Traffic Light Arrow Shape Recognition Using HOG Descriptors and SVM Classifiers

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Abstract – *Autonomous intelligent vehicles technologies research have expanded and more effort have been made to implement a better safety features in a transportation sector. The lack of visibility of the drivers to perceive the signal from the traffic light is one of the risks for safety. Hence, by introducing the detection and recognition of the traffic light arrow shape using image processing to deliver a clear signal to a drivers and eliminate their difficulties to perceive either the round or arrow shape of the traffic light, this risk can be reduced. The current research has focuses on the condition of the traffic light and not indicating the direction of the arrow. In this paper, an algorithm for traffic light recognition for arrow symbols at daytime has been proposed using digital image processing and machine learning. In the machine learning technique, the Support Vector Machine (SVM) classifier has been used for the learning process and conduct a classification process as well. The HOG descriptor was extracted from the feature extraction process for the purpose of the training and classification process. As a result, this algorithm has achieved 98.52% accuracy, 1.48% error, 98.52% precision and 98.68% of recall through the testing process.*

Keywords: *HOG Descriptor, Traffic light Arrow, SVM Classifier, Machine Learning, Image Processing*

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I. Introduction

In a real world, a traffic light has been developed by using either round or arrow shaped. A round shape of the traffic light denotes the colors which are consists of red, green and yellow while the arrow shape has four directions which are forward, right, left and U-turn arrow and using the same color concept. The colors of the traffic light refer to the precedence of the vehicles in a road junction while the arrow shape shown the intention of a drivers in a junction [1]-[2].

Basically, in a real atmosphere that has a lot of signs and buildings in a road, it has given difficulties to the driver in perceiving the signal of the traffic light. As for the consequences, huge amount of accidents which have led to horrible fatalities have been reported around the world involving the vehicles in the radius of traffic light junction [2]-[4].

The basic fact and naturality of the human are they cannot focus on too many things at same time and whenever there are a lot of disturbances played in their sight; their focus would be totally declined. In this case, it can be related to the vision of the driver during passing a road which has huge physical appearances which would be heavily interrupted when they want to focus on the signal of the traffic light arrow.

Previous works were focused on the general traffic light detection and recognition which involve on extracting the focus area to their specific color spaces[5]-[6], shapes [7]-[8] and finally identifying it as the traffic light. These methods adopted the ROI based and blob detection to detect the objects by binarizing the image and segmenting pixels [9]-[10]. It would detect the circular object or specific shape using machine learning such as deep neural network [11]-[13]. Prior to that features are extracted such as Histogram of Oriented

Gradients (HOG) and Sped Up Robust Features (SURF) [14]-[15]. Yet, all these researches do not concentrate on the direction of the arrow such as left, right, forward and U-turn.

Hence, in this paper, a method is proposed to interpret the direction of the arrows pointing by using HOG features and SVM classifier.

II. Dataset

The samples of the images in the dataset for the proposed algorithm have been captured manually in real time in the range below than one meter. Total of 150 samples, divided evenly for three groups which are the forward, left and right arrow with 50 on each of the group as in Fig. 1.

In each of the group it is even break further to two categories related to the color which are 25 for red and 25 for green. These images of the traffic light arrow have been captured in a different angle and under a slightly a different illumination which are sunny day and cloudy day as purpose to gain some variation in the dataset. The samples of the traffic light arrows in the dataset have been divided into two set which are training set and test set by process of the cross validation.

The training set has been fixed to70% of the samples from the dataset while the other 30% have been used to test set. From the cross-validation process, the samples of the traffic light arrows in the dataset have been randomly separated to the numbers of the training set and the test set. Basically, the training set has been used to train the SVM classifier while the test set was used to determine the performance of the SVM classifier. The dimension for all the samples of the traffic light arrow images that have been captured in the dataset were in frame of 360×640. The samples of the data depicted in Fig. 1.

(a)

(b)

(c)

Fig. 1. Samples of the dataset (a) Forward Arrow (b) Right Arrow (c) Left Arrow.

III. Proposed algorithm

Fig. 2 shows the pipeline for the proposed algorithm. Basically, the proposed algorithm is implemented by two techniques which are machine learning and image processing. In the machine learning algorithm, SVM classifier acts as classification model to learn each of the type for the traffic light arrows.

As a learning phase, the SVM classifier has used each type of the traffic light arrows in the training set as a process of training. In this case, each samples of the traffic light arrows in the training set have passed through the process of pre-processing, detection phase and hog descriptor before the training of the SVM classifier has been accomplished.

