International Journal of Engineering & Technology, 7 (4) (2018) 2515-2520

International Journal of Engineering & Technology

Website: www.sciencepubco.com/index.php/IJET
doi: 10.14419/ijet.v7i4.13725
Research paper

Improvement of sub region matching illumination transfer in hybrid shadow removal method for moving vehicle video

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Abstract

Intelligent Transportation System (ITS) is a concept to manage transportation based on technology development. Video from surveillance cameras can be used for monitoring the number of vehicles and speed using digital image processing. Shadows on the vehicle is one of the noise that must be removed in order to obtain better accuracy. Shadow is caused by the reflection of objects exposed to the light. In this study, we combined two methods to eliminate shadows on moving vehicle, the subregion illumination transfer method and the background-based Gaussian mixture model. Foreground image is used for sub-Region Illumination Transfer and gamma decoding processes is used to detect the presence of shadows The detected shadow is removed by replacing it with the background in that position. Experiments are done by making simulated video of moving objects without shadows and objects that have a shadow. By using the proposed method, the shadow will be omitted, and the results are compared with the object without the shadow. The experimental results are: mean value of PSNR for objects moving closer to the camera with a light intensity of 0.8 is 53.47. While on the moving object with a small shadow area, we obtained an average PSNR of 51.87927dB.

Keywords: *Shadow Removal; Gaussian Mixture Model; Gamma-Decoding Method; Intelligent Transportation System; Moving Object.*

1. Introduction

Along with government policies in accelerating the develoment of infrastructure, the smart cities are developed very rapidly. One of the supporting factor of smart city is the Intelligent Transportation Systems (ITS). In ITS, automation in traffic management plays an important role. Vehicle calculations and estimated vehicle speed are among the examples that can be done automatically. The main obstacle in vehicle transportation is the presence of shadows due to the influence of sunlight. Therefore, this research is quite important as to support the development of ITS.

Intelligent Transportation System (ITS) is a concept which is part of smart city system that works for transportation management. ITS as a digital highway management and monitoring system generally utilizes digital-based CCTV (Closed Circuit Television) cameras. Video from surveillance cameras can be used for monitoring the number of vehicles and speed using digital image processing. Shadows on the vehicle is one of the noise that must be removed in order to obtain better accuracy. This results in an error in the introduction of the object because often the shadow considered as part of the object. So the information obtained becomes less and not as expected.

In digital imaging, the shadow is an area affected by a lighting change. In other words when the object is placed between the light source and the background surface, the object will block the light to get to the background surface. Basically shadow consists of two categories, namely umbra and penumbra. Based on the the above conditions, the shadow is one of the noise in a video or digital image that affected to the accuracy of image recognition or object counting. So the special treatment is needed to eliminate the shadow.

Shadow removal was investigated using the Subregion Matching Illumination Transfer method, but only for single input In addition, one of the weaknesses of this method is that when used for image data that has a complex structure, such as the variations of umbra, penumbra, and various non-uniform color structures, and the conditions of illumination are varied, then this method needs further development [1]. Some previous other research related to this topic were conducted by Chin-Teng Lin in 2010 using Gaussian Mixture Model method as substraction method background and foreground and this research is done with uniform light distribution [2 – 5]. The shadow elimination for moving objects by updating the Gaussian parameters was also carried out in the research of Budi Setiyono et al [6 – 8]. Mohamad Toha et al, researches to remove the shadow of moving objects by estimating the image foreground with different frame and applying the gamma decoding method to segment the shaded area and object area [9] [10]. Gaussian Mixture Model is also used as the basic for tracking the vehicle and obtained accurate results [11]. Another study of shadow removal in moving object is done by combining the averaging method and Gaussian mixture model as subtraction method for background and foreground in HSV colour space. In this paper, we apply Gaussian mixture model to obtain the RGB background as the input of gamma decoding method to segment shadow pixels and object pixels from a frame of digital video [12], [13].

