Real-time Sign Detection and Recognition for Self-driving Mini Rovers based on Template Matching and Hierarchical Decision Structure

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Abstract: Sign detection and recognition play vital roles in the field of self-driving vehicles. The aim of this paper is to introduce a real-time methodology that can be implemented on affordable single-board computers to classify varied traffic signs from the camera feed. The approach is to detect and recognise the colour and shape of the signs at first, then use the acquired information to access a hierarchy structure of the database in order to extract features of pre-existing templates. Finally, the template matching algorithm is applied to compare those features with potential Region Of Interest (ROI) based on a threshold value. We installed our system on a mini rover and tested it on a control urban traffic scenario. The measurements showed processing time ranging from 230ms to 800ms and 480ms to 1900ms on Jetson Nano and Raspberry Pi 3 Model B+ respectively.

1 INTRODUCTION

Two of the most essential skills for drivers who commute on the roads are traffic signs detection and recognition. Traffic signs provide information regarding the state of the road (city road, urban road, priority road, etc.) or indicate the proper behaviours to drivers and pedestrians (drive slowly, give way, stop, yield, etc.). While human drivers can perform considerably well those tasks, the accuracy of their decisions can be affected by many subjective/objective factors such as physical condition (e.g. tired, drug effect, bad mood, etc.), environment conditions (snow, rain, extreme illumination, etc.) (Fletcher et al., 2003). In addition, self-driving vehicles have generated significant research interest in the last few years as a solution to resolve traffic congestion, traffic emission as well as enhance safety and efficiency in daily commute and logistic(Dobrev et al., 2017). Nevertheless, few researchers have addressed the problem of traffic sign detection and recognition in self-driving vehicles and the analysis of adapting those methods in the dynamic of physical vehicles. Therefore, the requirement of a real-time and reliable tool for sign detection and recognition is critically crucial.

The motivation of this paper is to develop an autonomous self-driving mini rover for the autonomous vehicle traffic competition – JRC AUTOTRAC 2020: *How the future road transport will look like?* (Cattaneo, 2019). In this competition, there would be an urban simulation scenario in which the rover must follow the instruction of traffic signs but still maintain the correct paths and avoid crashes with other rovers. The rover should not exceed the dimension of 150x200x200mm and weight of 2kg. (Fig. 1).

Several approaches regarding traffic sign detection and recognition were illustrated in the last decade such as Support Vector Machine (SVM) (Maldonado-Bascon et al., 2007) (Greenhalgh and Mirmehdi, 2012), Neural Networks (NNs) (Chiung-Yao Fang et al., 2003), You Only Look Once (YOLO) (Zhang et al., 2017), Template matching base on priori knowledge(Piccioli et al., 1996). State of the art methods including Machine Learning (SVM, NNs, YOLO, etc.) have demonstrated their outstanding performance, however, they either require a bulky stationery processing unit or might be problematic in real-time application (Chen et al., 2014). Due to the fact that our robot - Hammy is a small mobile rover which travels in scale model of control urban environment, plus there are a limited number of traffic signs need to be classified in the competition, we developed a system which did not demand excessive computation and was able to perform adequately on common embedded systems such as Jetson Nano and Raspberry Pi 3 Model B+.

In this paper, a system for traffic sign detection and recognition based mainly on template matching and other techniques of Computer Vision is introduced. Later, experiments of this system on Hammy

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among different control urban environments are discussed.

2 SYSTEM ARCHITECTURE

One of the priorities of Hammy is the ability to self-drive and behave associating with traffic signs, lanes and other objects on the roads. For this reason, the rover requires an engine unit to deliver torque; a control unit to process data from sensing system and perform computations; and a portable power source.

As for the engine unit, the 2 common selections are combustion engine and electric motor. The first one can provide greatly high torque but can be considerably heavy and bulky. Furthermore, combustion engine is also noisy, difficult to control and requires a large transmission unit to deliver the torque. Electric motor does not generate as high torque as combustion engine but has a much smaller weight. It is also easier to control and more environmentally friendly compared to combustion engine. Because the purpose of this paper is to develop a reliable solution and algorithm for self-driving scaled-model vehicles, experiments would be conducted in small scale and laboratory tracks. Therefore, 2 DC motors equipped with gearboxes were selected which would drive 2 wheels separately.

The sensing system consists of an Ultrasonic Sensor HC-SR04, 2 Reflective Infrared IR Optical Sensors (Optional) and a Camera Raspberry Pi V2. Hammy would depend mainly on the data from the camera to adjust its motor speed as well as steering angle. It should be noticed that humans use only biological vision without the need of any distance/infrared/LIDAR (Light Detection and Ranging) sensors, but still can perform very precisely driving task. Hence, self-driving algorithm of Hammy was developed principally focused on computer vision with the reference of data from external sensors in an attempt to improve the accuracy of the decision.

Hammy requires a portable but adequate processing unit in order to compute data from the camera and sensors. In our experiment, Jetson Nano - a small but powerful computer was selected. Later, a less powerful but more affordable single-board computer: Raspberry Pi 3 Model B+ was experimented.