As a validation process, the samples of the traffic light arrows from the test set has been used to evaluate the performance of the trained SVM classifier. After the process of the evaluation of the SVM classifier has been accomplished, the input video for each type of the traffic light arrows which have recorded under sunny day have been processed to yield an outcome from the algorithm that has been proposed into the output video.

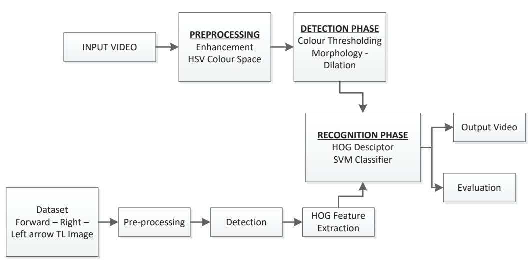

Fig. 2. Proposed Algorithm in the System.

A. Pre-processing

In the proposed algorithm, the pre-processing technique has been used to enhance the image and convert the state of image to HSV color space. To enhance the image, the technique of the histogram has been implemented. Basically, the images of the traffic light arrow that have been appeared were in low contrast and blur [16]. This could cause the processing to get difficult because the targeted part in the image which can contribute to the extraction of the desire information would solely look invisible at the end of the process.

Hence, by implementing the technique of the histogram equalization, the intensity and poor contrast of the images of the traffic light arrow can be upgraded as this technique has a capability to spread out the high contrast portion to the whole border of the image[16]-[17].

In another step, the natural RGB color space of the images for the traffic light arrow has been converted to HSV color space. Basically, HSV color space has three main elements which are hue for the selection of the color, saturation for the intensity of the color while value is to measure the luminance of the color in the image. From these three elements, it has allowed HSV color space to be interpreted as identical with the vision of human and immune with light illumination [3], [18]-[20].

B. Detection phase

- Color Thresholding

Color thresholding is the method that has been used to conduct a segmentation process to the image [10]. To acquire the only pixel for the shape of the traffic light arrow in the image, the color thresholding algorithm has been used by separating the color channel in the HSV color space [19], [21].

In this case, to segment the region of the green traffic light arrow in the image, the green color channel has been fixed up its value based on the hue, saturation and value and same thing goes to segmentation process the red traffic light arrow. Like has been explained in the pre-processing phase, the HSV color space has its own value for hue, saturation and value which are each of these three elements has its own function. By using this fact, the green color channel and red color channel have been set their value for each component of hue, saturation and value.

The criteria that have been taken into the consideration to decide the formation of each of the color channel are the selection of the color, the intensity of the image and the lightness of the color. After the thresholding value for the green color channel and red color channel has been fixed, any region in the images which have lied within the pixel of the green color channel and red color channel will automatically segmented and appear as a major region in the resultant binary image.

Hence, the shape of the red traffic light arrow in the image can be acquire through the thresholding value of the red color channel while the green color channel has been used to gain a major region of the shape for the green color arrow in the binary image.

- Morphology Dilation

Morphology dilation is an algorithm that has been used to repair the broken part in the image and restructure the damaged region. To accomplish this task, the morphology dilation has a capability to add more pixels into the image and enlarge the invisible part [21]-[22].

Basically, the image which seems slightly broken or unstructured has lost its pixel within the border of the image. Thus, to tackle this issue, the morphology dilation has made a deep process to the image by inserting more pixels to replace the missing pixel in the image and as a consequence the resultant image has turned out to be more visible.

C. Recognition phase

- HOG Descriptor

HOG descriptor is an algorithm used to extract the feature of the image [5], [23]. This algorithm is classified under a computer vision technique for feature extraction process [20], [24]. Feature extraction process is very crucial because it is a process that has a capability to gain and collect the information from the image. Hence, to obtain the information from each type of the traffic light arrow, the hog descriptor has been used to extract the feature for each of the traffic light arrow type.

Basically, this algorithm utilizes the local oriented gradient histograms to summarize the occurrences of gradient orientation in local parts of the image [23]. By using this fact, the hog descriptor has been able to gain the information from each type of the traffic light arrow by separating the image into a block. A block slightly overlaps with its neighbors. Each block is further divided into non-overlapping regions called cells. For each cell, histograms are generated by gradient orientation and magnitude.