This paper is structured as follows: The proposed method of improvement of sub region matching illumination Transfer is explained in Section 2. In Section 3, we will present the experiment

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design. In section [4] presents the results and discussion, and we finish with conclusions in Section 5

2. Proposed methods

In general, our proposed method consists of several steps: frame extraction, background subtraction using Gaussian mixture model, RGB background formation, frame difference, gamma decoding method, shadow detection, and shadow removal. The detailed procedure can be seen in Figure 1. The first step we use is frame extraction, where the input is a video and then the video is split into frames. This is done so that the next process can be done more easily. Background subtraction process is done by using Gaussian mixture model. In the proposed method, a gamma decoding process is added to improve the weaknesses of the Sub Region Illumination Transfer method.

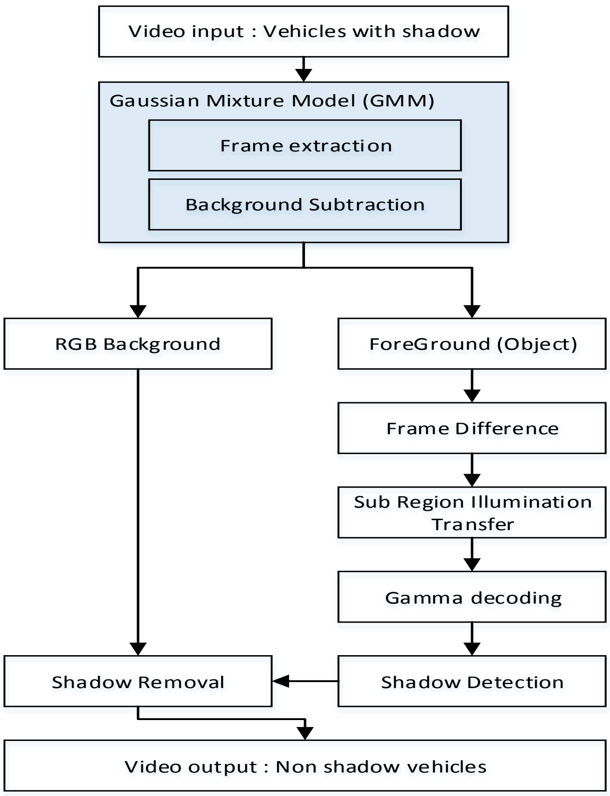


Fig. 1: Proposed Method Steps.

2.1. Background subtraction-using GMM

This method is used to obtain the background so that the separation of moving objects on a video can be detected or better known as foreground. The GMM concept is based on the Gaussian distribution used to group the data in each video frame pixel in order to obtain an appropriate background model. There are several stages in the selection of background distribution: define the input to the distribution of matching stage, and stage elections that reflect the distribution that is above the background ratio. Additionally, it will be considered as foreground. These stages are described as follow :

a) Distribution Matching

At this stage, the input is matched to all distributions to find the most suitable distribution. A pixel is in a distribution if the pixel values are within 2.5 standard deviations of a distribution :

$$\mu_k - 2.5\sigma_k < X_t < \mu_k + 2.5\sigma_k \quad (1)$$

b) Parameter update

At this stage, we update the values of the parameters of GMM which will be used to process the next input. Updated values consisted of weight, mean and variance. Weight value is updated for every extracted frame. To update the value of weight, mean and variance, we use the following formula :

$$\omega_{k,t} = (1-\alpha)\omega_{k,t-1} + \alpha(M_{k,t}) \quad (2)$$

$$\mu_{k,t} = (1-\rho)\mu_{k,t-1} + \mu X_t \quad (3)$$

$$\sigma_{k,t}^2 = (1-\rho)\sigma_{k,t-1}^2 + \rho(X_t - \mu_{k,t})(X_t - \mu_{k,t}) \quad (4)$$

where $\omega_{k,t}$ is weight of k^{th} Gaussian at frame t, $\mu_{k,t}$ is mean of k^{th}Gaussian at frame t,$\sigma_{k,t}$ is the standard deviation of k^{th} Gaussian at frame t, α is the learning rate, ρ is $\frac{\alpha}{\omega_{k,t}}$, and $M_{k,t}$ is 1 if the model matched and 0 otherwise.

