Daytime Road Marker Recognition Using Grayscale Histogram and Pixel Values

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***Abstract*— Rapid economic and industrial growth has impelled the use of motor vehicle on the roads worldwide. Despite the advancement in road systems that can handle the vehicle upturn, the increase in traffic accidents has yet to be contended. Road markers are very informative to the drivers while driving and different sets of markers are normally used between the highways and the normal road. Significantly, recognizing the correct road marker is highly essential due to the different types of marker (broken lane, continuous lane, double lanes) which can alert the drivers on the condition especially on the non-highway roads to warn the drivers from not to overtaking at the prohibited area. At day time, from morning until evening, the illumination plays major roles where the light from the sun could impact the images captured on the road. The proposed lane marker detection method is a vision system using new algorithm applying the gray level histogram average median in defining the threshold value to counter the illumination issues and the average median pixel count algorithm for the road marker classification process classifying the correct types of marker throughout the day. The algorithm had been tested at 3 different times namely in the morning, afternoon and evening. The best accuracy is in the afternoon at 98% due to excellent illumination condition whereas the accuracy were lower in the morning and evening at 81.13% and 94.84% respectively due to low light condition, effecting the markers illumination on the road.**

***Index Terms*— Lane marker, Real-Time, graylevel histogram, pixel count algorithm, illumination.**

I. Introduction

THE statistic on traffic accidents in Malaysia has spawned a concerning increase at an average of 9.7% yearly over the last three decades. It is believed that the increase in road accidents is linked to the rapid growth of population, economic development, industrialization, and motorization development experienced by the nation [1]. Generally, the accidents are caused by the combination of these three factors which are road user errors, road environment faults and vehicle defects [2]. Some examples of road user errors which contribute to the increase in road accidents are deliberately overtaking on prohibited areas especially at double lines, continuous lines, and astonishingly; the emergency lanes. There are also those who switch lanes without giving prior signals causing longer reaction time towards and emergency situation. Another concerning contributing factors of users errors are driving when feeling fatigue and sleepy. Hence the development of the vision based for lane detection and lane changing system could be explored and implemented to assist road users while driving.

The research related to the lane detection and its subdivision, had been active in these past two decades with considerable outputs made in the past few years [3-4]. More autonomous features are developed and added to the Auto-Assist Driving System (ADS) such as Lane Departure Warning (LDW) – the most portions where the attention had been given. Adaptive Cruise Control (ACC), Lane Keeping (LK), Lane Centering (LC), Lane Change Assist (LCA) and Turn Assist (TA). For LDW, the main objective is to warn the unintentionally lane departure events, while LCA is to assist the driver for a safer process of lane changing. In LCA studies, some examples of the works are, the research on the distance estimation between cars for safety prior of changing lanes [5-6] and the issues on the unseen area by the driver called blind spot, which is done by scanning the blind zone area to make it safe prior to the lane changing event [7]. With these features, the driver will be alert and informed that it is safe to change lane or overtaking at that particular time.

However, while changing lanes are allowed by using these features, still the fundamental of lane markers recognition is essential for driver to know whether the area is safe for the action. Common road markers are as shown as in Fig 1.

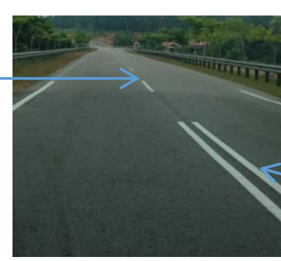

Fig. 1. Road Markers

Currently, the recognition of the lane marker types in

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determining the road condition for driver's alert, for LCA is not yet resolved. This is when the lane marker recognition would be a useful parameter for the ADS in making better and safer decision while changing lanes. For example, the double lane is strictly hazardous area and the driver is not allowed to overtake others to avoid accident while broken lane is vice versa. As the changing lanes will require the vehicles to be in the moving state, this is why the real-time recognition system is important to recognize the pattern sequence of the markers and able to alert and disallow driver from overtaking intentionally at the prohibited area.

The proposed vision system in this paper is using the new algorithm in image processing techniques to detect and recognize the marker in the non-urban road (broken and double lane) which can be used as one of the features for lane changing warning system decision to avoid driver from overtaking at the prohibited area and causing accident. The graylevel histogram is used for the thresholding limit to cater the illumination issue and the calculation on the total white pixels comparison used to recognize the types of the lane markers.

