Detection of Moving Vehicle using Adaptive Threshold Algorithm in Varied Lighting

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***Abstract*— Designing an accurate tracking algorithm of vehicles captured by a camera, which move from frame to frame in a video sequence is continuing to leave substantial obstacles. The biggest challenges come from different conditions of significant lighting changes, shifting positions of moving vehicles, vehicle´s non-linear deformations, noise gained in data retrieval as well as vastly switching backgrounds. Vehicle tracking from videos recorded at night has a higher difficulty level than the one at daytime. The lighting changes, particularly at night, produce a very low-quality video recording and the resulting image. The reason is that the intensities of lighting at night often change rapidly and drastically. Background subtraction method is frequently used in solving vehicle tracking problems. Nevertheless, it has a weakness which gives noise or disturbance effects. By proposing the adaptive threshold algorithm derived from the Fuzzy C-Means (FCM) algorithm in this study, the accuracy of detecting moving vehicles in minimal lighting can be improved. The results of this algorithm are examined by using Mean Square Error (MSE) and Peak Signal Noise Ratio (PSNR) parameters.**

Keywords*— *vehicle tracking, adaptive threshold, background subtraction, FCM

I. Introduction

In transportation, vehicle detection systems can be defined as systems capable of detecting vehicles and measuring traffic parameters such as traffic count, speed, incident, and others. Vehicle detection can also be implemented for various transportation applications such as vehicle navigation system, vehicle security, real-time traffic control system, and others. The identification of vehicles with video cameras is one of the most promising non-intrusive technologies for large-scale data collection and adoption of sophisticated traffic control and management schemes. Vehicle detection is also the basis of vehicle tracking. Correct vehicle detection results in better tracking. Vehicle tracking methods are highly influential in tracking results[1], [2].

Object detection has many applications aimed to reduce the existing distortion in sequence. However, visual tracking causes many obstacles in practical applications. Also, it produces various problems that cause noise or disturbance effects. Traditional object detection method is performed on each frame or when the object first appears. As the first step in video surveillance, accurate object detection becomes crucial [3]. Nevertheless, it is achieved with great effort because there are still problems with light intensity constraints, shades of detected objects (false detection). To overcome these weaknesses, many applications of object tracking have been developed [3]–[5]. The general approach for object detection is to use information from each frame [4]–[9].

According to Soeleman [8], the first step in the tracking of a moving-object is the process of detecting objects. The purpose of object detection is to distinguish between foreground and background objects. The first stage of object detection is the initialization of scene background. Then the next step is to detect the foreground pixel by using the current background and frame model at the detected pixel level, which depends on the background model used to update the current background idealization and to adapt dynamic scene changes. The output of foreground detection contains noises, generally due to various factors such as camera noise, background colored object noise, and reflectance noise. Noise can be reduced by filtering techniques. Low pass filters and morphological operations can be applied to the pixel map to remove noise caused by those problems. According to [10], the OTSU algorithm is the most classical algorithm utilized to segment images. In determining the threshold, OTSU algorithm cannot detect image optimally when dealing with other images in gray.

The shortcomings of the OTSU algorithm have been resolved by several researchers. One of them is the FCM algorithm (Fuzzy C-Means) [11], [12]. FCM is a clustering algorithm employed to cluster pixels into two groups of foreground and background. Furthermore, FCM is also cluster algorithm without supervision, which has been successfully applied to some problems in pixels. Research conducted by [11] can produce the same degree of membership in each cluster such as color segmentation and image grouping. This study is focused on the tracking of moving objects conducted in environments that have variations of illumination recorded in static video cameras. By proposing the adaptive threshold algorithm obtained from the FCM algorithm, it is expected that the accuracy of moving object detection in the various lighting is improved.

II. Previous Work

There are numerous studies, which have been done concerning the detection of moving objects [6][7]. However, the researches, which have been done for the detection of moving objects in low-light ambiance have not received attention so far compared to the ones with sufficient light conditions. One of the most important factors to deal with the object detection in the low-light atmosphere is that the targeted object is not clearly visible. There are various approaches to overcome this problem as shown in TABLE 1.