c) Distribution Selection

At this stage, we choose a model or distribution that reflects the background. In the first step, models are sorted by ω/σ^2 so the best distribution that describes the background stays on top and the ones that do not describe the background will be replaced by any other distribution. Notice that T is a threshold value that has been predetermined. In order to choose B, the first distribution is used as the background distribution :

$$B = \mathrm{argmin}_b(\textstyle\sum_{k=1}^{b}\omega_k > T) \quad (5)$$

The chosen distribution will be used as a distribution to determine whether the input pixel is a background or an object using (1)

2.2. Shadow segmentation using frame difference

After the frames extraction result and RGB background from GMM, then processed in the frame difference method to obtain differences in the k^{th} and the RGB background. Mathematically the frame difference process can be presented in the equation below.

$$D_k = |I_k - B_k| \quad (6)$$

D_k is the result of the frame difference, I_k is the result of k^{th} frame extraction, and B_k is the RGB background . The process is a segmentation process to get the image object from background, as follow in figure 2. So that the image object can be separated from the existing background. It should be noted that the intended image object is including the shadow of the object.

(A)

(B)

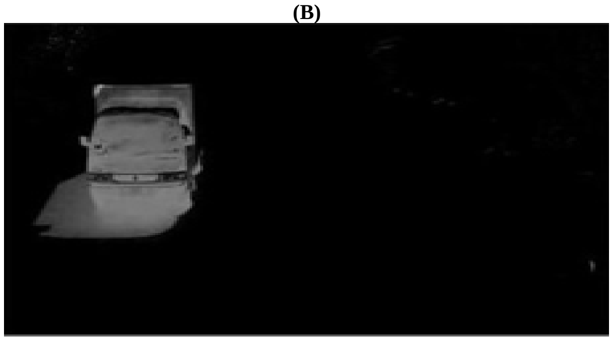


Fig. 2: A) Frame before Any Process B) Frame after Frame Difference Method.

The result of this process will facilitate the gamma decoding method to perform splitting of image pixels and image pixels, since almost uniform background pixels can be ignored.

2.3. Improvement shadow removal and gamma detection

Sub-region Illumination Transfer method works on the HSI space, by filtering the input image to reduce noise, and then mapping ratio [1] as follow:

$$\mathrm{r(x) = H(x)/(I(x) + 0{,}01)} \tag{7}$$

r (x) is the mapping ratio used, I(x) and H(x) represent the intensity and hue value on pixel x. Ratio mapping results are used to separate objects and shadows using certain threshold. Figure 3 is the stage of the improved subregion matching illumination transfer process.
Threshold T is used to separate shadows under the following conditions :

$$\mathrm{S(x)} = \begin{cases} 1, \mathrm{r(x)} > \mathrm{T} \\ 0, \text{ other} \end{cases} \tag{8}$$

S(x) =1 represents the pixel of the object, whereas S(x) =0 as the pixel of the shadow. As the study [1], the weakness of this method occurs when the image has a complex structure, colors are not uniform and lighting conditions are changing. Therefore, in this research, we propose to improve the method by adding gamma detection. Gamma Correction or better known as Gamma is a nonlinear function used to mark (encode) and read luminance (decode) marks on an image, either video or a single image [14]. Gamma Correction is simply defined as the result of the gamma rank on each image pixel value

$$\mathrm{V_{out}} = \mathrm{A} * \mathrm{V_{in}^{\gamma}} \tag{9}$$

Where the non-negative result of the v_in input value will be increased by γ and multiplied by the constant A

