Nighttime Traffic Surveillance Using Glare Reduction and Zero-DCE-Based Low-Light Image Enhancement

1st Duman Care Khrisne
Doctoral Engineering Department
Udayana University
Denpasar, Indonesia
duman@unud.ac.id

2nd Made Sudarma*
Doctoral Engineering Department
Udayana University
Denpasar, Indonesia
msudarma@unud.ac.id

3rd Ida Ayu Dwi Giriantari
Doctoral Engineering Department
Udayana University
Denpasar, Indonesia
dayu.giriantari@unud.ac.id

4th Dewa Made Wiharta
Doctoral Engineering Department
Udayana University
Denpasar, Indonesia
wiharta@unud.ac.id

***Abstract*—High-quality image plays a critical role in computer vision tasks such as object detection and scene understanding. However images captured in night traffic conditions usually suffer from low light and glare problems, which increases the difficulty of subsequent computer vision tasks. In this paper we propose a new approach to using Zero-DCE for image enhancement in low light on traffic surveillance cameras at night. We added a glare reduction (Reduce Glare) stage after the image enhancement process was carried out using Zero-DCE. This has been proven to help improve quality and maintain enhanced image structural information. The proof is the increase of the average PSNR from 28.91 to 31.07 and SSIM values from 0.55 to 0.88, for the enhanced images using the proposed approach compared to Zero-DCE alone. Subjective tests also carried out to see the condition of the image before and after processing. The outcomes of the suggested method were able to improve the image's brightness and contrast, visibility of details, and subjective visual quality. The impact can be felt directly by practitioners and parties involved in traffic monitoring, paving the way for more effective and reliable systems. These results not only overcome challenges in low-light conditions, but also open opportunities for the development of better surveillance technologies in the future.**

Keywords—Night Traffic, Low light Enhancement, Zero-DCE, Glare Reduction,

I. Introduction

Today, vehicular traffic is an integral aspect of daily life and has a daily impact on a wide range of human endeavors and services. Therefore, effective road traffic management is essential for efficient transit, especially in metropolitan regions where people frequently commute. To maintain traffic flow, video surveillance is a crucial part of smart transportation [1]. Computer systems can further extract and evaluate features from the images produced by video surveillance systems installed on urban streets since they include a wealth of visual and semantic data. High-quality image plays a critical role in computer vision tasks such as object detection and scene understanding. However, in reality, photos captured by urban street surveillance cameras are inevitably damaged by light and of poor quality, particularly if they are captured at night in areas with very low light [2]. Low brightness, low contrast, narrow grayscale, color distortion, substantial noise, and inadequate edge information are characteristics commonly displayed by photos captured at night in relatively low light conditions [3]. Besides the poor lighting, glare caused by vehicle headlights is another common problem with surveillance cameras that occur at night [4]. The ability of the camera to perform to the fullest extent as a monitoring tool is compromised by dazzling light, which prevents the camera from taking detailed photographs.

In this work, we attempted to improve nighttime traffic monitoring and address the issues of glare and poor light in nighttime monitoring conditions, by using Glare Reduction and Zero-DCE-Based Low-Light Image Enhancement [5] Algorithm. It is hoped that this application will serve as the basis for future visual-based intelligent traffic management systems, particularly when surveillance cameras must deal with monitoring situations that are carried out at night.

II. Related Work

Poor visibility often affects nighttime image acquisition, which has an adverse effect on subsequent processing for outdoor computer vision applications [6]. Therefore, it is highly desirable to improve the visibility of low-illumination images to ensure the dependability of outdoor vision systems at night. Research [7] utilizes the de-haze technique [8] and makes a new approach to overcome the low-light image problem, by inverting the image and applying the de-haze technique, which directly utilizes the dark channel prior which is also used by [9]. Another approach is used in [10], using illumination map estimation, they first calculate a rough illumination map by looking for the highest pixel intensities in the RGB channels, then they refine the rough illumination map using a prior structure.

