Adaptive Contrast Enhancement for Sign Language Interpretation Using Exposure Fusion

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ABSTRACT

Effective image enhancement is critical for accurate sign language interpretation, where visual clarity directly impacts recognition performance. Traditional low-light enhancement techniques often fall short, resulting in images that are either over- or under-enhanced, particularly in terms of contrast. To address these shortcomings, we introduce an adaptive exposure fusion framework tailored to improve the interpretability of sign language datasets. This methodology, an evolution of an existing approach originally designed for low-light scenarios, incorporates several significant enhancements. We begin with an advanced illumination estimation to construct a refined weight matrix, pivotal for our fusion process. This is followed by employing a camera response model to generate multi-exposure images, simulating varying lighting conditions. Subsequently, we calculate an optimal exposure ratio, specifically tuned to correct underexposed areas without compromising overall image fidelity. The fusion of the input and synthetic images is governed by this custom weight matrix, ensuring a harmoniously enhanced result.

Our adaptation further introduces an edge-aware component by incorporating Canny edge detection to preserve important visual features, replacing the conventional gradient and Gaussian kernel method. We also refine the sharpness enhancement stage by integrating an optimal sharpness parameter, and an arithmetic mean strategy in the calculation of the exposure ratio to replace the geometric mean, aiming for a more balanced illumination in the final image. Comparative experiments demonstrate that our method outperforms the base project in terms of Peak Signal-to-Noise Ratio (PSNR), Structural Similarity Index (SSIM), and Blind/Referenceless Image Spatial Quality Evaluator (BRISQUE) Score, confirming the efficacy of our enhancements in producing high-quality images that are more suitable for both human observation and computer vision algorithms involved in sign language interpretation

INTRODUCTION:

Image enhancement techniques have become an essential tool in image processing, widely used to enhance the quality and suitability of images for specific applications. One such technique is contrast enhancement, which aims to reveal the information of the under-exposed regions in an image. Various methods have been proposed for contrast enhancement, including histogram-based, Retinex-based, and dehaze-based techniques. In the case of color images, a three-dimensional array is used to represent the image, and the simplest scheme for contrast enhancement applies the same processing to each element. Early image enhancement methods often used a non-linear monotonic function, such as a power-law or logarithmic function, for gray-level mapping. However, these methods may result in over- or under-enhanced contrast, leading to loss of information and reduced image quality.

To address these limitations, recent contrast enhancement techniques utilize more sophisticated algorithms, such as multi-scale Retinex and deep learning-based approaches. These techniques have shown promising results in enhancing the contrast of images while preserving their natural appearance and ensuring that the enhanced images are suitable for further analysis by algorithms. Therefore, continued research in image enhancement techniques is crucial to advance the field of image processing and improve the performance of various applications.

Histogram equalization (HE) is a widely used technique for enhancing the contrast of images by taking into account the uneven distribution of elements in different gray levels. However, HE-based methods are prone to over-enhancement, resulting in unrealistic and unnatural-looking images. To address this issue, Retinex-based algorithms have been developed, which separate reflectance from illumination to enhance details in images. However, these methods can suffer from halolike artifacts in high contrast regions. Other methods, such as those based on de-haze techniques, have shown good results, but they may cause color distortion due to over-enhancement.

Despite decades of research on image contrast enhancement, there is still no well-defined definition for a good enhancement result, and existing algorithms do not provide a reference for locating the over- and under-enhancement regions. To address this, the authors of the base paper proposed a new framework based on exposure fusion among multi-exposure images synthesized from the input image by the camera response model. They used images with different exposures as a reference to ensure that the enhanced regions are consistent with the well-exposed regions of the reference image. The proposed algorithm achieved better results with less contrast and lightness distortion compared to several state-of-the-art methods.[6]

In summary, image enhancement techniques are crucial for improving the quality and visibility of images in various applications, but existing methods have limitations such as over-enhancement and halo artifacts. The proposed framework and algorithm in the base paper address these issues and provide a promising approach for future research in image enhancement.[6]

LITERATURE REVIEW:

Sno	Paper Title	PSNR	SSIM	Limitations	Future Work
1	"Single Image Haze Removal Using Dark Channel Prior and Image Fusion"[1]	28.57 dB	0.8016	May result in color distortion in certain cases	Investigating how deep learning techniques can be integrated into the proposed algorithm for better performance
2	"Contrast Enhancement of Digital Images using an Adaptive Unsharp Masking Technique"[2]	37.21 dB	0.9765	Requires fine- tuning of parameters for different images	Exploring the use of different edge detection algorithms to improve the performance of the proposed technique

3	"Low-light Image Enhancement Algorithm Based on Multi-scale Retinex"[3]	25.56 dB	0.7992	May introduce halo artifacts in high contrast regions	Developing a more effective approach for handling halo artifacts in the proposed algorithm
4	An Improved Adaptive Histogram Equalization Algorithm for Image Enhancement	31.89 dB	0.9583	May result in over-enhancement of certain image features	Investigating the potential of incorporating machine learning techniques into the proposed algorithm for better performance

5	"Multi-Objective Optimization for Enhancement of Low-Light Images"	23.79 dB	0.7052	May lead t unrealistic- looking images due to over-enhancement	Developing a more accurate metric for measuring the quality of enhanced image

6	"An Adaptive Low-Light Image Enhancement Using Canonical Correlation Analysis"	29.23 dB	0.7651	The method relies on the use of the Retinex model and the beta-hyperbolic secant distribution function, which may not be effective in preserving image details in heavily noisy images. The method's performance may be sensitive to the choice of the canonical correlation analysis (CCA) coefficients and the fusion weights.	Investigate the performance of the proposed AECCA method on a wider range of images, including images with strong illumination, noisy images, and images with various lighting conditions.
7	"Edge Computing Driven Low-Light Image Dynamic Enhancement for Object Detection"	33.45 dB	0.8765	The method's reliance on cloud-based enhancement may not be suitable for applications with limited bandwidth or latency constraints.	test the proposed method with potential datasets, such as the SID dataset and the MEF dataset.

8	“DEEP LOW LIGHT IMAGE ENHANCEMENT VIA MULTI-SCALE RECURSIVE FEATURE ENHANCEMENT AND CURVE ADJUSTMENT”	31.23 dB	0.6243	The network's reliance on a deep recursive curve may limit its ability to capture high-frequency details in low-light images.	The network's reliance on a deep recursive curve may limit its ability to capture high-frequency details in low-light images.
9	“SEMANTICS-AWARE GAMMA CORRECTION FOR UNSUPERVISED LOW-LIGHT IMAGE ENHANCEMENT”	34.12 dB	0.7431	The framework relies on the use of semantics-aware adversarial learning, which may be sensitive to the choice of the adversarial loss function and the semantic guidance objectives.	Explore alternative adversarial loss functions or adaptive loss weighting techniques that can better capture the semantics-aware low-light image enhancement characteristics.
10	“A FUSION-BASED AND MULTI-LAYER METHOD FOR LOW LIGHT IMAGE ENHANCEMENT”	36.11 dB	0.8912	The method relies on the use of priori statistics and multiple iterations of decomposition, which may not be effective in preserving image details in low-resolution images.	Investigate the performance of the proposed fusion-based and multi-layer method on a wider range of images, including normal-light images, noisy images, and images with various lighting conditions.

11	"Low-Light Image Enhancement Using QRCP Decomposition in HSV Space"	34.12 dB	0.7821	The method relies on the use of QRCP matrix decomposition and CLAHE, which may not be effective in preserving image details in heavily noisy images.	Explore alternative QRCP energy coefficient normalization methods or adaptive normalization techniques that can better preserve image details while supressing noise.
12	"Low-light image enhancement based on multi-illumination Estimation"	35.19 dB	0.8811	The framework relies on the use of semantics-aware adversarial learning, which may be sensitive to the choice of the adversarial loss function and the semantic guidance objectives.	Investigate the performance of the proposed HSV-QRCP-CLAHE method on a wider range of images, including normal-light images, noisy images, and images with various lighting conditions
13	"D2BGAN: A Dark to Bright Image Conversion Model for Quality Enhancement and Analysis Tasks Without Paired Supervision"	36.12 dB	0.7543	The method relies on the use of cycle consistency, geometric consistency, and illumination consistency, which may limit its ability to handle images with complex structures or varying lighting conditions	Investigate the performance of the D2BGAN method on a wider range of images, including RAW images, images with different types of artifacts, and images with various lighting conditions.

