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Methods and Models for Image Enhancement in Low-light Conditions

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***Abstract*— This article reviews current research on various approaches to improving images captured in low-light or dimly lit conditions. To address this issue, an adaptive ensemble method is proposed that combines several, specifically, four classical image processing algorithms and automatically distributes weights among them based on local quality. The developed system uses CLAHE, gamma correction, the Retinex algorithm, and automatic contrast stretching as its basic components. A comparative analysis of the developed method with the modern Deep Learning approach, Zero-DCE, was conducted on the real-world LOL dataset. The experimental results show that the proposed classical ensemble approach achieves a PSNR of 17.91 dB, outperforming the machine learning model by 14.2 percent, while the method does not require a training phase on datasets or GPU computations.**

Keywords—image enhancement, low-light enhancement, ensemble methods, CLAHE, Zero-DCE, adaptive weighting, image processing.

I. INTRODUCTION

In daily life, some fields require high-quality and clear images, such as biomedicine, aerospace, transportation, military, etc. But sometimes, the shooting will be affected by the environment or the equipment used, resulting in the inability to capture clear and high-quality images.[1][2]

Image recognition is usually presented as a multi-class classification problem in which the identification of a relevant set of specific features which performs best is a difficult task [3].

This challenge has a wide range of practical applications across many fields, from mobile photography and video surveillance systems to autonomous vehicle control systems and medical imaging. The main problems that can arise when working with such images include a very low signal-to-noise ratio, high noise levels from camera sensors, significant loss of detail in shadowed areas, and a significant distortion of the natural color reproduction of objects in the image.

Current research in this field can be broadly divided into two main methodological categories. The first category includes classical image processing methods based on mathematical models and heuristic approaches. These methods are characterized by the clarity of their results, do not require significant computational resources, and can be effectively applied without a pre-training phase. However, the drawbacks of such methods include frequently limited result quality when processing complex scenes with uneven lighting, high noise levels, or a wide dynamic range.

The second category consists of deep learning-based approaches that have recently achieved impressive results across a variety of image processing tasks. Convolutional neural network models can capture complex nonlinear relationships between images captured under low-light and normal lighting conditions, enabling high-quality image enhancement. At the same time, such approaches require large amounts of paired training data and significant computational resources for training, and are

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characterized by limited interpretability of their internal processes.

The aim of this study is to develop and investigate an ensemble approach to improving images captured in low-light conditions that combines the advantages of classical algorithms via adaptive weighting. The study also aims to conduct a thorough comparative analysis of the proposed method against modern machine learning approaches using real-world datasets.

II. Review Of Existing Solutions

A. Heading Classical image processing methods

The CLAHE (Contrast Limited Adaptive Histogram Equalization) algorithm is an image processing technique designed to enhance local contrast, particularly in images with very dark or bright regions.[4] CLAHE divides the input image into rectangular blocks of fixed size and applies an equalization procedure to each block. The transformation can be written as (1):

$$J_k = (CDF(T_k) - CDF(min) \, * \, \frac{(L-1)}{CDF(max) - CDF(min)} \quad (1)$$

where J_k is the equalized intensity value, T_k is the original pixel intensity, $CDF(\cdot)$ denotes the cumulative distribution function, and L is the number of possible intensity levels.

A critical feature of the method is the limitation of the maximum contrast enhancement factor via the clip limit parameter, which helps avoid excessive noise amplification in relatively homogeneous image regions. The method demonstrates high effectiveness in enhancing local details and textures, but may introduce increased noise in dark image areas if the parameters are set incorrectly.