The presence of machine and deep learning in image processing also opens up hope for solving the problem of low-light image enhancement, the two main approaches are CNN-based and GAN-based methods. Both are excellent techniques for fixing low-light image problems. However, there is a very prominent weakness of this approach, namely training data. The majority of CNN-based approaches [11]–[13] require paired data for supervised training, making them resource-intensive. For this reason, studies have emerged to address this training data problem. GAN-based techniques are one of them, the benefit of using unsupervised GAN-based techniques is that they do not require paired data for training. EnlightenGAN [14] is trained using intricately crafted loss functions and discriminators. But Unsupervised GAN-based solutions, typically demand careful selection of unpaired training data.

Another approach exists to overcome the weaknesses regarding training data that deep learning has in low-light image enhancement. Research [5] built an artificial neural network with the name Given an input image, the Deep Curve Estimation Network (DCE-Net) is intended to calculate a set of Light-Enhancement curves (LE-curves) that suit the input image the best. It can be trained without using paired training data. Research [2], [5] demonstrate the superiority of Zero-DCE against existing light enhancement methods.

Even though the Zero-DCE research is used to carry out the low-light image enhancement process very well. However, traffic monitoring images usually experience problems with low light and glare. This is created by the large amount of light provided by vehicle lights during night traffic monitoring and the lack of lighting around the road. So in this research, a new approach was developed that combines glare removal techniques and utilizes Zero-DCE to improve the quality of traffic monitoring images.

III. Proposed Approach

For the purpose of improving the quality of camera captures during night surveillance, we propose an image enhancement technique. Since the input was video, the video must be transformed into images since a video is just a series of frames. We loop through each frame of the video, extract it, and use it as an image input. We worked the image enhancement out in two main steps. The glare reduction process is taken to reduce glare caused by both nearby lighting and vehicle light. The Zero-DCE-based low-light image enhancement is a process to correct the lack of brightness experienced by the image. These two main steps will be discussed further in the following sections.

A. Glare Reduction

For images with glare or car headlight glare, there is usually high contrast, high brightness in the illuminated areas of the image, and most of the other pixels are low intensity. To overcome the problem of high contrast differences in images, we can use exposure compensation algorithms such as Histogram Equalization, Gamma Correction, etc. However, in terms of car headlight glare, relying solely on the exposure correction algorithm has proven to be ineffective for images with too much contrast in specific region (such as car headlight glare) [15]. So we need a new approach, in this study glare reduction was carried out using two simple approaches, that is:

- Increase the brightness of the dark area
- Reduce the brightness of the glare area

Naturally, we will achieve the same outcome as the exposure compensation method if we utilize threshold values linearly at each pixel (as in point processing). We must create a polynomial function for the procedure of altering the pixel value to the threshold in order for the two specified phases to be carried out effectively. For that reason, in this research, two polynomial functions are used. The first and second polynomial functions respectively are as follows:

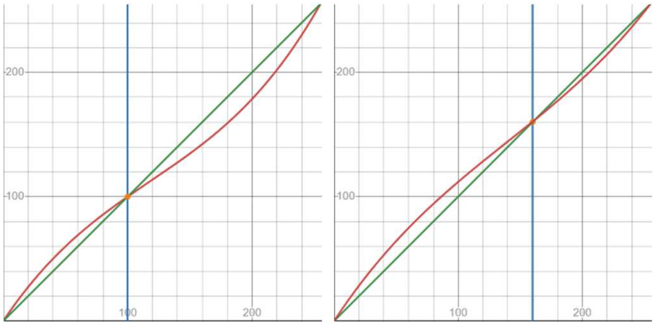
$$f(x) = 1.4975x - 0.0069x^2 + 0.0000195\, x^3 \qquad (1)$$

$$f(x) = 1.5128x - 0.0051x^2 + 0.0000124\, x^3 \qquad (2)$$

Where :

x: Pixel value

$f(x)$: Pixel value after transformation



(a) (b)

Fig. 1. (a) First polynominal function plot. (b) Second polynominal function plot.