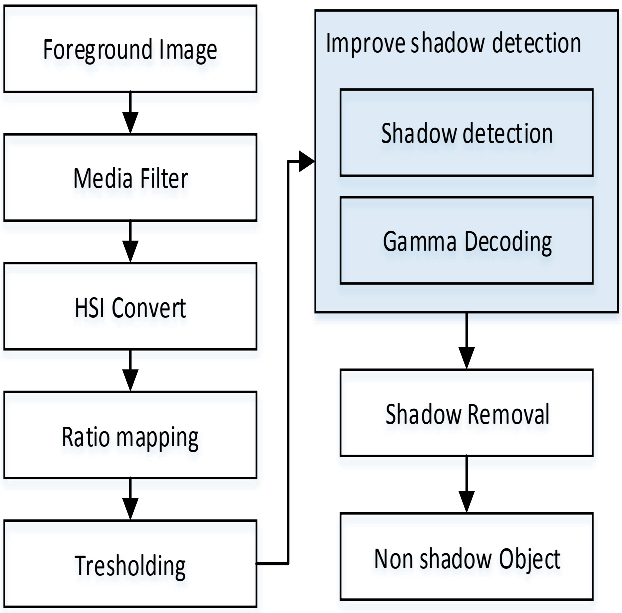
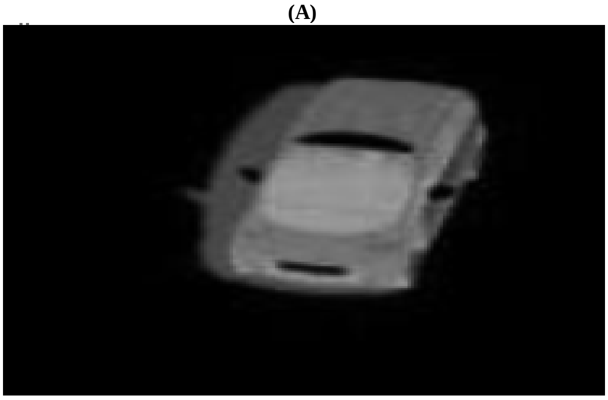


Fig. 3: Shadow Removal Improve with Gamma Decoding.

Generally the value A = 1 and the result is within the [0, 1] range. The gamma value γ <1 is called encoding gamma which is often used in the compression process, whereas the gamma value γ> 1 is called a gamma decoding process that applies more to gamma expansion. Gamma decoding method will be used in the process of identifying shadow pixels on the object. Based on the image illumination information on the image, gamma decoding can "darken" the shadow of the object. It can optimize the thresholding process to separate its shadow and object. Figure 4 is the results of gamma decoding and otsu thresholding to the identified image pixels as shadows and objects.

(A)



(B)

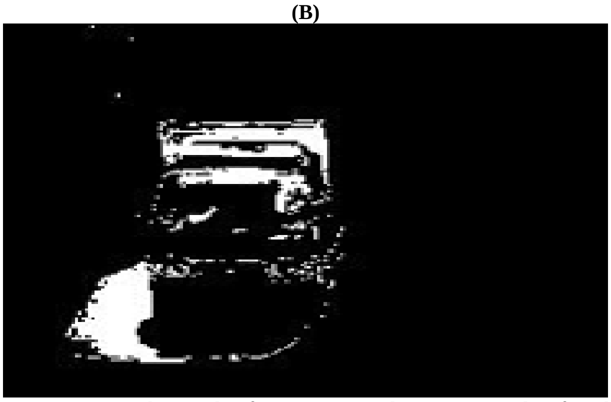


Fig. 4: A) Example Result of Gamma Decoding B) Example of Otshu Thresholding.

3. Experiments design

In this study, [9] simulation videos were used and [1] video that was recorded directly on the highway.
Block diagram to get the PSNR value shown in figure 5, the original object without a shadow is given a shadow by giving lighting. Objects with these shadows are used for testing experiments. Some of the things done in this test are:

i) Shadow removal method used in this study was tested by calculating the value of PSNR (Peak Signal to Noise Ratio). This test is done by comparing the image without the shadow and the image with the shadow to be omitted by the method. So the results obtained can show the level of image reconstruction quality obtained by the method. In this test the data used is simulation video data created using 3Ds Max Community software.
ii) This test is done with several variations of direction of moving objects that is approached the cam-era, away from the camera, flashed in front of the camera and its combined with some variations in light intensity that is 1, 0.8, and 0.5 and some shadow size.
iii) There are two experimental scenarios, using video simulation and video recordings of moving vehicles on the highway. The first scenario, video simulation is used to find out the proposed system reliability, in the following: (i) Create a video simulation with an object without a shadow, called v. (ii) Adding a shadow to v, called v'. (iii) Eliminates the image on v' with the proposed method, yields v''. (iv) Compare

v'' and v to determine performance using PSNR. The simulation layout design design can be seen in figure 6.

