VOL. 10, NO. 16, SEPTEMBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

www.arpnjournals.com

BLOB MODIFICATION IN COUNTING VEHICLES USING GAUSSIAN MIXTURE MODELS UNDER HEAVY TRAFFIC

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ABSTRACT

This study uses Blob Analysis technique to optimize Gaussian Mixture Model method performance in detecting and counting cars and motorcycles under heavy traffic conditions. It is profound that by optimizing the minimum and maximum blob area in order to obtain proper blob size from a video image's region of interest will also improve the accuracy of system. The result shows that appropriate parameter settings can increase accuracy by 28.02% for motorcycles and 10.84% for cars.

Keywords: intelligent transportation system, gaussian mixture models, blob analysis, heavy traffic condition.

INTRODUCTION

The need for fast and convenient transportation led to increasing the number of vehicles. This increase in the end makes the field of research Intelligent Transport System (ITS) likely to continue to be developed. One of ITS research areas in the Advanced Traffic Management System is Traffic light performance optimization. Future traffic light system is a combined system with Artificial Intelligence (AI) where the traffic light's rolling time adapting to traffic crowd on the road in order to reduce traffic jam and traffic violations [1].

AI implementation on traffic light certainly requiring a process that is capable of recognizing and calculating traffic density as studied by Indrabayu *et al.* which uses Viola Jones method to detect and calculate the vehicle [2]. This study applying image processing techniques in the tracking process and counting vehicle objects. Although it manage to recognize and count vehicle objects, yet this studies has not reached the best accuracy and can only detect one type of vehicle, therefore development in this research are continuously conducted by optimum identification in Region of Interest (ROI) using Gaussian Mixture Models (GMM) under heavy traffic conditions [3]. The "Heavy traffic" is a condition where the vehicles are moving slowly due to crowded traffic through a road section, or a complex traffic junction that can be described as chaotic traffic [4].

This study resuming the previous studies that using GMM method because it is one of popular method in vehicles detection and calculation to distinguish and count vehicle on the main road. This method is quite reliable in the background extraction and foreground segmentation process so the characteristics of a moving object in video surveillance are easier to detect [5-6]. It is also proven to be powerful method for moving object detection using background extraction techniques [5-7,8,9]. The use of this method is still being developed, that optimizes the background and foreground segmentation on GMM using Simplified Mean Shift Filter and K-Means Clustering [10].

Although this scheme is fairly effective and has been developed for vehicle detection and counting, this method still possess several weaknesses in its implementation, which are quite sensitive to light variance and shadow, video resolution, and vehicle density on the road [11]. Hence, by looking deeply of these factors possibility of optimizing the detection and counting of vehicles are opened widely. In addition, some research also look in optimizing of foreground segmentation by adjusting GMM system parameters [12], [13].

In the previous analysis which only optimize the performance of GMM by adjusting ROI technique, the best accuracy for motorcycles is obtained at the front of ROI with average accuracy of 74.03% and for the cars at the back of ROI with an average 86.46% of accuracy [3]. Obviously it is still expected to increase because the adjusting ROI in the study is not associated by analysis technique that can optimize foreground size from vehicles object, where in this study will be combined with blob modification technique by analysis range value.

RELATED WORK OVERVIEW

Numerous Research using GMM has been done for video surveillance. Generally are used to detect object movement. Moving object in a static area in this method referred as foreground. While static area that does not perform any significant movement on frame stream will be considered as background [14]. Although the foreground size area will reveal the detected type of object, there are possibility of error in determining the foreground. This risk occurs due to many factors, such as vehicle's shadow is detected as object and a condition where 2 close vehicles considered as single object [11].

To optimize moving object detection in frame stream using blob analysis, Tao JIA *et al.* [15] make comparison with Symmetric difference and single-mode background models using Gaussian distribution, even though used objects are not devoted to vehicle as implemented in this study. In single- mode background process, blob analysis is used as a parameter to update

VOL. 10, NO. 16, SEPTEMBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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background models. Three-class threshold region are made to carry out this model. Study analysis illustrated by showing foreground segmentation results without analytical statistic like obtained accuracy value, and the absence reference value of optimal blob analysis that is optimal to implement in frame area.