During this process, grouping of orientations and magnitudes are performed for better results [24]. As a result, the resultant magnitude and orientation for each cell in the image will be stored as a nine bin of histogram. The nine bins of histogram will represent the appearances of the shape for the traffic light arrow which is in form of resultant vector.

- SVM Classifier

SVM classifier is an algorithm which is classified under a machine learning technique to make a classification process for each of the traffic light arrow [10]. There are three processes in SVM classifier which are training, validation and recognition phase.

To be able to make recognition for each of the traffic light arrow, the mandatory step has been taken by SVM classifier to learn each type of the traffic light arrow first and it is called by training phase. Basically, the SVM classifier has learned about each type of the traffic light arrow based on its feature. It is natural for the forward arrow, right arrow and left arrow to have different features because their head and tail placed to different orientation.

From this different type of features, the SVM classifier has been able to accomplish the learning process and the data for each type of the traffic light arrow has been stored by itself. After the training process has been finished, the SVM classifier has passed the validation process to compute their performance in the training phase.

In the validation process, the SVM classifier has made recognition to the samples for each type of the traffic light arrows from the test set. In recognition phase, the input video for each type of the traffic light has been processed until the output video can be acquired. In this phase, the SVM play a vital role after it has been used to classify the type of the traffic light arrow before the output video will present the result from the whole algorithm.

IV. Results

A. Training set

- Pre-Processing

In the process of the histogram equalization, all the samples for the traffic light arrows have been successfully enhanced after their low contrast in the original images have been improved Fig. 3 shows that all the images for the traffic light arrows in the test set look brighter and clear after their intensity has been able to be upgraded after the process of the histogram equalization.

Fig. 3. Results of the traffic light arrow after the process of histogram equalization.

After the process of the enhancement using histogram equalization, the traffic light arrow samples in the dataset have been successfully converted to HSV color space as in Fig. 4.

- Detection Phase

Since the process to HSV color space has been accomplished, the color thresholding has been successfully segmentize to all the samples for the traffic light arrow in the test set. From the result that has been shown in Fig. 5, all the shapes for each type of the traffic light arrow in the samples of the test set have been appeared as major region in the binary image as their background have been eliminated.

From the result shown in Fig. 5 by using HSV color space, the shape for green color of the traffic light arrow have been acquired in the image after it had been thresholded by the pixel of green color channel while the red shape for the traffic light arrow was segmented through the range of the red color channel.

For the morphology dilation, the purpose of the process is to repair the damaged part in the shape of the traffic light arrows. From the color thresholding process, it was appeared that some of the shape of the traffic light arrows in the dataset look broken and unstructured. After the process of morphology dilation, the result as in Fig. 6 has shown that the shape of the traffic light arrow image look visible with their broken part has been restructured.

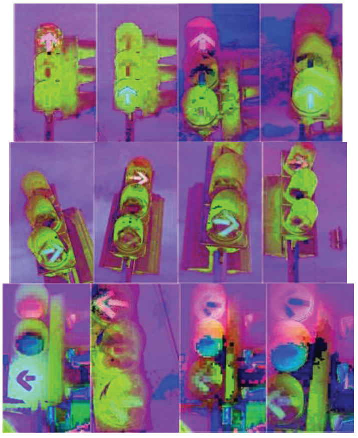

Fig. 4. Results of the traffic light arrow after the process of conversion to HSV color space.

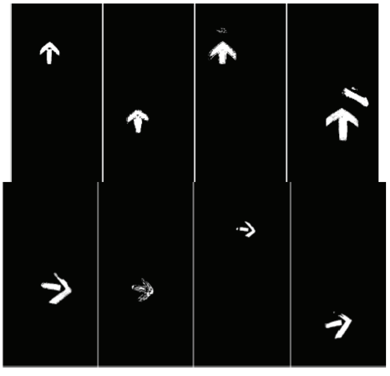

Fig. 5. Results of the traffic light arrow after the process of color thresholding.

- HOG Descriptor

This process is very crucial because they will feed the data about each of the traffic light arrow in the dataset to the SVM classifier to accomplish the training phase. From the morphology dilation process, the samples of the traffic light arrow in the dataset have passed the hog descriptor process for feature extraction process.

The appearance of the traffic light arrow images in the dataset after the process of color thresholding were in the binary image which the shape of the traffic light arrow has a value pixel of one while their background has zero pixel value. In Fig. 7, it has shown that the feature for the shape of the traffic light arrow in the dataset from the process of the hog descriptor which computed the gradient for each of the pixel in the images and as consequence the resultant image of the traffic light arrow was in form of the vector.