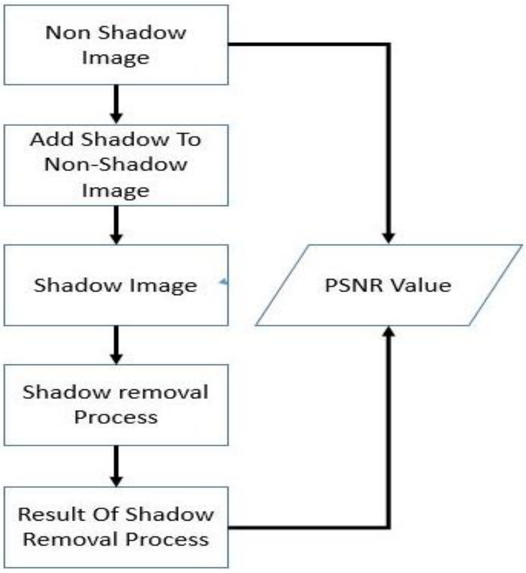


Fig. 5: Simulated Scenario of Experiment to Obtain PSNR Value.

Figure 6 is a simulated video layout, with the position of the light source and position of the camera such that a shadow is obtained on the object. The original object without a shadow is given a shadow by giving lighting The second scenario, we record the video of moving vehicles on the highway..

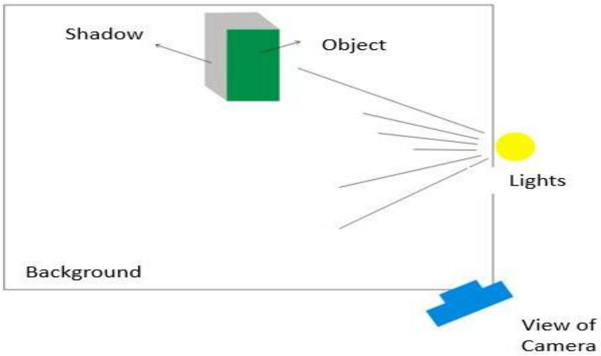


Fig. 6: Layout Design for Simulation Video.

Camera position over the highway, with the direction of the vehicle to the camera, as shown in figure 5. Video recording is done when the sunlight causes the shadow of the vehicle. To obtain the proposed method, our method is done in the following way: (i) tracking and counting the number of moving vehicles.

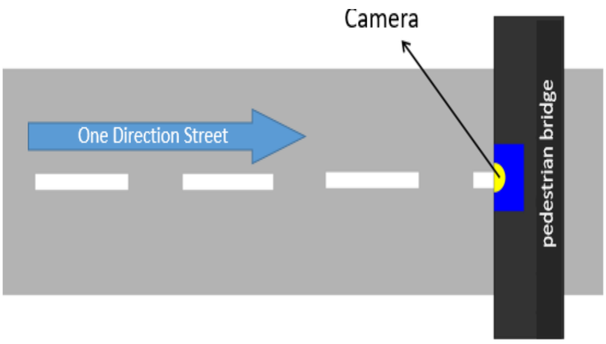


Fig. 7: Layout Design for Real Video.

We are looking for two vehicles that run close together, the shadow of one vehicle befall another vehicle, in this case the shadow of the car on the motorcycle. (ii). Perform a shadow removal on the video, using our proposed method.

(iii) Counting the number of vehicles before the shadow is removed and after the shadow is eliminated. Shadow removal method was also tested with field video test data taken on A. Yani street, Surabaya. The design of the experiment of field data can be seen in figure 7.

4. Result and discussion

Tests of shadow removal methods performed meet some predetermined scenarios. The test was performed on several simulation videos with different light intensity used to obtain PSNR on each test frame. So we know the effect of changes in light intensity on the performance of the method. The intensity variations used are 1 (dark shadow), 0.8, and 0.5 which respectively decrease the value affects the light intensity affecting the shadow, Figure 8.

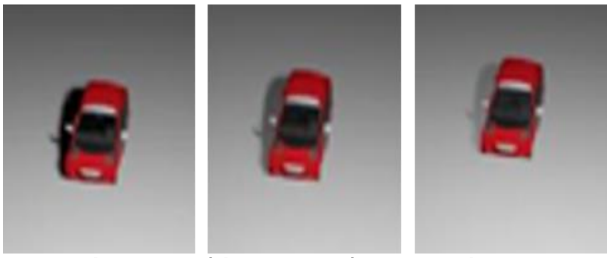


Fig. 8: Simulation Data of the Variation of Intensity Lights A) 1 B) 0.8 C) 0.5.