Yoginee B. Bramhe (Pethe), and PS Kulkarni [16] using GMM in computer vision to perform graying process, binarization, denoising and moving targets detection. Target object in the study are specific to the car on the road while this research is done for cars and motorcycles. The maximizing detection process uses blob analysis so the foreground area size that will be considered as car will be easier to identify. Stages in detecting moving objects is carried out by developing a boundary block detection algorithm, writing chain codes, and detecting boundaries in the boundary block. Meanwhile, Thou-Ho (Chao-Ho) Chen *et al.* [7] uses blob analysis techniques to maximize objects detection. Using two-way flow of vehicles to detect cars and motorcycles. The study is quite optimal with an average accuracy of 91.7% for 320 x 240 pixels video resolution. However the sampled traffic intensity in that study are categorized as loose traffic.

GAUSSIAN MIXTURE MODEL

Gaussian Mixture Models (GMM) is a type of density model consisting of Gaussian function components. This algorithm is good enough to perform background extraction process because it is reliable towards light variances and repetitive object detection conditions [18]. This method is one of the old semi-supervised learning methods and often used in image processing [8].

This algorithm method, each pixel in image frame is modeled into a *K* Gaussian distribution. *K* stand for the number of Gaussian distribution model usage. Each Gaussian model represents a different pixel color. In this case, grayscale image use scalar value, while the RGB image use vector value. Selection of used models is based on image resolution consideration, computer system performance, and background models complexity. For each image frame, each pixel will be matched with every *K* Gaussian distribution model on the corresponding pixels, starting from distribution model that carry the largest to smallest probability as formula (1). A pixel is confirmed match with one of Gaussian distribution model if it is included in 2.5 deviation standard range. On the contrary, if a pixel has value beyond 2.5 deviation standard then the pixel is declared unfit the Gaussian distribution model.

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

Chance of *K* Gaussian distribution function modeling is described as follows.

$$P(X_t) = \sum_{k=1}^{K} \omega_{k,t} \cdot \eta(X_t, \mu_{k,t}, \Sigma_{k,t}) \quad (2)$$

where the *K* value indicates the number of distribution, $\omega_{k,t}$ is the weight of Gaussian function to-*K* at time *t* and $\eta(X_t, \mu_{k,t}, \Sigma_{k,t})$ is Gaussian probability density function. Gaussian probability density function is formulated as follows.

$$\eta(X_t, \mu_{k,t}, \Sigma_{k,t}) = \frac{1}{(2\pi)^{n/2}|\Sigma_{k,t}|^{1/2}} e^{\left\{-\frac{1}{2}(X_t - \mu_{k,t})^T \Sigma_{k,t}^{-1}(X_t - \mu_{k,t})\right\}} \quad (3)$$

where the $\mu_{k,t}$ value shows mean value and $\Sigma_{k,t}$ shows covariance of Gaussian functions to-*K* at time *t,* with covariance matrix value is originated as.

$$\Sigma_{k,t} = \sigma^2 \cdot I \quad (4)$$

for computational reasons these formula assumes that the red, green, and blue pixel values are independent and have the same variances [18].

The next step is selecting and determining which pixels are included in foreground and background objects. Selection initially sorting the existing model based on ω/σ^2 (fitness value), where the most optimal distribution as background remain placed on top priority, while the the most distribution that do not reflect background is laid on the lowest priority. From several distribution models, several highest value are selected until weight values meet the predetermined threshold value. Selected distribution model then later on will be the background candidate.

If the pixel colors are categorized to one of background model candidates, the pixel will be considered as background (pixels rated 0 or black). Other than, pixels that not included in background models category will be considered as foreground (pixel rated 1 or white) and binary image results will be processed in further process. The selection value of distribution use the following formulation to start.

$$B = arg\ min_b\left(\sum_{k=1}^{b} \omega_{k,t} > (1 - c_f)\right) \quad (5)$$

where the c_f value states maximum data portion in the foreground object. Follow-up process is forming box detection, counting, and object classification.

In addition, using more model in each pixel will cause the background extraction process is more adaptive since more color components can be modeled in every pixel. But it is certainly will compensated by drain large system resources, especially when the used imagery resolution is quite large, though this can be optimized as described in [19].

Region of Interest

An image processing that focus on specific area detection needs Region of Interest (ROI). Through optimizing ROI, the image space will be easier to capture and also beneficial in faster processing. A moderately wide area in an image area makes computation process for calculating each pixel value will only be a burden, besides it does not need to be done entirely. On image preprocessing sometimes only certain parts are needed to produce data that is ready to be processed into the next stage. In the vehicle object detection using GMM methods, optimizing ROI placement sometimes necessary to optimize the process which has been done in previous studies [3]. Data input from CCTV fully display in all traffic lane of vehicles. Though the focus area is only a few parts of the course. Therefore it requires preprocessing adjustment so that vehicle detection process can be focused and optimized.