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TABLE I. RELATED RESEARCHES

Name, Year	Research	
	Problem, Method	***Result***
Medeiros, Park and Kak, 2008 [4]	Moving object tracking applied to network sensors, by proposing a distributed object tracking system, which uses Kalman filter based on a cluster in a wireless cameras network	Distributed object tracking tools are capable to achieve tracking accuracy comparable to patented tracking methods while requiring a much smaller number of message transmissions in the network
Bhargava and Sharma, 2016 [3]	Conduct a survey of various approaches of object tracking, using the Fuzzy K-Means clustering algorithm	The best results for grouping are achieved using Fuzzy K-Means clustering algorithm. But the best segmentation quality is obtained using Fuzzy C-Means clustering algorithm
Rawat and Raja, 2016 [5]	Tracking objects by modifying each frame's shift, using the average shift algorithm	The detection of moving objects has been done using simple background reduction and single moving object tracking has been performed utilizing the modified mean shift method and Kalman filter
Dhanachandra, Manglem, and Chanu, 2015 [13]	Segmentation employing clustering method, applying K-means algorithm	The comparison of RMSE and PSNR results was conducted for the K-means method with subtractive cluster and classical K-means algorithm, which found that the proposed method had better performance result.

III. PROPOSED APPROACH

The following diagram in Fig. 1 exhibits the stages performed on the proposed method. FCM is applied to deliver the boundary between pixel as foreground and background, which is processed by employing background subtraction. Finally, Morphology is used to gain a well defined object in detection.

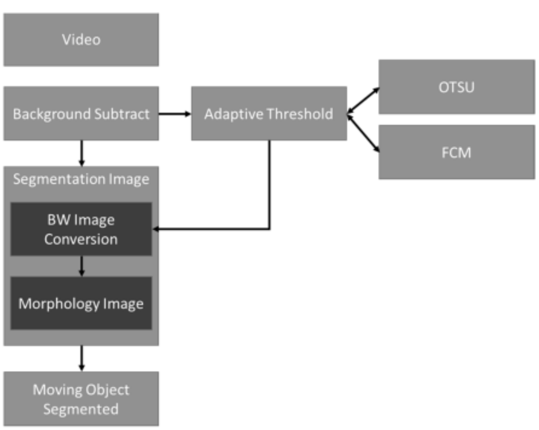


Fig. 1. Proposed Algorithm

A. Data Collection

The data source in this study is collected in the form of video at night approximately from 5:00 to 7:00 PM using a handy-camera (handy-cam). Handy-cam is placed on a stable position pointing to the object.

B. Preliminary Data Processing

Basically, a video is a collection of image sequences. Therefore, the first thing to do is to convert or extract video data into one image, then the image will be processed and analyzed.

C. Methods

1) OTSU:

OTSU performs discriminant analysis by determining a variable by distinguishing between two or more groups naturally. The OTSU method starts with normalizing the histogram image as a discrete density probability function as follow:

$$p_r(r_q) = \frac{n_q}{n}, dimana\ q = 0,1,2,\dots,L-1 \quad (1)$$

where n is the total number of pixels in the image, n_q is the number of pixels r_q, and L is the total number of image intensity levels.

In determining the value of T by maximizing between class variance is defined as follows: $\sigma_B^2 = \omega_o(\mu_0 - \mu_T)^2 + \omega_1(\mu_1 - \mu_T)^2$ (2)

where obtained from:

$$\omega_o = \sum_{q=0}^{k-1} p_q(r_q) \ \ where\ \omega_1 = \sum_{q=k}^{L-1} p_q(r_q)$$

$$\mu_0 = \sum_{q=0}^{k-1} \frac{q p_q(r_q)}{\omega_o} \ \ where\ \mu_1 = \sum_{q=k}^{L-1} \frac{q p_q(r_q)}{\omega_o}$$

$$\mu_T = \textstyle\sum_{q=0}^{L-1} q p_q(r_q) \quad (3)$$

2) Fuzzy C-Means Algorithm:

FCM generates a matrix that contains ownership of multiple objects in each cluster. In FCM, the threshold is defined as the average value of maximum on the object with the smallest and minimum center with the middle center.