II. Related Works

A. Previous Work

The lane detection process locates the painted lane markings on a road surface with many of them using vision-based systems. Since the lane detection would need to track the marker, the pre-process marker recognition also may also apply the same process. This is achieved by using one or two cameras placed at the front of the windshield. The video recorded in a digital format are then analyzed to extract the features related to the lane for the recognition process. Researchers would agree that, object tracking may be exigent due to unbridling issues encountered while developing the algorithm. Various approaches have been used to accomplish the task either using a single mode camera or stereovision camera for 3D setup [8-9]. Nevertheless, the type of markers detection on the road had not been explored due to majority of the researchers was working on the road lane detection and its application.

The latest camera sensor technology can capture images either in color or black and white enabling researchers to choose whether to process images in grey scale or color, or both when selected for optimum pre-processing method. Devising optimum pre-processing method is vital because failure to detect accurate result will lead to more hitches that may call for rectification during post-processing leading to further exhaustive procedure. The input images or videos taken are either in the form of straight lanes, complex clothoid or spline models. The images will be processed and the features such as textures, colors, edges, local gradient, contours, frequency domain and geometrical shapes [10-13] can be used in representing the lanes. Edges are one of the features frequently used in lane detection process where it identifies the contour of an object by looking on the pixel brightness changes in sharp output and has no discontinuities.

The gradient of the pixels plays major roles in recognizing the contour lines of an object in an image. This is because the on the road surface, the paint and concrete create strong edges implying the large gradients between the road and lane exists due to their differences in their intensities. Many researchers are using the conventional gradient-based feature method to solve this problem [14].

In video or image processing, the region of interest (ROI) is very important to be defined before the image is processed. This is to reduce the computational complexity because most information is useless in an image color spaces may be selected in color processing to the desired model such as the RGB, HSL, HSV or others. Prior to establishing the image threshold, some researchers would enhance their input video by filtering and eliminating noise interference. One of the most popular filtering methods is Gaussian Blur which is to improve the detection of the edge and producing more accurate output [15]. Other researchers have attempted other methods such as by converting the binary image back to its grey level to enable the edge detection process and finally detecting the lane [16]. Issues related to the illumination, occlusion, shadow, road condition and etc., still a contributing factor for the researchers to improve the accuracy and the capability of the tracking and recognition system. While the lane recognition system is important, research should also look on the typical road sign marker as and its function to embed the feature in the ADS.

III. Proposed Method

The complete proposed method for the system is shown as in Fig. 2.

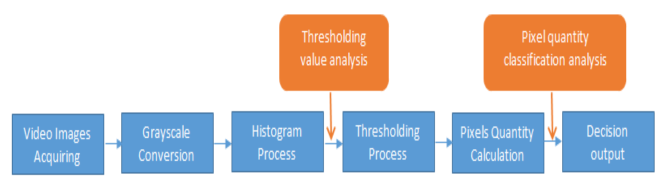


Fig. 2. Proposed Method

The process started with the video image acquiring process and going through the image processing steps. In the thresholding for the binary image, samples of data were used in deciding the value for the thresholding process which is important to cater the illumination issues contributed by the sunlight – discussed in section III-C. The binary images from the image will then been analyzed on the level of pixel quantity in the classification of the road marker type as discussed in section III-D. The result from the pixel quantity calculation will be used as the threshold to differentiate the type of the marker in the last output decision.

A. Camera Setup and Positioning

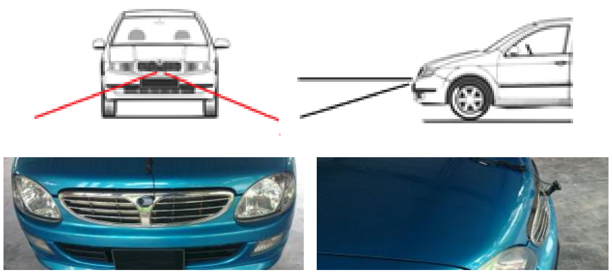


Fig. 3. The positioning of the USB camera

By using the USB type camera with video resolution of 1280×720 and 30fps (HD 720p) and 5MP still images, the camera is located at the center of the car as in Fig. 3. The video of the road images are recorded for analysis. Three different main time (the worst case scenario) are recorded namely in the morning, afternoon and in the evening to check the effect of the illumination issue on the road marker as shown in Fig.4. The contrast of the lane marker versus the road is higher in the afternoon due to the high intensity of direct sunlight and its angle. While in the morning and evening, the intensity of the sunlight and the shadow of the car might affect the images from the video.