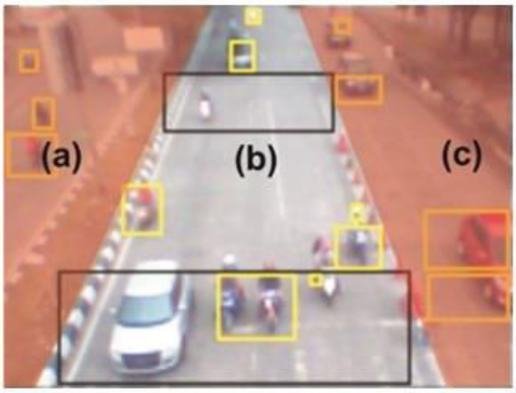

Figure-1. ROI on vehicle detection preprocessing. (a) and (c) are not lane area of interest. (b) lane area of interest.

Figure-1 shows three consecutive lanes where (a) and (c) are not considered to be part of observation. The only lane that comes to interest of this research is lane (b). However, since both (a & c) lanes are included in the interest area, some vehicle on the lanes are also detected. This give importance of ROI for object detection process in image processing primarily for vehicle detection on a heavy traffic.

Blob Analysis

In an image processing that uses the foreground segmentation, blob analysis algorithm is a technique used to declare pixel area of an image that becomes the focus detection [15]. To determine the blob value, there are things to be considered in producing optimal blob. On computer vision, several parameters that should be look closely i.e. AreaOutputPort, CentroidOutputPort, BoundingBoxOutputPort, ExtentOutputPort, OutputData Type, MinimumBlobArea, MaximumBlobArea, and MaximumCount [12].

Laplacian of Gaussian is used as formulation for searching blob value on computer vision method as described in [20]. The process starts by marking area that is considered as foreground object, then collecting data area into the blob such as initial pixel position, length of the x-axis and y-axis, and the pixel area. A blob area figured as in Figure-2.

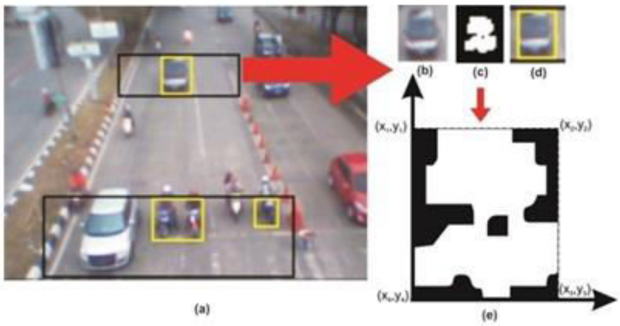

Figure-2. Blob analysis process in vehicle detection. (a) Big frame of the original image. (b) Cropping object. (c) Foreground segmentation. (d) Object detection using bounding box. (e) BLOB area in x, y axis direction.

As in Figure-2, point (a), (b) and (d) are visible object detection process that is obtained through foreground area detection from binarization process as point (c). Determining blob area can be analyzed by setting pixel vector values as point (e).

PROPOSED METHODOLOGY

There are several processes carried out in this study. Starting from implementing GMM process based on Computer Vision performance and optimize object detection process that is conducted by adjusting of ROI and blob analysis. GMM process as previous research in [3] with the proposed approach in general are shown in Figure-3 below.