$$SSE = \textstyle\sum_{i=1}^{N}\sum_{j=1}^{C} u_{ij}^m \left\|x_i - c_j\right\|^2,\ 1 \le m \le \infty (4)$$

where for the above formula shows the ownership of each pixel in the cluster:

$$\sum_{i=1}^{c} u_{ij} = 1,\ \ 1 \le j \le n$$

$$u_{ij} \ge 0, 1 \le i \le c, 1 \le j \le n$$

$$\textstyle\sum_{i=1}^{n} u_{ij} = 1,\ \ 1 \le i \le c$$

(5)

FCM algorithm consists of the following steps:

- Search for data input in the image
- Select the number of the cluster and its value
- Calculate the division of the matrix using: $u_{ij} = 1/\sum_{j=1}^{c}\left(\frac{d_{ik}}{d_{jk}}\right)^{\frac{2}{m-1}}$ (6)
- Change the cluster in the center with a new cluster: $c_j = \frac{\sum_{k=1}^{n} u_{ik}^m x_k}{\sum_{k=1}^{n} u_{ik}^m}$ (7)

IV. DESIGN OF EXPERIMENT

A. The Result of Background Subtraction

Background subtraction aims to remove the background image so that the foreground can be seen clearly without any various backgrounds. In this study, the result of background subtraction is shown in Fig. 2. Consisting of picture (a) obtained from the subtraction of the image No. 1. The pictures (b), (c) and (d) are image No. 101, 201, and 301 taken from the reduction of those image numbers with the images *t+1*.

Herewith, the results of background subtraction methods:

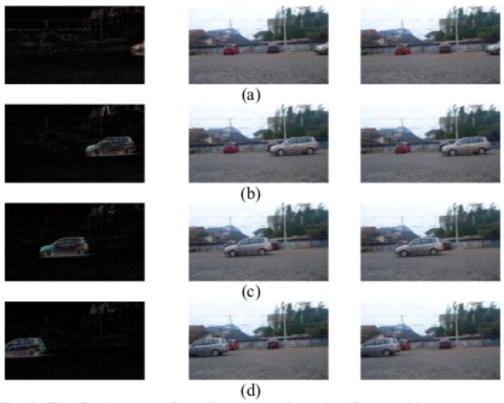


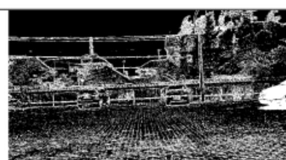
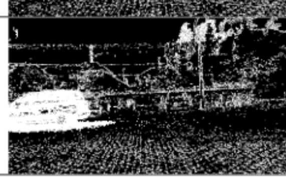
Fig. 2. The final output of moving object detection from a video sequence

B. FCM Process

FCM process follows these steps:

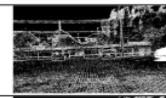
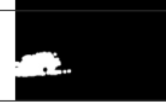
1) *Conversion of RGB to Black and White (BW) using FCM threshold value:*
The threshold delivered from FCM is used as a reference to convert the RGB image to BW image. TABLE II shows the results of image conversion using threshold values obtained from FCM.

TABLE II. IMAGE CONVERSION RESULT FROM RGB TO BW

No. Frame	Threshold	BW Conversion Image
1	0.043140	
101	0.039482	
201	0.030945	
301	0.025980	

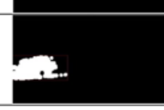
2) *Morphology to remove noise brought from the defined threshold of FCM method*
The result of segmentation delivered from FCM still leaves noises. The noises can be eliminated by the Morphology method. TABLE III demonstrates the outcomes of segmentation to remove the noises brought from the threshold results.

TABLE III. RESULT OF MORPHOLOGY USAGE

No. Frame	BS Conversion	After *Morphology*
1		
101		
201		
301		

3) *The result of objects tracked by FCM threshold*
In this study, the object is said to be successfully tracked if it is contained in a red box. TABLE IV represents the outputs of the images that were successfully tracked.