Figure 9 show several variations of the width of the shadow. Some samples of moving video simulation data created using 3ds Max Community software. Another test scenario is to know the effect of shadow removal method, on the direction of the vehicle.

Fig. 9: Simulation Data of the Variation of Shadow Size as Category A) 1 B) 2 C) [3].

There are 3 directions, namely through the camera, leaving the camera and toward the camera, as shown in Figure 10.

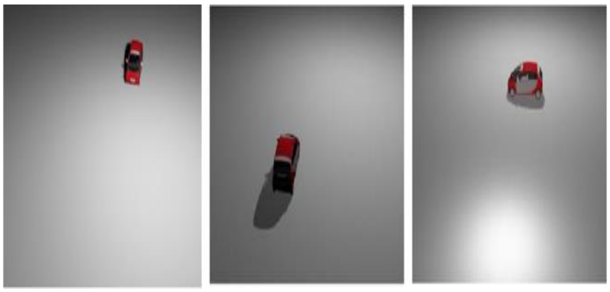


Fig. 10: Simulation Data of the Variation of Direction Moving Object A) Towards the Camera B) Leaving from the Camera C) Through of the Camera.

Therefore, the retrieval of PSNR data has a distance of five frames and three frames. The sample of the experiment that we presented is shown in Table 1. The first test example is, an object with the intensity of shadow 1 (dark), the direction of the movement of objects toward the camera. 52,728. The decrease in PSNR values is influenced by the size of the object. The closer an object to the camera, the value of PSNR tends to decrease, as shown in Figure 11. However, this decrease is not continuous, because when the object leaves the ROI, the next object will pass again.

Table 1: PSNR of Condition Direction of Moving Object Approached the Camera and the Intensity Lights Equals to 0.8

Frame-	R	G	B	Average
30	51.9745	51.5468	51.5735	51.69827
35	51.5587	51.2343	51.141	51.31133
40	51.0086	50.6809	50.738	50.80917
45	50.6029	50.2998	50.1094	50.33737
50	49.6308	49.3309	49.4128	49.45817
Average	50.9551	50.61854	50.59494	50.72286

Furthermore, the two objects move toward the camera alternately. This experiment is to show that, the PSNR value will not take care of continuously, as shown in Table 2 and Figure 12.

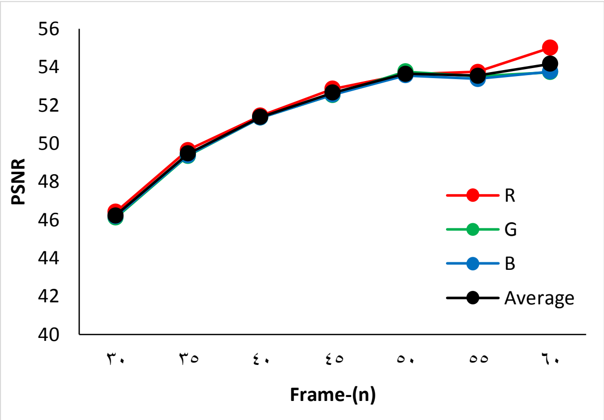


Fig. 11: Graphic of Condition Direction of Moving Object Approached the Camera and the Intensity Lights Equals To 0.8.

Figure 12 shows the value of PSNR on the 125th frame increases again, this is due to the frame, there is a new object into the ROI, while the old object has left the ROI.

Table 2: PSNR of Two Moving Objects Toward to the Camera Alternately

Frame-	R	G	B	average
55	48.0811	48.4851	48.9686	48.5116
60	46.2381	46.7741	47.0751	46.69577
65	41.5257	41.4123	41.5007	41.47957
70	42.8946	42.2598	42.3073	42.48723
125	50.6581	50.5425	50.7721	50.65757
130	49.2232	49.2628	49.4292	49.30507
135	47.3119	47.4593	47.5671	47.4461
140	47.8752	47.8435	47.9259	47.88153
average	46.72599	46.75493	46.94325	46.80805

This suggests that the proposed method of removing the shadows increases accuracy, especially for the calculation of the number of vehicles