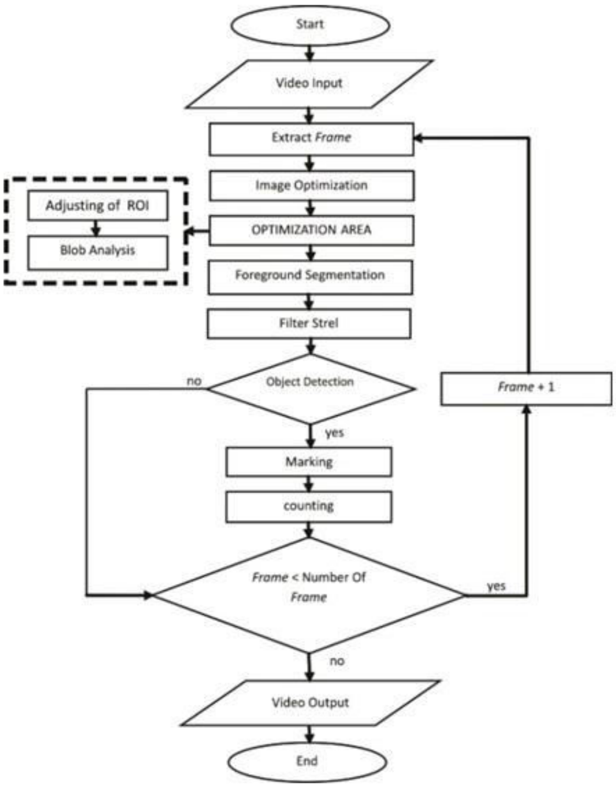

Figure-3. GMM flowchart with the proposed methodology.

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GMM process as in the flowchart, starting with the video input process, in this study used 30 fps video data for 33 seconds and 120x160 pixels resolution with six data files. The data video is firstly converted into several frames that furtherly processed into images. For the image optimization process, the original RGB image color transformed into grayscale format. Furthermore, foreground segmentation process serves to separate foreground and background. Foreground and background separation process described in formula (1)-(5). But before foreground segmentation process, the image processing optimized by adjusting of ROI approach that has been developed from previous studies [3] and updating value of blob as parameters that analized in this study as seen in Figure-4. *Strel Filter* function is used to perform filtering so it can easily be distinguished between target objects and noise. The process continued by detecting and counting the vehicles until all the frames processed.

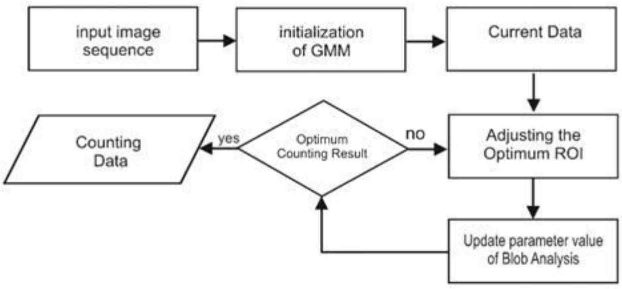

Figure-4. Adjusting the ROI scheme with blob analysis.

This study used two ROI to analyze the influence of blob parameter value initialization towards accuracy improvement. Area ROI on image frame as shown in Figure-5.

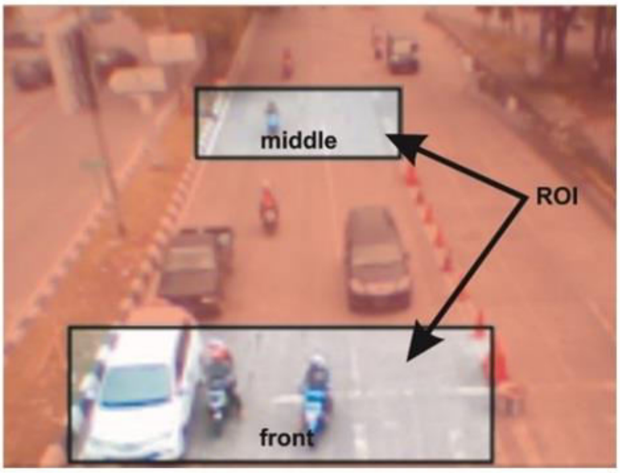

Figure-5. ROI in an image.

Furthermore, to maximize detection and counting process on ROI that has been setup, system conduct corresponding blob parameter analysis. Blob parameter values in programming process provided as following *pseudocode*.

```
%Blob Analysis
%Set parameter of Blob Analysis
1. Setup bounding box = true
2. Setup MinimumBlobArea=int
3. Setup MaximumBlobArea=int
4. Setup ratio for detecting > 0.2
5. Counting result from ratio
```

In the two sets of ROI each given three blob parameter values that has been previously analyzed by vehicle area coverage that passes through a ROI. Given parameter values as shown in Table-1.

Table-1. Parameters of Blob analysis.