Retinex, is a commonly used image enhancement method based on scientific experiments and analysis. The theory of Retinex is based on the idea that the color of an object is determined by its ability to reflect long-wave (red), medium-wave (green), and short-wave (blue) illumination rather than the absolute value of the reflected light. [5] The Single-Scale Retinex algorithm estimates the illumination component by applying a Gaussian filter with a large smoothing radius to the logarithm of the input image. By subtracting the logarithm of the estimated illuminance from the logarithmic representation of the input image, we obtain the reflection component, which effectively corresponds to the enhanced image. The parameter σ of the Gaussian filter determines the scale of the illuminance estimation and significantly affects the final quality of the result. The model is expressed as (2):

$$\begin{gathered} \log R(x,y) = \log I(x,y) - \log L(x,y) \\ L(x,y) = F * \log I(x,y) \\ F = Gaussian(\sigma) \end{gathered} \quad (2)$$

where $R(x,y)$ is the reflectance component, $I(x,y)$ is the input image, $L(x,y)$ is the estimated illumination, F is a Gaussian smoothing filter, and σ controls the scale of illumination estimation.

Gamma correction is a crucial process in digital imaging systems, aiming to compensate for the nonlinear relationship between input signal and luminance output. [6] The gamma correction method applies a nonlinear power transformation to pixel intensities. This means raising the normalized intensity to the inverse of the gamma parameter. When gamma values exceed 1, brightness increases primarily in dark areas of the image, while bright areas undergo minimal change, helping preserve contrast. The simplicity of the method and its low computational complexity make it attractive for real-time applications; however, a single global gamma parameter does not allow adaptation to local features of the illumination distribution in different parts of the image. The transformation is defined as (3):

$$I_{out} = 255 \cdot \left(\frac{I_{in}}{255}\right)^{\frac{1}{\gamma}} \quad (3)$$

where I_{in} is the input pixel intensity, is the corrected intensity, and γ is the gamma parameter controlling the strength of the brightness adjustment.

The automatic contrast stretching method, linearly expands the original digital values of the remotely sensed data into a new distribution. By expanding the original input values of the image, the total range of sensitivity of the display device can be utilized. [7] In the first stage, the image's dynamic range is evaluated, typically using histogram percentiles to exclude outliers. After that, the interval between the defined boundaries is linearly stretched to cover the full range of possible intensity values. Using percentiles instead of absolute minimum and maximum values makes the method more robust against isolated excessively dark or bright pixels, which may be caused by noise or artifacts. The method effectively utilizes the entire available dynamic range of the display or storage system, but does not account for local features of the contrast distribution.

B. Deep Learning-Based Approaches

The Zero-DCE model trains the parameters of curves used for stepwise brightness correction at the pixel level. Architecturally, it consists of seven convolutional layers, each generating eight sets of curve parameters for iterative application to the input image. Within each iteration, a quadratic transformation is performed, which is determined by the corresponding curve parameters. It can cope with diverse lighting conditions including nonuniform and poor lighting cases. [8] The model contains approximately 79,000 parameters and exhibits very fast inference. A critical feature of Zero-DCE is its unsupervised training mode, which does not require paired low-light and normal-light image data. Instead, the model is trained using a combination of four specialized loss functions. Color instability is used to maintain the natural balance of color components in the enhanced image. Loss of exposure control ensures brightness level correction by bringing the average intensity of local areas closer to a specified optimal level. Loss of lighting smoothness helps create a uniform brightness distribution within the scene and prevents sudden lighting changes. The Spatial Consistency Loss maintains the spatial structure similarity between the input and output images. This approach allows the model to be trained even in the absence of paired data, which is a significant advantage in practical applications.

C. *Ensemble Approaches in Image Processing*

Ensemble methods combine the results of several algorithms to obtain a more stable and accurate final result than any single method can provide. Compared to standalone single-network systems the proposed ensemble methodology blends sequential and parallel processing methods to produce an optimized enhancement performance. [9] In image processing tasks, this is most often achieved through weighted aggregation of the outputs of base models or algorithms. In this context, weighting coefficients can be determined empirically, optimized using validation data, or calculated based on the quality metrics of each individual method. This approach makes it possible to offset the shortcomings of some algorithms with the strengths of others, which ultimately improves the overall robustness and quality of the final result, especially when working with heterogeneous input data. More sophisticated adaptive methods evaluate the quality of each model's results locally for different parts of the image and dynamically determine optimal weights for each spatial location. This adaptability allows for the automatic selection of the best method for the specific characteristics of a local region of the image. However, early implementations of adaptive ensembles often suffered from visible pixelation artifacts, arising from abrupt weight transitions between neighboring image blocks during block-wise quality estimation without sufficient smoothing.