Fig. 4. Video Images for three different time zones (morning, afternoon, evening)

In this experiment, the shadows, obstacles and the sun location which is opposite to the camera causing glaring which affecting the video quality is ignored. The speed of the car recording the video is between 50-60 km/h.

B. Image Processing and Feature Extraction Process

The video image will be filtered to get the Region of Interest (ROI). With the region, less computing will be achieved by removing all the unnecessary information in the video images. In this video, only the small part, the trapezium will filter the important part of the images for the processing. This process is done by masking the video images using the bitwise AND operation [14] as in equation (1) where $dst =$ destination, $src =$ source. In this process, a mask is created with a binary value 0 and 1. The area which requires to be passed on will be set as 1 in the mask filter. By using this method, only a partial of area or the ROI can be filtered and used for the processing.

$$dst(I) = src1(I) \wedge src2(I) \text{ if } mask(I) \neq 0 \qquad (1)$$

The function in equation (1) calculates the pre-element bitwise conjunction for two arrays when $src1$ and $src2$ have the same size.

C. Thresholding value and Image Histogram

The thresholding [15] as in equation (2) is the process to get the best value for differentiating the white lane and the road as background where $dst =$ destination, $src =$ source, $x = x$ pixel coordinate and $y = y$ pixel coordinate. In this segmentation method, the separation is based on the intensity between the lane and the road.

$$dst(x,y) = \begin{cases} \max Val & if \ src(x,y) > thresh \\ src(x,y) & otherwise \end{cases} \qquad (2)$$

To calculate the threshold value, the one-stage thresholding approach is used, where an image is separated into two classes of pixels: the foreground pixels (the white lane) and background pixels (the road). In this process, the road images captured in the morning, afternoon and evening are analyzed to get the best value for the thresholding. The images are converted to the grayscale images and by using the histogram method [15] to decide the threshold value to differentiate the lane and the road. In the histogram, the range to differentiate the lane and the background will be analyzed. Each of the data set (morning, afternoon, evening) will provide the range median value from the histogram for the bin value < 200 pixels which situated between the bin for the markers pixel and the road pixel, as in equation (3) where $T =$ Time Taken (morning, afternoon, evening) and $n = 2,3,4,\ldots$. The average value from these three data will be calculated as in equation (4) and will be used as the final threshold value.

$$Med_T = \frac{BinValue_{T1} < 200\,pixels_{\min} + BinValue_{Tn} < 200\,pixels_{\max}}{n} \qquad (3)$$

$$Ave_{Th} = \frac{\sum_{i=1}^{n} Med_{Ti}}{n} \qquad (4)$$

The average threshold value is calculated from the data, and later used in the thresholding process. The images are then converted to binary where the white lane detected is converted to 1 and the rest is 0 which resembles the road background.

D. Pixel calculation and decision

$$Med_T = \frac{DoubleLane_{MinPix} + BrokenLane_{MaxPix} < 200\,pixels_{\max}}{2}$$

(5)

$$Ave_{PixTh} = \frac{\sum_{i=1}^{n} Med_{Ti}}{n} \tag{6}$$

IV. RESULTS

A. Data collection and pre processing

The color video images are recorded for different time zone namely in the morning, afternoon and in the evening. The bitwise AND method is used by a mask binary image to filter the video images to get the ROI. In the result, the square shape is used to filter the important information to reduce the processing time as shown in Fig. 5.

Fig. 5. The process to filter for the Region of Interest (ROI)

Various patterns for the double and broken lanes captured as in Fig. 6, were processed to extract the features and detect the type of the markers. Double lane marker captured having more or less on the same patterns, while the broken marker consists a sequence of different patterns.

(a)

(b)

Fig. 6. Patterns captured (a) sequence of double lane (b) sequence of broken lane

B. Thresholding value

The histogram is used to find the best value for the thresholding. Separately analyzed according to the different time zone (morning, afternoon & evening), the data from the afternoon video is giving a significant difference between the white lanes and the background, whereas both in the morning and in the evening, the graylevel values got shifted and getting nearer between both the background and the white lane as shown in Fig. 5. This is due to the illumination issue based on the sunlight angle direction and the intensity of the light which affected the color of the lane marker causing it to be easier in differentiating the lanes and the background compared to lower light situation such as in the morning and in the evening.