Blob value	Car		Motorcycle	
	Front	Middle	Front	Middle
1	min=50, max=500.	min=10, max=100.	min=4, max=20.	min=5, max=10.
2	min=500, max=5000.	min=100, max=1000.	min=20, max=100.	min=5, max=20.
3	min=250, max=2500.	min=50, max=500.	min=10, max=50.	min=2, max=10.

min = MinimumBlobArea, max = MaximumBlobArea

After inserting blob value in every adjusting of ROI, then analyze process to measure the influence of inserted parameter values towards accuracy. Although the designed system may occur errors (false positives), but this study only evaluates accuracy Influence (True Positives). Therefore in measuring and increasing accuracy of previous results used the following formula.

$$\%\,Accuration\,(Acc) = \frac{True\ Positif\ (TP)of\ object}{Actual\ Object} * 100\% \quad (6)$$

$$\%\,Improvement = \frac{Current\ Result - Starting\ Result}{Starting\ Result} * 100\% \quad (7)$$

On formula (6) accuracy measured by comparing vehicle calculation results that are true positive is detected using optimized system towards manual calculation results (actual counting). Whereas formula (7) is used to measure improvements gained after blob analysis is implemented into the system (current result) towards the accuracy results of previous studies (starting result).

EXPERIMENTAL RESULTS AND DISCUSSION

Based on data analysis result by placing designed system parameters, so in the Table-3,4,5,6 shown results of vehicle calculation derived from same actual data in previous studies [3]. Vehicle counting results from previous study that compare in this paper as shown in Table-2.

Table-2. Vehicle counting results from ROI aprroach.

ROI	Motorcycle acc (%)	Car acc (%)
Front	**74.03**	79.72
Middle	55.74	83.27
Back	27.09	**86.46**

acc = accuration, ROI = Region of Interest

VOL. 10, NO. 16, SEPTEMBER 2015 ISSN 1819-6608
ARPN Journal of Engineering and Applied Sciences

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Motorcycle Counting Result

Table-3. Motorcycle counting result in front detection.

Data	Actual	True Positif of Motorcycle					
		BV.1		BV.2		BV.3	
		a	acc (%)	a	acc (%)	a	acc (%)
1	132	101	76.52	106	80.30	122	92.42
2	129	102	79.07	111	86.05	124	96.12
3	130	96	73.85	120	92.31	120	92.31
4	186	157	84.41	174	93.55	180	96.77
5	128	102	79.69	109	85.16	119	92.97
6	150	126	84.00	145	96.67	147	98.00
Average			79.59		89.00		94.77

a = counting result, acc = accuration, BV = Blob Value

Table-4. Motorcycle counting result in middle detection area.

Data	Actual	True Positif of Motorcycle					
		BV.1		BV.2		BV.3	
		a	acc (%)	a	acc (%)	a	acc (%)
1	132	52	39.39	50	37.88	111	84.09
2	129	97	73.48	120	93.02	114	88.37
3	130	88	69.84	120	92.31	25	19.23
4	186	72	40.22	165	88.71	145	77.96
5	128	70	55.55	114	89.06	96	75.00
6	150	84	56.00	123	82.00	117	78.00
Average			55.75		80.50		70.44

a = counting result, acc = accuration, BV = Blob Value

Based on counting results data in Table-3 for motorcycle detection in front area obtain optimum results in blob value 3 with average accuracy by 94.77, while for motorcycle detection in middle area optimum results obtained at blob value 2 with an average accuracy reach 80.50 as shown in Table-4.

Car Counting Result

Table-5. Car counting result in front detection area.

Data	Actual	True Positif of Car					
		BV.1		BV.2		BV.3	
		a	acc (%)	a	acc (%)	a	acc (%)
1	57	52	91.23	3	5.26	21	36.84
2	32	31	96.88	5	15.63	21	65.63
3	39	38	97.44	15	38.46	28	71.79
4	50	47	94.00	13	26.00	24	48.00
5	46	35	76.09	4	8.70	8	17.39
6	54	53	98.15	13	24.07	38	70.37
Average			92.30		19.69		51.67

a = counting result, acc = accuration, BV = Blob Value

Table-6. Car counting result in middle detection area.

Data	Actual	True Positif of Car					
		BV.1		BV.2		BV.3	
		a	acc (%)	a	acc (%)	a	acc (%)
1	57	43	75.44	1	1.75	6	10.53
2	32	31	96.88	7	21.88	20	62.50
3	39	36	92.31	18	46.15	25	64.10
4	50	40	80.00	8	16.00	24	48.00
5	46	35	76.09	11	23.91	22	47.83
6	54	40	74.07	6	11.11	17	31.48
Average			82.46		20.13		44.07

a = counting result, acc = accuration, BV = Blob Value

Based on counting results data in Table-5 for car detection in front area obtain optimum results in blob value 1 with average accuracy by 92.30%, while for cars detection in middle area optimum results obtained at blob value 1 with an average accuracy reach 82.46 as shown in Table-6.