III. Proposed Method

A. *Ensemble System Architecture*

The SmoothAdaptive Ensemble system combines four classical image processing algorithms into a single ensemble structure, supplemented by a mechanism for adaptively weighting the results. The first component is based on the CLAHE method with an adjustable contrast threshold and local block size, allowing for enhancing local contrast without excessively increasing noise artifacts. The second component applies gamma correction with a typical coefficient to enhance the brightness of images captured in challenging low-light conditions. The third component implements the Single Scale Retinex algorithm using a large-scale Gaussian filter, which allows for the estimation of the spatial distribution of scene illuminance and ensures more accurate extraction of the reflection component.[11] The fourth component performs automatic contrast stretching by clipping 2% of the pixels at both ends of the histogram to improve robustness against outliers. This combination of methods covers a range of image enhancement techniques, from local contrast to global tonal mapping.

B. *Detailed Algorithm for Adaptive Weighting*

The adaptive weighting process consists of five sequential stages, each of which is crucial for obtaining the final result. In the first stage, the input image is processed simultaneously by all four base models, which operate independently. Each model performs its own image transformation, resulting in four intermediate results that reflect different approaches to image enhancement.

In the second step, a spatial map of local quality is computed for each of the four intermediate results. This process is implemented by dividing the image into overlapping blocks measuring 128 by 128 pixels with a step size of 64 pixels, ensuring 50% overlap between adjacent blocks. Two quality metrics are calculated for each block. The first metric is based on the standard deviation of pixel intensities within the block, reflecting local contrast and the presence of detail. The second metric is the average gradient within the block, computed using the Sobel operator and reflecting the sharpness of edges and textures. The combined quality score for a block is computed as a weighted sum of the normalized standard deviation and the average gradient, with weights of 1/50 and 1/100, respectively. A critical step is to apply Gaussian smoothing to the resulting quality map with a kernel size of 99×99 pixels and a sigma parameter of 30. This smoothing eliminates abrupt transitions between the quality estimates of neighboring blocks, a key factor in preventing pixelation artifacts.

In the third step, the quality maps are normalized to calculate spatially variable weights. For each spatial location in the image, the four quality values from the different models are normalized so that their sum equals one. This transformation allows the weights to be interpreted as probabilities or relative contributions of each model to the final result for a given spatial location. After the initial normalization, an additional Gaussian smoothing with a kernel of 51 by 51 pixels and a sigma parameter of 15 is applied to each of the four weight maps. This second smoothing further smooths the spatial transitions of the weights. After smoothing, the weights are renormalized to restore the condition that their sum at each point equals one. This double-smoothing procedure is an innovative aspect of the developed method and is critical for achieving visually smooth results without blocky artifacts.

In the fourth step, an adaptive weighted merge of the four intermediate results is performed using the calculated spatially variable weights. For each spatial location in the image and for each color channel, the final intensity value is calculated as the weighted sum of the corresponding values from the four intermediate results. The weights used in this combination are spatially variable and automatically adjusted based on the local quality of the results from the different models. This means that across different parts of the image, the final result may be closer to that of different base models, depending on which performs best in that area.

In the fifth and final step, post-processing of the final result is performed. Intensity values that may exceed the acceptable range due to smoothing and combination operations are clipped to a range from zero to two hundred fifty-five. The result is converted to an unsigned 8-bit integer, which is the standard image format. The final image is saved in JPEG format with a high quality level of 95% to minimize compression loss.

IV. EXPERIMENTAL STUDY

A. Experimental Methodology and Evaluation Metrics

To objectively verify the effectiveness of the proposed method, the LOL dataset was selected, which is one of the standard test sets in the tasks of improving images obtained under low-light conditions. It contains five hundred pairs of images, where each pair represents one scene recorded both in a dark environment and in normal light. The majority of the set, namely four hundred and eighty-five pairs, is used for training the models, while the remaining fifteen pairs are used for final quality testing. All images are real photographs taken in natural conditions without synthetic generation, which increases the realism of the experiments and allows for a correct assessment of the method's performance in practical scenarios.