TABLE IV. RESULT OF TRACKED FRAME

No. Frame	BW	RGB
1		
101		
201		
301		

C. OTSU Process

OTSU process follows these steps:

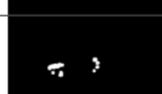
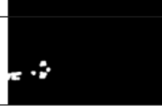
1) *Conversion of RGB to Black and White (BW) using FCM threshold value*
The threshold results conveyed from OTSU are utilized as a reference to convert the RGB image to BW image. TABLE V displays the products of image conversion employing threshold values obtained from OTSU.

TABLE V. IMAGE CONVERSION RESULT FROM RGB TO BW

No. Frame	Threshold	BW Conversion Image
1	0.125490	
101	0.152941	
201	0.156863	
301	0.145098	

2) *Morphology to remove noise brought from the defined threshold of OTSU method*
The segmentation outputs obtained from OTSU still leaves noises. The noises can be thrown out by the Morphology method. TABLE VI reveals the products of segmentation to remove the noises brought from the threshold results.

TABLE VI. RESULT OF MORPHOLOGY USAGE

No. Frame	BS Conversion	After *Morphology*
1		
101		
201		
301		

3) *The result of objects tracked by OTSU threshold*
Similar to the FCM method, the object is said to be successfully tracked if it is contained in a red box. TABLE VII represents the products of the images that were successfully tracked.

TABLE VII. RESULT OF TRACKED FRAME

No. Frame	BW	RGB
1		
101		
201		
301		

V. Result Analysis and Discussion

TABLE VIII displays the errors generated by FCM and OTSU. It can be seen that FCM generates the smallest errors of 3 experiments out of 4 experimental results showed.

TABLE VIII. MSE RESULT OF FCM AND OTSU

No Frame	OTSU	FCM	No Frame	OTSU	FCM
1	0.090531	0.034573	101	0.019065	0.022943
6	0.049897	0.033976	106	0.047027	0.028292
11	0.038849	0.023331	111	0.050962	0.040204
16	0.027238	0.014801	116	0.047735	0.033061
201	0.045123	0.035989	301	0.0429	0.042039
216	0.02759	0.027431	316	0.043512	0.034763
221	0.025598	0.032792	321	0.039707	0.034884
256	0.023392	0.025542	356	0.030802	0.029232
261	0.023497	0.032723	361	0.030096	0.028589
271	0.047864	0.034238	371	0.045641	0.02973

TABLE IX exhibits the results of PSNR based on the biggest difference produced by FCM and OTSU. It shows that FCM produces the largest PSNR values of 3 experiments out of 4 experimental results displayed.

TABLE IX. PSNR RESULT OF FCM AND OTSU

No Frame	OTSU	FCM	No Frame	OTSU	FCM
1	58.5628	62.7435	101	65.3285	64.5244
6	61.1501	62.8190	106	61.4073	63.6142
11	62.2370	64.4514	111	61.0584	62.0881
16	63.7790	66.4278	116	61.3425	62.9376
201	61.5869	62.5691	301	61.8063	61.8943
216	63.7233	63.7485	316	61.7447	62.7196
221	64.0487	62.9731	321	62.1421	62.7046
256	64.4402	64.0583	356	63.2451	63.4722
261	64.4207	62.9822	361	63.3458	63.5689
271	61.3307	62.7857	371	61.5373	63.3988

No. Frame	FCM	OTSU
1	63.7535	59.5638
101	64.6254	65.3275
201	62.5792	61.6879
301	61.8842	61.9073

A. Daylight Condition

The comparison results of MSE and PSNR calculated from different frames tracked under daylight conditions are represented in Fig. 3 and 4. In Fig. 3, the mean MSE obtained from the OTSU and FCM methods were 0.038424889 and 0.030901884 respectively. The resulting error value is said to be better if it is closer to 0. Therefore, it can be concluded that FCM has the lowest error in comparison to OTSU for tracking during the day.