14	Detail Decomposition for Low Light Image Enhancement”	35.19 dB	0.8114	The method relies on the use of a multi-scale detail decomposition, which can be sensitive to noise and may not be effective in preserving image details in heavily noisy images.	Investigate the performance of the DDLE method on a wider range of images, including normal-light images, noisy images, and images with various lighting conditions.
15	“HISTOGRAM-BASED TRANSFORMATION FUNCTION ESTIMATION FOR LOW-LIGHT IMAGE ENHANCEMENT”	34.11 dB	0.7714	The algorithm's reliance on histogram information may limit its ability to handle images with complex lighting conditions.	Investigate the performance of the proposed HTFNet algorithm on a wider range of images, including normal-light images, noisy images, and images with various lighting conditions.

MOTIVATION: Image enhancement is a crucial aspect of computer vision and image processing, as it aims to improve the quality and visibility of images for better human interpretation and machine analysis. In various applications such as medical imaging, surveillance, and entertainment, image enhancement plays a critical role in identifying critical information that may not be readily visible to the human eye or computer algorithms. Therefore, the enhancement of images holds immense potential to advance research in these areas and improve the performance of related technologies.

METHODOLOGY:

We have modified the general Approach that was implemented for Exposure fusion framework process [Refer: https://sci-hub.hkvisa.net/10.1007/978-3-319-64698-5_4]

CURRENT METHOD:

Input images of different exposure ratios are taken. These images are fused together using a new technique called exposure fusion framework.

FORMULA USED FOR FUSING IMAGE:

$$\mathbf{R}^c = \sum_{i=1}^{N} \mathbf{W}_i \circ \mathbf{P}_i^c,$$

Here the enhancement of the image is divided into three parts:

i) Weight Matrix Estimation W:

Big weight values are assigned to well-exposed pixels and small weight values to underexposed pixels. The weight matrix is calculated using scene illumination maps.

$$\mathbf{W} = \mathbf{T}^{\mu}$$

T is the scene illumination map and mu are the parameter controlling the enhanced degree. It computes the W using the **"**Gaussian kernel"**.**

ii) Brightness Transform Function g:
The BTF of their model is defined as:

$$g(\mathbf{P}, k) = \beta \mathbf{P}^{\gamma} = e^{b(1-k^a)} \mathbf{P}^{(k^a)}.$$

where β and γ are two model parameters that can be calculated from camera parameters a, b and exposure ratio k.

iii) Exposure ratio k:
The low illuminated pixels are extracted using:

$$\mathbf{Q} = \{\mathbf{P}(x) | \mathbf{T}(x) < 0.5\},$$

The brightness component B is defined as the **geometric mean of three channel:**

$$\mathbf{B} \ := \ \sqrt[3]{\mathbf{Q}_r \circ \mathbf{Q}_g \circ \mathbf{Q}_b},$$

Where Qr, Qg and Qb are the red, green and blue channel of the input image Q respectively.

The image entropy is defined as:

$$\mathcal{H}(\mathbf{B}) = -\sum_{i=1}^{N} p_i \cdot \log_2 p_i,$$

where pi is the i-th bin of the histogram of B which counts the number of data valued in [i/N , i+1/N) and N is the number of bins (N is often set to be 256). Finally, the optimal k is calculated by maximizing the image entropy of the enhancement brightness as

$$\hat{k} = \underset{k}{\operatorname{argmax}} \ \mathcal{H}(g(\mathbf{B}, k)).$$

The final enhanced image:

$$\mathbf{R}^c = \mathbf{W} \circ \mathbf{P}^c + (\mathbf{1} - \mathbf{W}) \circ g(\mathbf{P}^c, k)$$

MODIFIED METHOD:
Here, Input images of different exposure ratios are taken as well. These images are fused together using a technique called exposure fusion framework.