Fig. 1 shows us a plot of the polynomial function (1), from the plot we can see the threshold value we used in first polynominal function is 100. We choose this value to ensure the pixel value is in the low-middle of the range of possible pixel values (0-256). This causes the pixel values below 100 (dark area pixels) to be raised to close to 100 and the pixel values above 100 (glare area pixels) to be lowered to close to 100. Not only that the polynomial function is made to greatly increase the pixel values in dark areas and do the opposite to glare area. Fig. 2 shows us a plot of the polynomial function (2), the threshold value we used in the second polynominal function is 160. We choose this value to ensure the pixel value is in the high-middle of the range of possible pixel values. This causes the pixel values below 160 (dark area pixels) to be raised to close to 160 nonlinearly and the pixel values above 160 to be lowered to close to 160 nonlinearly.

To complete the glare reduction step, the image output from the polynomial function process will also be passed through a gamma correction process, with a gamma correction factor of 0.75. In summary, the glare reduction process in this study is as follows:

- Input image to glare reduction function
- Apply the first polynominal to the image
- Gamma correction with factor of 0.75
- Apply the second polynominal function to the image
- Gamma correction with factor of 0.75
- Output image as glare reduction image

B. *Low* Light Image Enhancement

In this study, to overcome the low brightness value in images that still occurs after the glare reduction process, we use the Zero-DCE Framework. Deep networks are used in

Zero-Reference Deep Curve Estimation (Zero-DCE) [5] to tackle the problem of low-light image enhancement in a curve estimation task. Given an input image, DCE-Net attempts to estimate a set of light enhancement curves (LE-curves) that suit the input image the best. The framework then applies the curves repeatedly to map all of the RGB channels of the input's pixels to produce the final improved image. Three crucial elements make up the Zero-DCE framework [5]: the LE-curve, the DCE-Net, and the non-reference loss function.

1) Light Enhancement Curve: A light-enhancement curve, is a type of curve that can automatically translate a low-light image to its enhanced counterpart. In Zero-DCE Instead of focusing only on the illumination channel, the light-enhancement curve is independently applied to the three RGB channels. The three-channel adjustment can lessen the chance of over-saturation and better preserve the natural color.

2) Deep Curve Estimation Network (DCE-Net) : DCE-Net learns to map an input image to the curve parameter maps that would best match it. Fig. 2 shows us the architecture of the DCE-Net model. From Fig. 2 we see that DCE-NET is a straightforward CNN composed of seven symmetrically concatenated convolutional layers. Each layer consists of 32, 3×3 convolutional kernels with stride 1 and activation function (ReLU). The last convolutional uses the Tanh activation function that produces 24 parameter maps within 8 iterations, each iteration requires three curve parameter maps, to be used by the three image channels.

3) Loss Function: To enable zero-reference learning in DCE-Net, the Zero-DCE Framework use a set of differentiable zero-reference losses that allow us Zero-DCE evaluate the quality of enhanced images. According to [5] we use Color constancy loss (CCL), Exposure loss (EL), Illumination smoothness loss (ISL), and Spatial consistency loss (SCL).

IV. RESULT

We trained DCE-Net in this study using a color image dataset that has different exposures used in [5] totaling 2002 training images which are part of the SICE dataset [16]. However, in this study we only used 800 images, the first 400 images from the dataset were used for training data and the last 400 images were used for validation data. We did the model training process using 200 epochs. Table 1 shows the history of loss changes when model training is carried out, while Table 2 shows the history of loss values when validation is carried out in an epoch during the training process. Fig. 3 better illustrates the loss value over training and validation process of the model. From Fig. 3 we know since the 100th epoch the total loss (combined of all losses) from the test and validation data has not decreased (decreased very little), the training losses and validation losses have also converged so that it can be said that the model has not experienced overfitting.