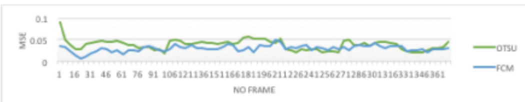


Fig. 3. MSE of Daylight Condition

In Fig. 4, the mean PSNR produced from the OTSU and FCM methods were 57.10052251 and 58.01900696 respectively. The PSNR value is said to be improved if it is greater than 0. Thus, it comes to the end that FCM has the highest PSRN compared to OTSU for tracking during the da

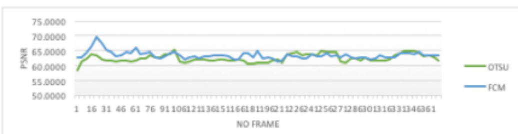


Fig. 4. PSNR of Daylight Condition

B. Condition from 5:00 to 5:30 PM

The FCM and OTSU methods are applied to the data in lighting conditions between the hours of 5:00 and 5:30 PM. Histogram of the threshold values at this time interval is depicted in Fig. 5.

The results exhibit the advantages and disadvantages of each method compared to the results of the manual tracking approach. As shown in Fig. 5, OTSU gets a very large threshold value. This will greatly impact the color conversion results, which will also affect the tracking decision making.

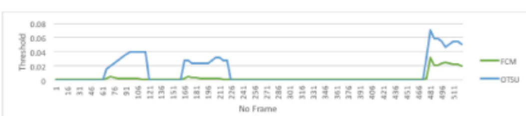


Fig. 5. FCM and OTSU Threshold from 5:00 to 5:30 PM

C. Condition from 6:00 to 7:00 PM

The histogram of the threshold values at this time interval is shown in Fig. 6. In Fig. 6, OTSU gets a very large threshold value. This will greatly influence the color conversion results, which will also be significant to the tracking decision making.

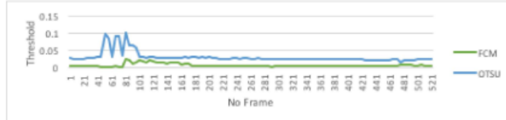


Fig. 6. FCM and OTSU Threshold from 6:00 to 7:00 PM

The histogram of the MSE values of FCM and OTSU at the time interval from 6:00 to 7:00 PM can be seen in Fig. 7.

Based on the graph shown in Fig. 7, there are many values of MSE, which are 0. It demonstrates that there are no moving objects in the frame or the results of FCM and OTSU compared to the results of manual tracking looks no difference. When there are moving objects, the results obtained by FCM and OTSU have values higher than 0. However, it can be concluded as well that the FCM method is able to get detail changes on each frame while OTSU less able to obtain the detail correctly so that the error produced FCM can close to 0.

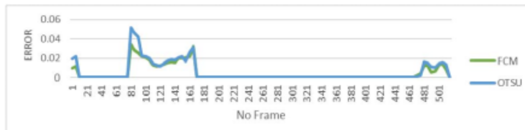
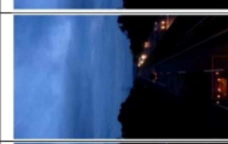
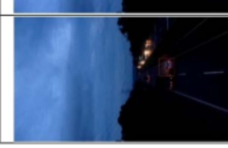


Fig. 7. MSE of FCM and OTSU from 6:00 to 7:00 PM

The pictures in TABLE X show the difference of vehicle detection generated by the FCM method at time intervals from 5:00 to 5:30 PM and from 6:00 to 6:30 PM. The tracking results gained from normal lighting conditions are good enough compared to ones from less lighting conditions. The reason is that lighting greatly affects the captured object so that the results of tracking at night cannot be done maximally by applying the background subtraction method.

TABLE X. COMPARISON OF ERROR OF FCM FROM 5:00 - 5:30 PM AND 6:00 - 6:30 PM

No.	FCM AT 5:00 - 5:30 PM	FCM AT 6:00 - 6:30 PM
1		
2		
3		

VI. CONCLUSION

The important findings of the research on the detection of moving vehicles in varied lighting can be then summarized as follows:

a) Moving vehicle detection in varied lighting uses the FCM algorithm because the cluster algorithm without supervision, which has been successfully applied to some problems in pixels is FCM (Fuzzy C-Means).
b) Adaptive threshold applied in FCM improves the accuracy of moving vehicle detection in varied lighting.
c) The assessment based on MSE and PSNR reveals that FCM algorithm generates fewer errors so that applying FCM algorithm to detect moving vehicles in varied lighting is more promising.

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