In the histogram, the range between the white lane and the background contains pixel lower than 200 units are selected.

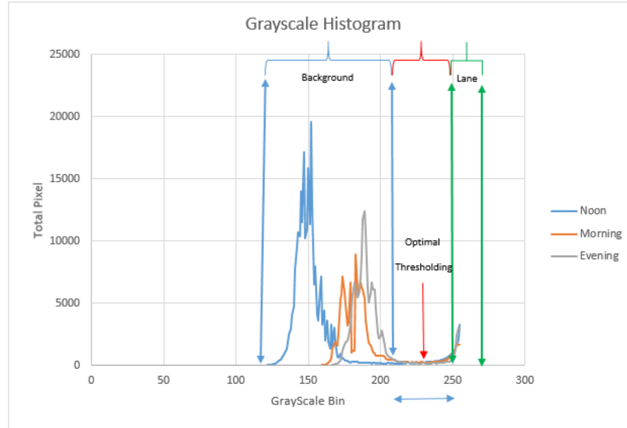


Fig. 7. Grayscale Histogram for three different time zones

Based on the combination of different output histograms as in Fig.7, the final value for optimal thresholding calculated must be between the ranges of the three data lines. The median of the range will be selected to be the threshold setting value. The calculation of the threshold value is shown in Table 1.

TABLE I

THRESHOLDING VALUE ANALYSIS

BIN NUMBER	**TIME**		
	Morning	Afternoon	Evening
Range Bins with < 200 pixels	182-236	218-235	216-247
Median	209	226.5	231.5
Average Median (Threshold value)		**222**	

The selected threshold value is used and the output would be a binary image as in Fig. 8.

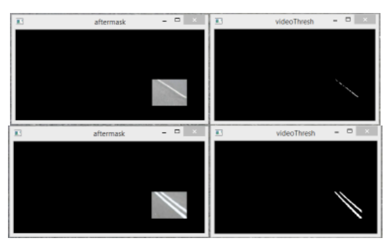
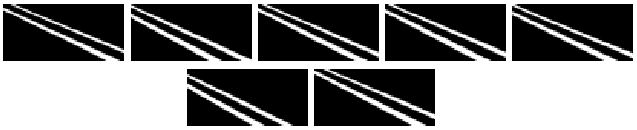


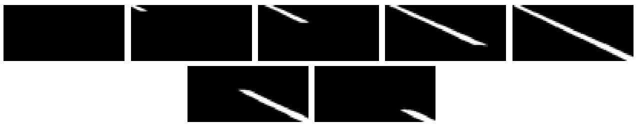
Fig. 8. The output from the thresholding process for broken and double lane markers

C. Pixel Total Decision

The results of the thresholding process of the images as shown as in Fig.9. For double lane, the white areas are more or less the same on each of the frame, whereas the broken lanes had shown that the totals of white pixels are changing throughout the full sequence while the car is moving.



(a)



(b)

Fig. 9. The thresholding output (a) sequence of double lane (b) sequence of broken lane

Based on the three data sets from three different time zone (morning, afternoon and evening), the median of each range between the total pixels of double and broken lane is calculated. From the graphs as in Fig.10-12, the count of pixels for both double and broken can be seen separated due to the total white pixels lane are different in quantity. The higher range of pixel count in the morning and the evening are due to the illumination factor causing the differentiating process between the lane and the background getting harder in the thresholding process prior to the pixel count process. The calculation of the pixel value count for the classification is shown in Table 2 starting from getting the median for three different times and finally the averaging process.