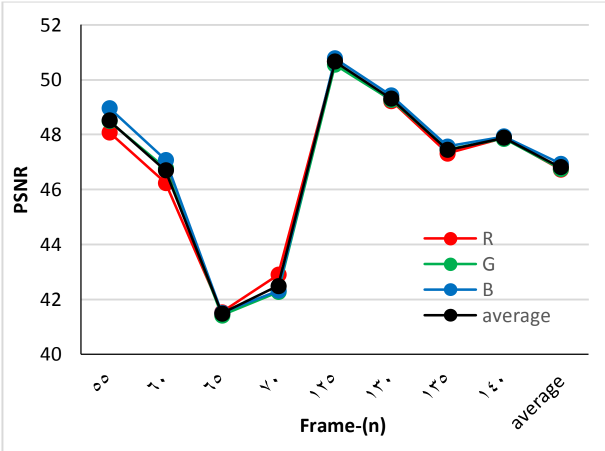


Fig. 12: Graphic of Condition Direction of Moving Object Toward to the Camera and the Intensity Lights Equals to 0.8.

Testing the field, we recorded the video on the highway with the following conditions: two vehicles go hand in hand, one vehicle affected by the shadow of another vehicle

Table 3: Result of All Condition of Our Experiment

No	Testing Names	direction of moving object			Lights Intensity			Shadow Size			Average
		Approached camera	Leaving camera	trough of camera	1	0.8	0.5	1	2	3	
1	Scenario 1	V			v						52.72833
2	Scenario 2	V				v					53.47115
3	Scenario 3	V					v				52.90746
4	Scenario 4		v		v						47.76835
5	Scenario 5		v			v					49.39335
6	Scenario 6		v				v				49.67737
7	Scenario 7			v	v						49.59356
8	Scenario 8			v		v					48.49243
9	Scenario 9			v			v				48.36275
10	Scenario 10	V						v			51.87927
11	Scenario 11	V							v		48.39653
12	Scenario 12	V								v	46.68732
13	Scenario 13		v					v			50.66811
14	Scenario 14		v						v		48.54947
15	Scenario 15		v							v	48.73640
16	Scenario 16			v				v			31.74330
17	Scenario 17			v					v		33.26690
18	Scenario 18			v						v	34.53653

Under these conditions the calculation of the number of vehicles, as in Figure 13(a), obtains the result of the number of vehicles calculated only 1.

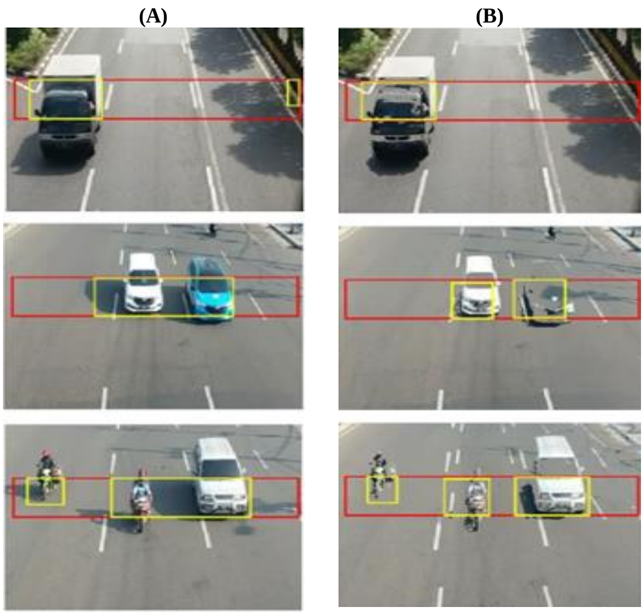


Fig. 13: Result of our Method Applied in Field Data Taken in Street Achmad Yani, Surabaya (A) Before Processing (B) after Processing.

Furthermore, in the same video, we will remove shadows by the proposed method, and calculate the number of vehicles again, as shown in Figure 13(b).Number of vehicles is counted to 2.

5. Conclusions

In this paper, we have described a hybrid method for removing shadows using improved subregion gaussian mixture model, we can concluded as follows : (i) The intensity of light affects the dark level of a shadow formed. It means that the intensity of light that is not too dark and not too vague gives good shadow removal results with this method. (ii)The smaller shadow width will have a better quality.