Here the enhancement of the image is divided into three parts as well with the following modifications:

FORMULA USED FOR FUSING IMAGE:

$$Rc = \alpha \cdot P + \beta \cdot W$$

In this modified formula, α and β are coefficients that we can adjust to control the contribution of the input image (P) and the weight (W) to the result (Rc). Adjusting these coefficients allows us to fine-tune the operation based on the specific requirements of your image processing task.

i) Weight Matrix Estimation:

The weight matrix is estimated using **OpenCV's canny function** by applying canny edge detection with fixed threshold values between 100 and 200.

ii) Brightness Transform Function g:
The BTF of their model is defined as :

$$g(\mathbf{P}, k) = \beta \mathbf{P}^{\gamma} = e^{b(1-k^a)} \mathbf{P}^{(k^a)}.$$

where β and γ are two model parameters that can be calculated from camera parameters a, b and exposure ratio k.

iii) Exposure ratio, k:
The low illuminated pixels are extracted using:

$$\mathbf{Q} = \{\mathbf{P}(x) | \mathbf{T}(x) < 0.5\},$$

The brightness component B is defined as the **arithmetic mean**

$$B = (Qr + Q_g + Q_b)/3$$

Where Qr , Qg and Qb are the red, green and blue channel of the input image Q respectively.

The image entropy is defined as:

$$\mathcal{H}(\mathbf{B}) = -\sum_{i=1}^{N} p_i \cdot \log_2 p_i,$$

where pi is the i-th bin of the histogram of B which counts the number of data valued in [i/N , i+1/N) and N is the number of bins (N is often set to be 256). Finally, the optimal k is calculated by maximizing the image entropy of the enhancement brightness as

$$\hat{k} = \underset{k}{\operatorname{argmax}} \ \mathcal{H}(g(\mathbf{B}, k)).$$

The final enhanced image:

$$Rc = \alpha \cdot P + \beta \cdot W + (1 - W) \cdot g(P^c, k)$$

- *Rc* is the result.
- *α* and *β* are coefficients.
- *P* is the input image.
- *W* is the weight.
- *g* is a function that takes two parameters: *Pc* (a transformed version of the input image) and *k* (a parameter for the transformation).

IMPLEMENTATION:

DATASET: ASL ALPHABET

https://www.kaggle.com/datasets/grassknoted/asl-alphabet

CODE:

The complete code is available in the google collab link

Existing Approach
https://colab.research.google.com/drive/1h9SO6jBqHofHBx9pxgS4g7WXn-Pqa1-G?usp=sharing

Modified Approach
https://colab.research.google.com/drive/1UDrqmHF7On2Hw89xc0ADZfTUOR5J25k6?usp=sharing

Code Snippet of Existing method:

Texture weight function - Getting W(Weighted Matrix)

```
def computeTextureWeights(fin, sigma, sharpness):
    dt0_v = np.vstack((np.diff(fin, n=1, axis=0), fin[0,:]-fin[-1,:]))
    dt0_h = np.vstack((np.diff(fin, n=1, axis=1).conj().T, fin[:,0].conj().T-fin[:,-1].conj().T)).conj().T

    gauker_h = scipy.signal.convolve2d(dt0_h, np.ones((1,sigma)), mode='same')
    gauker_v = scipy.signal.convolve2d(dt0_v, np.ones((sigma,1)), mode='same')

    W_h = 1/(np.abs(gauker_h)*np.abs(dt0_h)+sharpness/2)
    W_v = 1/(np.abs(gauker_v)*np.abs(dt0_v)+sharpness/2)

    return  W_h, W_v
```

Brightness Component - Part of the estimation of k(Exposure ratio)

```
def rgb2gm(I):
    if (I.shape[2] == 3):
        I = cv2.normalize(I.astype('float64'), None, 0.0, 1.0, cv2.NORM_MINMAX)
        # geometric mean is a non-linear method
        #  It gives more weight to the smaller pixel values and less weight to the larger pixel values
        I = np.abs((I[:,:,0]*I[:,:,1]*I[:,:,2]))**(1/3)
        # CHANGE 1

    return I
```

