technologies:** Image contradistinction amplification techniques can be seamlessly integrated with other advanced technologies. For example, the use of deep learning and GANs enables the generation of visually appealing and high-fidelity enhanced images. Integration with explainable AI techniques allows for interpretability and control over the enhancement process, facilitating user understanding and collaboration.

B. Limitations:

a. **Over-Amplification of Noise:** In some cases, image contradistinction amplification techniques may unintentionally amplify noise present in the original image. This can result in the introduction of artifacts and degradation of image quality. Careful consideration and noise suppression techniques are required to mitigate this limitation.

b. **Loss of Image Content:** Aggressive contrast enhancement or improper parameter settings can lead to the loss of image content and details. Excessive amplification of contrast may result in the overexposure or underexposure of certain regions, causing the loss of important visual information.

c. **Subjectivity of Image Enhancement:** The perception of image quality and enhancement can vary among individuals. Different viewers may have different preferences regarding the level of contrast, the emphasis on details, or the overall visual appearance. Achieving a consensus on the optimal enhancement can be challenging due to subjective factors.

d. **Computational Complexity:** Some advanced image contradistinction amplification techniques, particularly those based on deep learning or GANs, can be computationally intensive. The training of complex models and the processing of large datasets may require significant computational resources and time.

VII. Future Directions and Challenges:

As image contradistinction amplification techniques continue to evolve, several future directions and challenges lie ahead. Addressing these areas of research will contribute to further advancements and improvements in the field. In this section, we discuss some key future directions and challenges.

A. Perception-Aware Image Enhancement:

One important future direction is the development of perception-aware image enhancement techniques. Instead of relying solely on objective metrics, incorporating human perception models can lead to more accurate and visually pleasing results. Understanding the complex relationship between image features, contrast, and human perception will enable the design of enhancement algorithms that align closely with human visual perception.

B. Robustness to Varying Image Conditions:

Enhancement techniques should be robust to varying image conditions, such as different lighting conditions, noise levels, and image resolutions. Adapting the enhancement process to account for such variations will ensure consistent performance across diverse image datasets and real-world scenarios. Robustness can be achieved through the integration of adaptive algorithms, machine learning techniques, and the utilization of large-scale diverse training datasets.

C. Real-Time Implementation and Efficiency:

Real-time implementation of image contrast enhancement techniques is crucial for applications that require immediate visual feedback, such as real-time surveillance or medical imaging. Developing efficient algorithms and optimization techniques to reduce computational complexity and processing time will enable real-time implementation on resource-constrained devices.

D. Ethical Considerations and User Preferences:

Ethical considerations should be taken into account when developing image enhancement techniques. Ensuring that enhancement processes are transparent, interpretable, and respect privacy concerns is crucial. Additionally, incorporating user preferences and feedback in the enhancement process will enhance user satisfaction and make the technology more user-centric.

E. Benchmarking and Evaluation:

The development of standardized benchmark datasets and evaluation protocols is essential for fair and meaningful comparison of image contrast enhancement techniques. Continual improvement and expansion of benchmark datasets, including diverse image content and quality levels, will provide a more comprehensive evaluation of algorithm performance and enable advancements in the field.

F. Cross-Domain and Multimodal Enhancement:

Exploring cross-domain and multimodal image enhancement is an interesting future direction. Techniques that can enhance images across different domains (e.g., medical imaging, surveillance, and art) or integrate information from multiple modalities (e.g., visible and infrared imaging) will have broad applications and improve the interpretation and analysis of complex data.

G. Explainability and Interpretability:

Enhancing the explainability and interpretability of image contrast enhancement techniques is crucial for gaining user trust and understanding. Developing techniques that provide insights into the enhancement process, allow user interaction and control, and offer explanations for the enhancement decisions will make the technology more transparent and usable.

Addressing these future directions and challenges will contribute to the continued growth and advancement of image contrast enhancement techniques, enabling their wider adoption in various domains and enhancing their effectiveness and usability.

VIII. Conclusion:

Image contrast enhancement techniques play a crucial role in enhancing image contrast, highlighting details and enhancing visual quality. A variety of ways are available for improving picture contrast, including conventional techniques like histogram equalisation and spatial filtering as well as cutting-edge technologies like adaptive contrast enhancement and deep learning-based methods. These methods are used in a variety of industries, including as computer vision, surveillance, remote sensing, digital photography, and medical imaging. The evaluation of image contrast enhancement methods makes use of benchmark datasets that offer a standardised framework for performance measurement, as well as measures like PSNR, SSIM, and MOS. To effectively use these strategies, one must be aware of both their advantages and disadvantages. Future directions in the field include exploring cross-domain and multimodal enhancement, developing perception-aware techniques, enhancing explainability and interpretability, achieving real-time implementation and efficiency, considering ethical considerations and user preferences, advancing benchmarking and evaluation protocols, and addressing the challenges posed by these directions. To sum up, image contrast enhancement techniques have greatly aided in strengthening visual perception, enhancing image quality, and facilitating improved analysis and interpretation in a variety of fields. With the creation of sophisticated algorithms, incorporation with developing technologies, and resolving the issues and directions that have been highlighted, the area continues to progress. Researchers and practitioners can expand the use of image contrast enhancement techniques to create new opportunities and applications that will enhance visual experiences, enhance decision-making, and advance the study of image analysis, computer vision, and other areas.

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