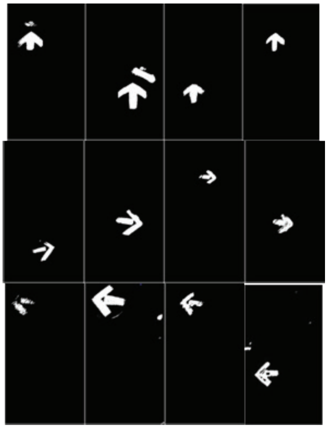

Fig. 6. Results of the traffic light arrow after the process of morphology dilation.

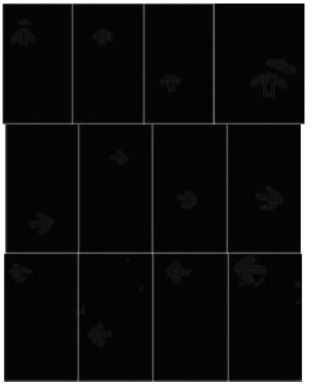

Fig. 7. Results of the traffic light arrow after the process of HOG descriptor.

B. Testing result

- Test 1

Total image for testing at 45 images is tested in 3 batches. The first batch which is test 1 is tested and the confusion matrix result is shown as in Fig. 8. The confusion matrix shows the true class for each type of the traffic light arrow alongside with the prediction class made by the SVM classifier.

From the confusion matrix, it can be concluded that the SVM classifier has made a right classification for all the samples of the traffic light arrows in the test set after each 15 samples of the type for the traffic light arrow lie align with their respective labels in the prediction class.

The performance of the SVM classifier for the test one has been summarized as in Table I. The SVM classifier took about 37.3719s to make a prediction for each samples of the traffic light arrows in the test set while its accuracy, precision and recall reach 100%. 0%

error has been made by the SVM classifier after all the samples of the traffic light arrows in the test set have been correctly predicted.

Hence, it can be analyzed that the performance of the SVM classifier in test one is great after has gained 100% accuracy, precision and recall for the classification process.

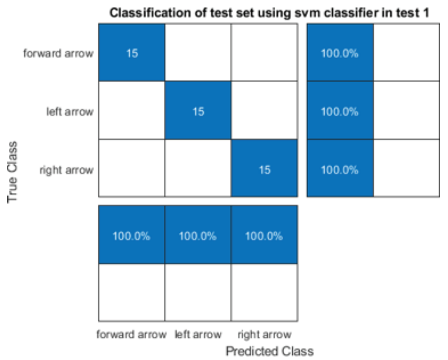

Fig. 8. Confusion matrix for Test 1.

TABLE I
PERFORMANCE OF SVM CLASSIFIER IN TEST 1

Processing time	37.3719 s
Accuracy	100%
Error	0%
Precision	100%
Recall	100%

- Test 2

For the second batch as for the test 2, the confusion matrix as Fig. 9 in has shown that both samples of the forward arrow and right arrow in the test set have been correctly predicted by the SVM classifier. Meanwhile, for left arrow, two samples have been misclassified after the SVM classifier has predicted them as a right arrow.

Hence, the column summarization has concluded that 88.2% has been correctly predicted by the SVM classifier while 11.8% has been misclassified for the right arrow samples. Besides, for the row summarization, the confusion matrix has shown that both of the true class for forward arrow and right arrow has reached 100% right recognition while the left arrow sample has 86.7% correct prediction by SVM classifier and other 13.3% was misclassified.

Meanwhile, Table II provides the summary for the performance of the SVM classifier after test two. In the test two, SVM classifier has achieved 95.56% accuracy, 4.44% error while the precision is 95.56% and the recall is 96.08%. In this test, the SVM classifier has failed to reach 100% accuracy, precision and recall because two of the samples for the left arrow have been misclassified to the right arrow and it has caused an error to reach 97%. In making a prediction to all the samples of the traffic light arrows in the dataset, the SVM classifier took almost 29.0153 s to finish the classification process.

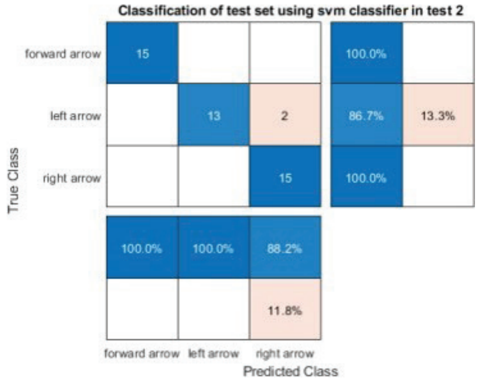

Fig. 9. Confusion matrix for Test 2.