This is because the pixel image processed in the method becomes less, so the shadow pixel identification error by method becomes smaller and the level of similarity with the video without the shadow becomes higher. (iii) The average PSNR obtained for moving objects with variations in light intensity is 53.47115 dB with the intensity of light = 0.8 and the direction of movement towards to the camera. So this scenario is the best scenario for the shadow removal method in this study.

Acknowledgement

Penelitian Dasar Unggulan Perguruan Tinggi (PDUPT) supported this work with the title of Sistem Deteksi Kecepatan Kendaraan Berbasis Pengolahan Citra Sebagai Pendukung Manajemen Transportasi from the Ministry of Research, Technology and Higher Education of the Republic Indonesia.

References

[1] C. Xiao, D. Xiao, L. Zhang, and L. Chen, “Efficient shadow removal using subregion matching illumination transfer,” Comput. Graph. Forum, vol. 32, no. 7, pp. 421–430, 2013. https://doi.org/10.1111/cgf.12250.

[2] B. Setiyono, D. . . Sulistyaningrum, Soetrisno, F. Fajriyah, and D. W. Wicaksono, “Vehicle speed detection based on Gaussian mixture model using sequential of images,” vol. 890, no. 1, pp. 0–6, 2017.

[3] D. a Reynolds, “Gaussian Mixture Models,” Encycl. Biometric Recognit., vol. 31, no. 2, pp. 1047–64, 2008.

[4] A. Agostini and E. Celaya, “Reinforcement Learning with a Gaussian mixture model,” 2010 Int. Jt. Conf. Neural Networks, pp. 1–8, 2010.

[5] T. Huang, H. Peng, and K. Zhang, “Model Selection for Gaussian Mixture Models,” pp. 1–27, 2013.

[6] B. Setiyono, D. Sulistyaningrum, I. Muhlash, and R. Augusta, “A New Approach Algorithm for Counting of Vehicles Moving Based On Image Processing,” Int. J. Comput. Sci. Inf. Secur., vol. 14, no. 10, pp. 366–370, 2016.

[7] B. Setiyono, D. . . Sulistyaningrum, Soetrisno, F. Fajriyah, and D. W. Wicaksono, “Vehicle speed detection based on Gaussian mixture model using sequential of images,” vol. 890, no. 1, 2017.

[8] D. W. Wicaksono and B. Setiyono, “Speed Estimation On Moving Vehicle Based On Digital Image Processing,” Int. J. Comput. Sci. Appl. Math., vol. 3, no. 1, pp. 21–26, 2017. https://doi.org/10.12962/j24775401.v3i1.2117.

[9] M. Taha, H. H. Zayed, M. E. Khalifa, and T. Nazmy, “Moving Shadow Removal for Multi-Objects Tracking in Outdoor Environments,” Int. J. Comput. Appl., vol. 97, no. 10, pp. 43–51, 2014.

[10] H. Prajapati, S. Longowal, B. Singh, and S. Longowal, “An Approach for Shadow Removal in Moving Object,” Int. J. Comput. Sci. Inf. Secur., vol. 14, no. 8, pp. 781–790, 2016.

[11] Y. Habibi, D. R. Sulistyaningrum, and B. Setiyono, “A new algorithm for small object tracking based on super-resolution technique,” AIP Conf. Proc., vol. 1867, 2017.

[12] A. Prati, I. Mikic, M. M. Trivedi, and R. Cucchiara, “Detecting moving shadows: Algorithms and evaluation,” IEEE Trans. Pattern Anal. Mach. Intell., vol. 25, no. 7, pp. 918–923, 2003. https://doi.org/10.1109/TPAMI.2003.1206520.

[13] Y. W. Shou, C. T. Lin, C. T. Yang, and T. K. Shen, “An efficient and robust moving shadow removal algorithm and its applications in ITS,” EURASIP J. Adv. Signal Process., vol. 2010, 2010.

[14] R. Hobbs, DIGITAL VIDEO AND HD- ALGORITHMS AND INTERFACES, SECOND EDI. No. November. Morgan Kaufmann Publishers, 2010.