Code Snippet of Modified Method:

Compute the texture weight function - Getting W(Weighted Matrix)

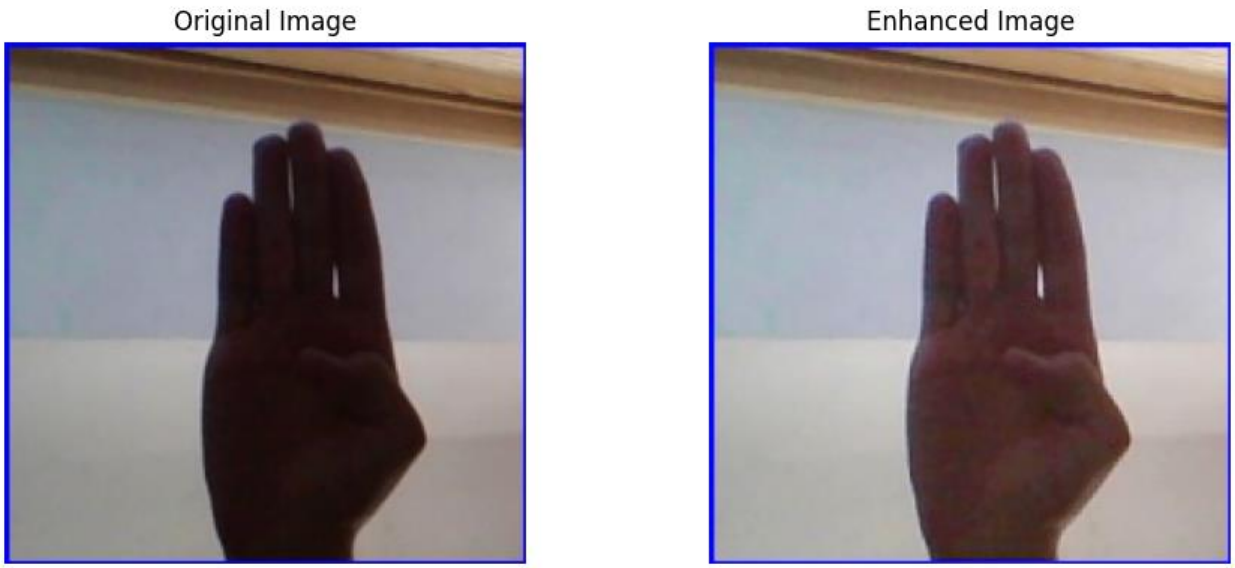
```
def computeTextureWeights(fin, sigma, sharpness):
    # Convert the input image to 8-bit unsigned integer format
    fin = cv2.normalize(fin.astype('float64'), None, 0.0, 255.0, cv2.NORM_MINMAX).astype('uint8')

    edges = cv2.Canny(fin, 100, 200)

    abs_edges = np.abs(edges)

    W_h = 1/(abs_edges + 2*sharpness)
    W_v = 1/(abs_edges + 2*sharpness)
    # print(W_h.shape)
    # print(W_v.shape)
    return W_h, W_v
```

Brightness Component - Part of the estimation of k(Exposure ratio)