For quantitative analysis of the quality of enhancement, a set of four widely accepted metrics was used, each characterizing a specific aspect of visual quality. The peak signal-to-noise ratio evaluates the accuracy of the reconstruction by comparing the enhanced image to a reference image of normal illumination, and higher values of this metric correspond to better reconstruction quality. The structural similarity index measures the degree of perceptual similarity between images, taking into account local brightness, contrast, and structural characteristics, where values close to unity indicate high similarity. The entropy determines the amount of information content of an image based on the distribution of pixel intensities, with higher values indicating a more detailed and informative image. The average gradient metric evaluates image sharpness by measuring the intensity of spatial changes across the image, highlighting edges and textures by computing horizontal and vertical gradients with the Sobel operator and averaging their magnitudes over the entire image.

B. Results of comparison of improvement methods

Figure 1 illustrates representative enhancement examples from the LOL dataset.

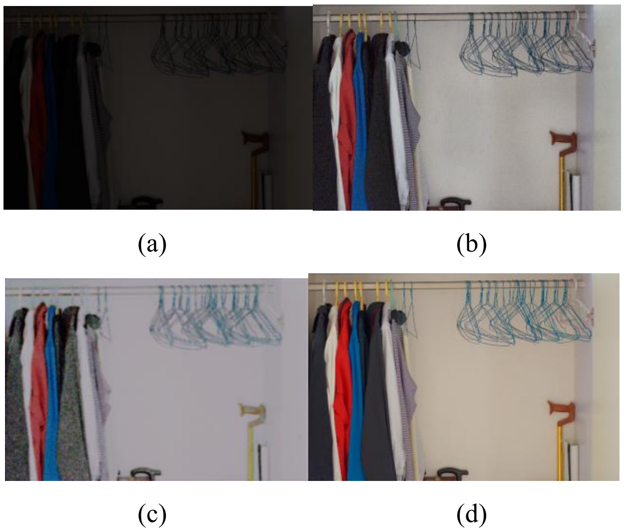

Figure 1. Visual comparison of low-light enhancement results on real LOL dataset images [own work]. (a) Input low-light image; (b) SmoothAdaptive Ensemble result; (c) Zero-DCE result; (d) Ground truth image.

The proposed method reduces underexposure while preserving texture structure, whereas the Zero-DCE output is visually cleaner in some regions but may lose fine local details. A systematic comparison of four different approaches to improving low-light images on fifteen test pairs from the LOL dataset was carried out. The first approach is represented by the developed SmoothAdaptive Ensemble method with a full adaptive weighting algorithm and double Gaussian smoothing. The second approach implements Blended Ensemble, which performs a simple unweighted averaging of the results of four base models without assessing local quality. The third approach uses Pyramid Ensemble, which processes images at three different scales and combines the results with weights of sixty percent for the original scale, thirty percent for half scale, and ten percent for quarter scale. The fourth approach is represented by the Zero-DCE model, which was trained on the training part of the LOL dataset for one hundred epochs with a batch size of four and a learning rate of one ten-thousandth.

The SmoothAdaptive Ensemble method demonstrated the highest PSNR among all the studied approaches, reaching a value of seventeen point ninety-one hundredths of a decibel. This result is fourteen point two tenths of a percent better than the Zero-DCE model, which showed a PSNR of fifteen point sixty-eight hundredths of a decibel. Blended Ensemble showed an intermediate result of sixteen point forty-six hundredths of a decibel, indicating the advantage of adaptive weighting over simple averaging. Pyramid Ensemble showed the lowest PSNR of fourteen point ninety-one hundredths of a decibel, which may be due to loss of detail when rescaling images multiple times.