In this study, we retrieved data from the Exclusively Dark (ExDark) dataset to test our proposed approach. We select images with the glare-prone car, bus, motorcycle, and bicycle elements. The test data consists of 44, jpg-formatted color images. We tested the proposed approach to improve image quality using 2 test aspects. The first test is a qualitative test (objective test) which we assess using Full-reference Image Quality Assessment (FIQA) metrics [3] that are:

- Peak Signal-to-Noise Ratio (PSNR, dB), measure the distortion in image before and after enhancement, higher PSNR value mean lower distortion.
- Mean Square Error (MSE), a lower MSE score in an evaluation of the image quality denotes a higher degree of similarity between the enhanced and original images.
- Structural Similarity (SSIM): SSIM measure the quality of the enhanced image with the original image. The minimum value is 0 and maximum value is 1. When the SSIM value is closer to 1, indicates fewer structural changes.

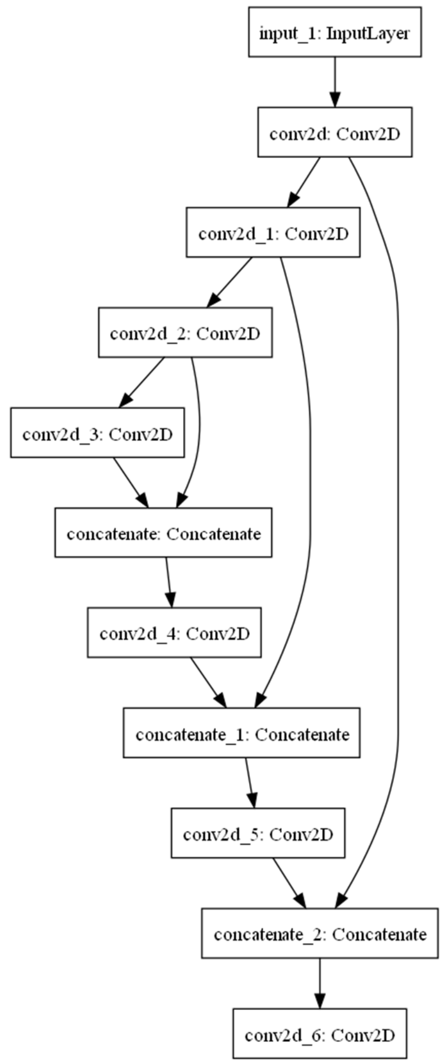


Fig. 2. Architecture of the DCE-Net model.

TABLE I. DCE-NET TRAINING LOSS VALUE OVER EPOCH

Epoch	Total Loss	CCL	EL	ISL	SCL
1	22.9703	0.0664	1.3341	21.5680	0.0019
10	1.9425	0.0319	1.2423	0.6658	0.0026
50	1.0761	0.0268	0.9276	0.0561	0.0656
100	**1.0375**	**0.0271**	**0.9083**	**0.0328**	**0.0692**
150	1.0260	0.0273	0.9011	0.0278	0.0698
200	1.0206	0.0274	0.8958	0.0275	0.0699

TABLE II. DCE-NET VALIDATION LOSS VALUE OVER EPOCH

Epoch	Total Loss	CCL	EL	ISL	SCL
1	21.1730	0.0318	1.1143	20.0259	0.0010
10	1.7797	0.0098	0.7264	0.6658	0.0027
50	1.0279	0.0111	0.8708	0.0853	0.0607
100	**0.9912**	**0.0112**	**0.8636**	**0.0520**	**0.0645**
150	0.9787	0.0113	0.8608	0.0407	0.0660
200	0.9734	0.0114	0.8585	0.0361	0.0673