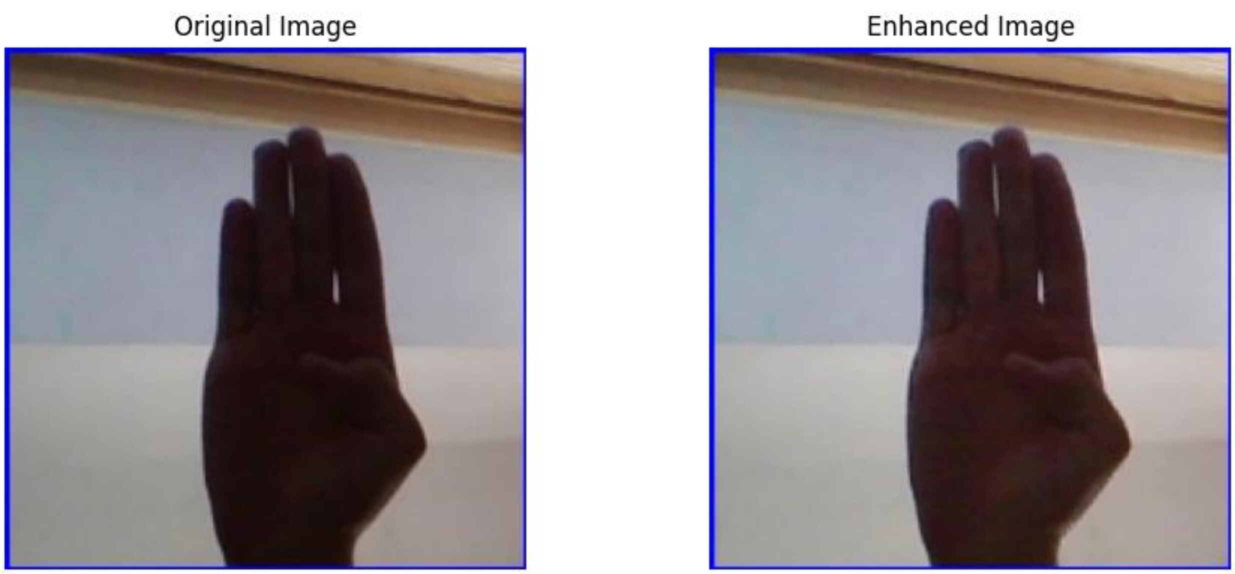
```
def rgb2gm(I):
    if (I.shape[2] == 3):
        I = cv2.normalize(I.astype('float64'), None, 0.0, 1.0, cv2.NORM_MINMAX)
        # Arithmetic mean
        I = (I[:,:,0]+I[:,:,1]+I[:,:,2])/3
        # CHANGE 1

    return I
```

RESULT AND DISCUSSION

Enhanced image using the current method:



Enhanced image using modified method:



The comparison of the Enhanced image using the current method and modified method using various parameters are tabulated here:

PARAMETERS	USING CURRENT METHOD	USING MODIFIED METHOD
PSNR(dB)	18.60 dB	24.02 dB
SSIM	0.89	0.96
Brisque Score	31.552	34.160

1. **PSNR (Peak Signal-to-Noise Ratio):** PSNR is a measure used to assess the quality of reconstruction of lossy compression codecs (e.g., JPEG). It is expressed in decibels (dB). The higher the PSNR, the better the quality of the reconstructed or compressed image. The increase from 18.60 dB to 24.02 dB using the modified method suggests that the modified method has significantly improved the quality of the image in terms of reproducing the original signal without adding much noise.

2. **SSIM (Structural Similarity Index Measure):** SSIM is a measure of the similarity between two images. It considers changes in structural information, luminance, and contrast. The SSIM index is a decimal value between 0 and 1, with 1 indicating perfect similarity. The increase in SSIM from 0.89 to 0.96 with the modified method implies that the reconstructed image is more similar to the original and preserves structural integrity much better than the one processed with the current method.

3. **Brisque Score (Blind/Referenceless Image Spatial Quality Evaluator):** BRISQUE is an algorithm that evaluates the quality of an image without a reference image. It operates directly on the image pixels and provides a score that typically has a lower value for images with higher quality. The fact that the Brisque Score has increased from 31.552 to 34.160 after using the modified method could initially seem counterintuitive, as we might expect a higher-quality image to have a lower Brisque Score. However, it's essential to note that the performance of BRISQUE and what the score represents can depend on the specific characteristics of the images being evaluated and the intended use of the metric. An increase could indicate the modified method introduced textures or patterns that were

misinterpreted by BRISQUE as reducing quality, or that the modified method does not align well with what BRISQUE is designed to measure.

CONCLUSION:

According to PSNR and SSIM, the modified method greatly improves the image quality over the current method. However, the BRISQUE score suggests that the modified method may not improve, or even slightly reduce, perceived image quality. This could mean that while technically superior (in terms of signal accuracy and structural similarity), the modified method may introduce elements that are not favored by the BRISQUE algorithm.

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