According to the SSIM metric, the best result was shown by Pyramid Ensemble with a value of zero point seven hundred and forty-three thousandths, which indicates the effectiveness of multi-scale processing in preserving the structural details of the image. Blended Ensemble achieved an SSIM of zero point seven hundred and sixteen thousandths. SmoothAdaptive Ensemble showed a value of zero point six hundred and seventy-eight thousandths, which is slightly lower than previous methods. The Zero-DCE model demonstrated an SSIM of zero point six hundred and forty-one thousandths, which is the lowest result among all methods.[10]

According to the Entropy metric, the developed SmoothAdaptive Ensemble achieved the highest value of seven point nineteen hundredths of a bit per pixel, which indicates the maximum information content and detail of the resulting images. Blended Ensemble showed six point eighty-four hundredths, Pyramid Ensemble six point thirty-eight hundredths, and Zero-DCE six point twenty-seven hundredths of a bit per pixel. This hierarchy of results is consistent with the PSNR scores and confirms the effectiveness of adaptive weighting in preserving visual information.

On the Average Gradient metric, which characterizes the sharpness of images, the SmoothAdaptive Ensemble also showed the best result of fifty-seven point thirty-four hundredths of one. Blended Ensemble achieved forty-three point eighty-six hundredths, Zero-DCE thirty-five point forty-eight hundredths, and Pyramid Ensemble only twenty-four point seventy-one hundredths of one. The high gradient of the SmoothAdaptive Ensemble indicates the effective restoration of sharp edges and textures in the enhanced images.

A critical difference between the classical ensembles and the Deep Learning approach is the processing speed. The Zero-DCE model demonstrated the fastest processing with a time of six hundred twenty-one milliseconds per image due to an efficient forward pass through a convolutional neural network on the GPU. SmoothAdaptive Ensemble requires six thousand seventy-three milliseconds, which is ten times slower. Blended Ensemble runs in five thousand three hundred thirty-three milliseconds, while Pyramid Ensemble is the slowest, with a time of six thousand nine hundred twenty-four milliseconds due to the need to process images at multiple scales.

V. Conclusions

Images captured under low-light conditions often suffer from (partially) poor visibility. Besides unsatisfactory lightings, multiple types of degradations, such as noise and color distortion due to the limited quality of cameras, hide in the dark. [11] This paper proposes and studies effective networks capable of producing brighter, clearer, and visually compelling images under diverse and challenging conditions.[12][13] The developed SmoothAdaptive Ensemble system combines four classical image processing algorithms through an adaptive weighting mechanism based on a local assessment of the quality of the results of each algorithm. The key innovation of the method is the procedure of double Gaussian smoothing of quality maps and weights, which completely eliminates pixelation artifacts characteristic of previous block adaptive methods.

Experimental research on the standard LOL dataset demonstrated that the developed classical ensemble approach achieves a PSNR of seventeen point ninety one hundredths of a decibel, which is fourteen point two tenths of a percent higher than the result of the modern Deep Learning model Zero-DCE after one hundred training epochs. High values of the Entropy and Average Gradient metrics confirm the effectiveness of the method in restoring details and preserving the information content of images. At the same time, the method does not require a training stage on datasets, GPU calculations and large amounts of training data.[14]

Comparative analysis revealed a clear trade-off between the quality of improvement and processing speed. The classical ensemble approach provides a higher quality of detail restoration, full interpretability of the algorithm, and no need for training, but works ten times slower compared to optimized Deep Learning models. This defines different niches of practical application: classical ensembles are optimal for offline processing and systems without GPU, while Deep Learning approaches are preferable for real-time applications and mobile applications after appropriate training.

The practical applicability of the developed method has been confirmed for scenarios of offline processing of photo archives, professional photographic retouching, embedded systems without GPU and prototyping before developing specialized Deep Learning solutions. The full interpretability of the method makes it especially valuable in applications where understanding and explanation of decisions made in image processing is required.

Similar insights into the importance of robust and interpretable image processing pipelines have been demonstrated in the context of road accident detection algorithms for modern machine vision systems, where the selection of suitable models and features significantly affects reliability. [15]

The results demonstrate that classical image processing methods remain competitive and practically applicable when properly combined with adaptive ensemble approaches. Further development of the method through specialized denoising, automatic parameter tuning, and GPU optimization can further expand the scope of its effective application.

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