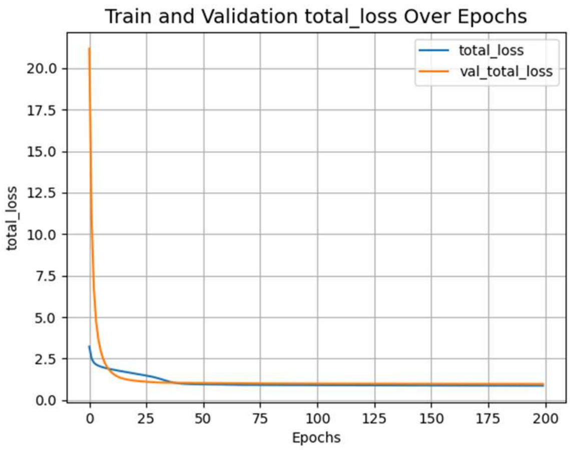


Fig. 3. Total loss of train and validation data over training epoch.

The second test was carried out to see the clarity of objects in the image (the subjective test). For this, we used the state-of-the-art YOLOv5 object detection algorithm [17]. We compare the object detection results in low-light images in the test dataset with the enhanced version of the images.

Table III shows a comparison of measurements using the FIQA metric (PSNR, MSE, SSIM). This value is obtained from the average measurement value of the images in the test dataset. Measurements were performed on the original image and the enhanced image using several methods such as LIME [10], EnlightenGAN [14], Zero-DCE [5] and our proposed approach. From Table III we can see that the approach proposed in this study, in particular by carrying out the Reduce Glare process after the image enhancement process using Zero-DCE, obtains the best and second-best scores compared to other methods.

TABLE III. QUANTITATIVE COMPARISONS IN TERMS OF FULL-REFERENCE IMAGE QUALITY ASSESSMENT METRICS.

Method	PSNR↑	MSE↓	SSIM↑
Zero_DCE [5]	28.91971252	1790.247876	0.554186794
RG + Zero-DCE	**32.78904906**	*248.6429589*	*0.809906968*
Zero-DCE + RG	*31.07164433*	**189.4227915**	**0.880501589**
Dual LIME [10]	28.07716455	2777.413358	0.334871841
EnlightenGAN [14]	28.01724938	2950.222114	0.376670629

Best result in bold, second best result italic

Apart from conducting quantitative tests, we also carried out subjective tests by comparing images before and after the image enhancement process was applied to the images. The initial low-light image is in the left column of Fig. 4, while the improved image is in the right. The figure makes it abundantly evident that the enhanced image's using our proposed approach (Zero-DCE + Reduce Glare) overall brightness and contrast are substantially better than those of the original, low-light input. Since the area included by the red border is darker in the original image, it is challenging to capture a significant quantity of detail. After network enhancement, the image brightness is noticeably better and the visibility of the details is better.

Fig. 4. Example of original dark image (left) compared to enhanced image using the proposed approach (right).

Fig. 5. Example of object detection result using YOLOv5 of original dark image (left) and enhanced image using the proposed approach (right).

The other subjective test is object detection using YOLOv5 on images from the test dataset. We investigate the performance of our proposed low-light image enhancement methods and compare the object detection result from the original test image and the enhanced version of the image. From Fig. 5 we can see that the YOLOv5 object detection algorithm can detect objects better, in images that have gone through the image enhancement process that we propose.

V. Conclusion

We propose a new approach of using Zero-DCE (Zero-DCE Based) and Reduce Glare for image enhancement in low light on traffic surveillance cameras. Our approach is Zero-DCE based so it can be trained end-to-end without reference images. The addition of the Reduce Glare stage is proven to be able to help improve the quality of the reconstructed image (the PSNR value increases from 28.91 to 31.07) in addition to maintaining the structural information of the reconstructed image (the SSIM value increases from 0.55 to 0.88), especially in images taken by traffic surveillance cameras at night. By adopting an innovative Zero-DCE based approach and incorporating a Reduce Glare stage, this research not only resulted in an increase in PSNR values, but also maintained the structural integrity of images in night traffic surveillance cameras. The impact can be felt directly by practitioners and parties involved in traffic monitoring, paving the way for more effective and reliable systems. These results not only overcome challenges in low-light conditions, but also open opportunities for the development of better surveillance technologies in the future.

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