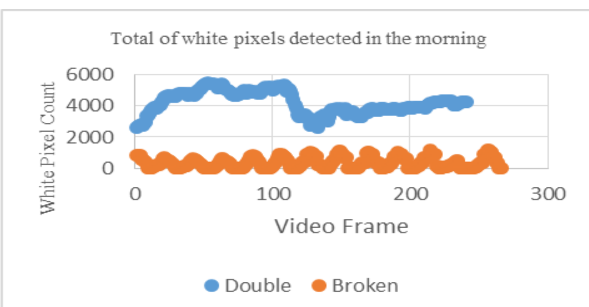


Fig. 10. Total of white pixel (lane marker) in the morning

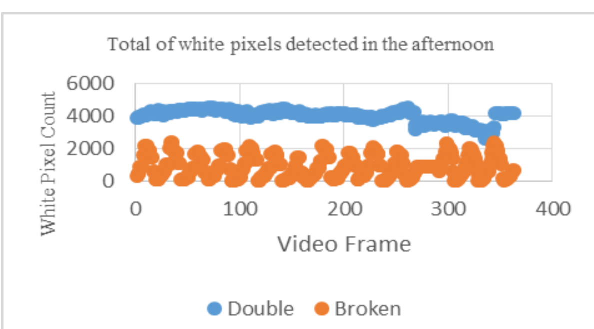


Fig. 11. Total of white pixel (lane marker) in the afternoon

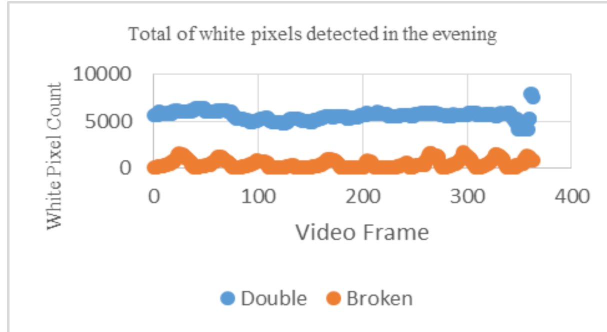


Fig. 12. Total of white pixel (lane marker) in the evening

TABLE II

PIXEL COUNT ANALYSIS FOR CLASSIFICATION THRESHOLD

PIXEL	**TIME**		
	Morning	Afternoon	Evening
Range for lowest pixel double lane and highest pixel broken lane	1868-2624	2418-2575	1721-4081
Median	2246	2496.5	2901
Average Median (Total pixel value)		**2547**	

D. Accuracy Testing

The average thresholding value for binary image conversion and the average value of the total pixel for classification obtained from the previous sections are used in the image processing algorithm and had been tested in the video images. Each of the output frames will be label as either broken or double lane on top left corner after the process of recognition completed as in Fig. 13. The proposed method is tested at 3 different times namely morning, afternoon and evening and the result as in Table 3.

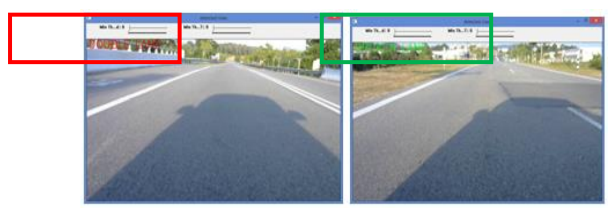


Fig. 13. The output of the video frames with label on top right

TABLE III

ACCURACY TESTING

	Total Frames Tested	Total Frames with correct result	Accuracy
Morning	1023	830	81.13%
Afternoon	1029	1027	99.8%
Evening	989	938	94.84%

From Table 3, the highest accuracy of the proposed algorithm is in the afternoon, where the light from the sun, is perpendicular to the road. The illumination effects, give no shadow and cause the white lane distinctly can be detected from the background in the image processing method. Whereas, the accuracy in the morning and evening are lower due to yellow lighting from the sun and also its angle, creating more shadows and glaring on the road, affecting the histogram value causing the white lane a bit harder to be detected from the background.

V. Conclusion

From the result, the type of lane marker recognition can be performed by using the image processing methods which are the grayscale histogram and the pixel count value. The average thresholding and classification value calculated at different time in a day is important for the system to accurately detecting the marker throughout the day. The illumination from the sun changing from the morning to evening will affects the accuracy of detecting the white lanes. Shadows from the other objects such as cars, trees and other, also has a notorious effect on the lane marker detection as the white pixel values and counts will differ. The best illumination time, namely in the afternoon, response better with the selected value from the thresholding analysis due to the better differences between the white lane and the background with the accuracy in the afternoon detection at 99.8%. In the low light condition and with certain angle illumination, the background appears to be nearly the same with the background, causing the algorithm to have errors in the classification with the data in the morning and evening at 81.13% and 94.84%. Future works is to find the image illumination factor for the system to enable the algorithm in enhancing the thresholding process for the low light condition (morning and evening) which to improve further on the detection accuracy. By detecting the right marker on the road, it can alert the driver about the condition of the road especially on the federal road and also to remind the drivers not to overtaking on the prohibited area.

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