TABLE II
PERFORMANCE OF SVM CLASSIFIER IN TEST 2

Processing time	33.6793 s
Accuracy	95.56%
Error	4.44%
Precision	95.56%
Recall	96.08%

- Test 3

For the third batch in Test 3, the SVM classifier has successfully made a correct prediction to all the samples of the traffic light arrows in the test set after the row summarization and the column summarization has shown 100% prediction for each of the traffic light arrow as shown in Fig. 10. Besides, all 15 samples for each of the traffic light arrow were placed in diagonal which lied parallel to their respective label in the predicted class. Hence, it can be concluded all the samples of the traffic light arrow in the test three been correctly recognized by the SVM classifier.

The summary of the confusion matrix in Fig. 10 as shown as in Table III. After making all the correct recognition for the samples of the traffic light arrow in the test set, SVM classifier has achieved 100% accuracy, precision and recall while the error is 0 %.

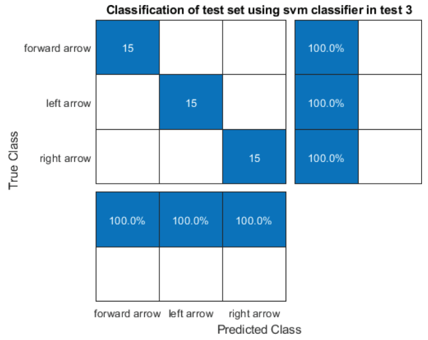

Fig. 10. Confusion matrix for Test 3.

TABLE III
PERFORMANCE OF SVM CLASSIFIER IN TEST 3

Processing time	29.0153 s
Accuracy	100%
Error	0%
Precision	100%
Recall	100%

- Average Performance of the SVM classifier

Table IV shows the average performance by the SVM classifier in the validation process. From the table, the SVM classifier had an accuracy of 98.52% for the prediction of each of the type for the traffic light arrow in the test set with 1.48% error. 1% error is approximately equal to the two samples from 45 total samples of the traffic light arrow in the test set. For the precision, the SVM classifier had 98.52% positive rate in the samples of the traffic light arrows in the test set. Besides, the SVM classifier had achieved 98.68% for recall in classification process for the samples of the traffic light arrow in the dataset.

TABLE IV
AVERAGE PERFORMANCE OF THE SVM CLASSIFIER IN TEST SET

Processing time	33.3555 s
Accuracy	98.52%
Error	1.48%
Precision	98.52%
Recall	98.68%

C. Simulation video

The input videos of traffic light that were recorded consist of forward arrow, left arrow and right arrow. All the videos have a frame rate of 30 fps and dimension of 360×640 under a sunny day illumination. All video duration is in the range of 10s to 20s which are enough to capture the transition of each of the traffic light arrow from green color of traffic light to red color of traffic light and vice versa. After passing a multiple process of pre-processing, detection phase and recognition phase, the input video of each of the traffic light arrow was converted to output video with a correct classification made by SVM classifier. All the types of traffic light arrows were successfully detected and recognized throughout the duration of the videos alongside with their respective colors. The green and red color of the traffic light arrow were able to be detected through the process of color thresholding and the outcomes were delivered to the extraction of the output video.

V. Conclusion

In a nutshell, the algorithm that has been proposed was proven to be valid and applicable to be used in real application after the simulation video that was conducted have shown that each type of the traffic light arrow was able to be detected and recognized in transition of traffic light from green to red and vice versa. The performance of the algorithm was tested on the three set of the samples of the traffic light arrows in the dataset. The test had achieved the accuracy of 98.52%, 1.48% of error, 98.52% of precision and 98.68% of recall.

Hence, it can be concluded almost all the samples of the images for each of the traffic light arrow were able to be correctly recognized by the SVM classifier with lack of the result for false positive, false negative and true negative. But, for a future recommendation, this algorithm can be improved to be utilized in the process of detection and recognition of traffic light arrow in the night-time and increase the range of the detection from the camera beyond one meter. Besides, to be more reliable and valid in real time application, this algorithm can be upgraded to be used in the real hardware implementation to meet the requirement for a real detection and recognition of the traffic light arrow.

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