Graph illustration of blob value parameter performance for vehicle detection and counting, as shown in Figure-6.7.

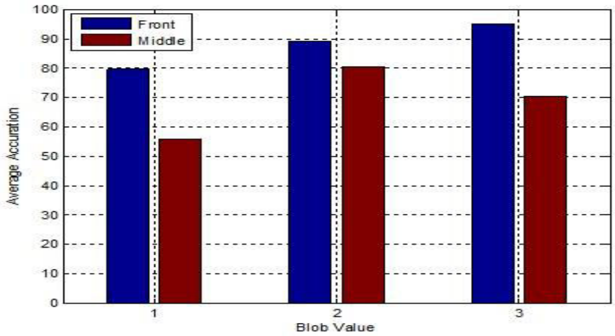

Figure-6. Performance BV for motorcycles counting.

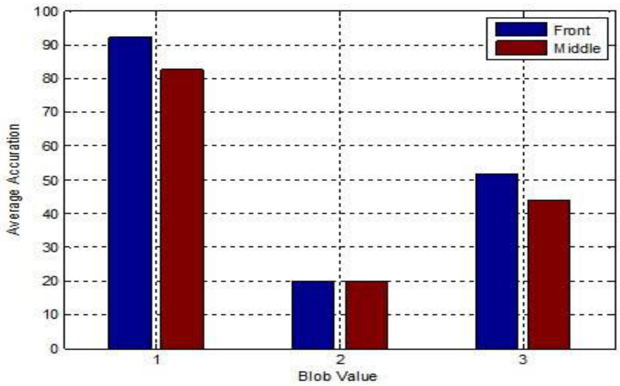

Figure-7. Performance BV for cars counting.

DISCUSSIONS

From counting results and average calculation accuracy, it appears that motorcycles and cars, obtained at the front ROI placement as the best results. For motorcycle the average accuracy rate reached 94.77% and 92.30% for cars. It is definitely influenced by ROI broad areas cover that traversed by vehicles. For disproportionate ROI, in this case the size setting of ROI is too small for a big vehicle or too wide for the small vehicles, can cause error rate of detection process be even greater and it will affect the calculation process. From the results of this study also found that by ROI placement, road lane that becomes the research target can be more focused and optimalized.

Nevertheless, adjusting a good ROI can not be separated from the good parameter setting of blob analysis as well. The result showed that for the motorcycle, blob parameter setup value minimum is 10 and maximum 50 pixels (BV.3) whereas for cars, minimum 50 and maximum 500 pixel (BV.1). It is seen that blob range value needs to be adjusted to object size that will be detected in a frame image. Minimum and maximum value decision with certain range, will mainly determine the type of vehicle. In this study, blob analysis adjusted with average blob size area for all types of motorcycles and cars. Motorcycles in real conditions tend to be smaller than a car. So blob analysis turn out to be very important concern. If a predetermined area fit to car it will be detected as car, same with the motorcycle. Hence from this study the decision of minimum and maximum blob area limit should be a reference to maximize the detection process.

Minimum and maximum blob decision has several factors apart from analysis of object size that will be detected. Those factors include the ratio of video data, and size of video resolution. The point is required more analysis for blob area of object within minimum and maximum range values. In addition to classify different types of cars that tend to be more varied, it require further blob analysis. Moreover, based on the best accuracy results in previous studies that shown in Table-2 and calculated using formula (7), then obtained accuracy improvement by 28.02% for motorcycles and cars by 10.84%. This increase surely would make GMM process optimization by combining both adjusting of ROI and blob analysis is very important to do on detection and calculation process of various types of vehicles. Therefore it deserves to be continued and implemented on an intelligent traffic light system.

CONCLUSIONS AND FUTURE WORK

In this paper,research has been conducted GMM performance optimization to calculate the number of vehicles using Blob Analysis modification techniques combined with adjusting of ROI in heavy traffic conditions. Data results shows that the GMM performance optimization can improve accuracy. The accuracy of motorcycle attained 28.02% and cars by 10.84%. For further research can be made by analyzing ROI influence with Blob Analysis on data with various ratio and resolution and also influence of this techniques for false positif rates.

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