Generally, when Hammy approaches to a potential traffic sign, it firstly tries to detect and recognise the colour and contour of the sign through its camera. The closer it reaches to sign, the larger of colour area it detects. If this area exceeds a defined threshold, the rover will slow down/stop and try to recognize the sign from the ROI using template matching. Since traffic sign usually follows a size standard, ROI can be defined utilizing the center of colour area as well as the sign's width and length. If the confidence of classification is satisfactory, Hammy will act regarding the indication of the sign. Fig. 2 demonstrates the software architecture of our system.

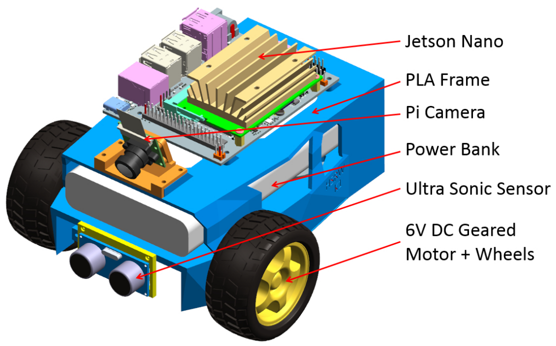


Figure 1: CAD design of Hammy.

3 METHODOLOGY

3.1 Camera Calibration

Distortion and bad representative colour are common flaws when capturing images from cameras. Those flaws can generate disturbing effects on the input images (e.g. straight-line turns to curved line, incorrect colour level) and deteriorate noticeably the performance of Hammy in detecting and recognizing traffic signs. In an attempt to avoid those unfavourable elements, it is necessary to perform camera and colour calibration before conducting further steps.

The most common method for camera calibration is to utilize a planar pattern which contains at least two distinguishable dimensions (Zhang, 2000). In this paper, a chess board frame was used as the reference pattern for Hammy's camera calibration.

According to (Zhang, 2000), considering (x_i, y_i) and (x, y) are respectively processed distortion-free coordinates and real distorted coordinates, the distortion effect can be solved as below:

$$\begin{aligned} x_i &= x + x\left[k_1(x^2+y^2) + k_2(x^2+y^2)^2\right] \\ y_i &= y + y\left[k_1(x^2+y^2) + k_2(x^2+y^2)^2\right] \end{aligned} \tag{1}$$

in which k_1 and k_2 are the radial distortion coefficients. OpenCV library (Bradski, 2000) was adopted to extracts radial distortion coefficients from sample images.

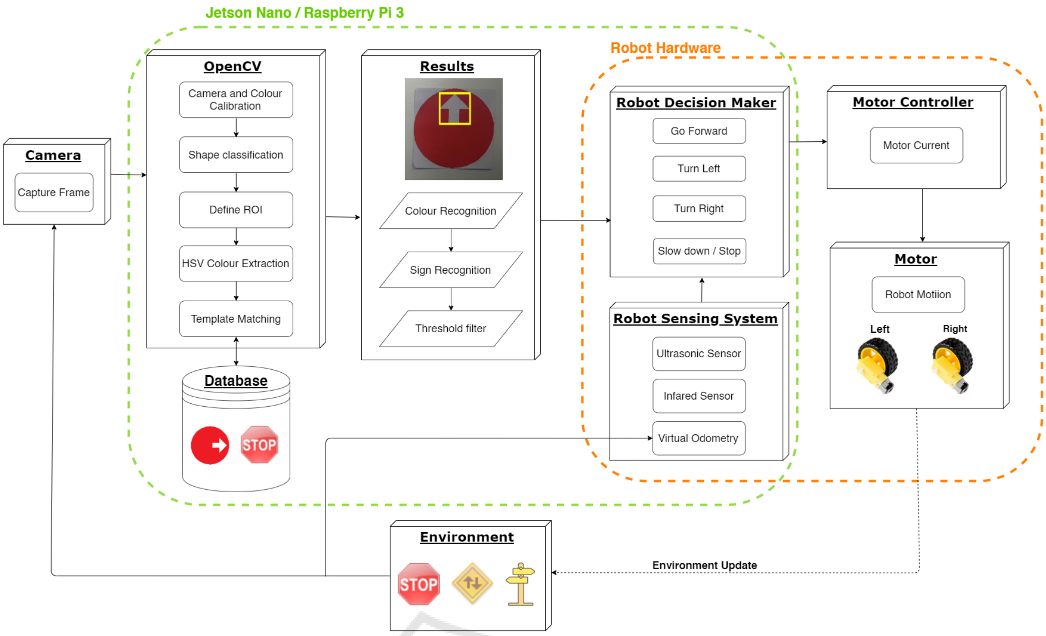


Figure 2: Schematic of the Hammy software architecture.

In several circumstances, the illumination of external environment and affect unfavourably to the recognition ability of Hammy. For instance, high intensity of light can cause the rover mistaking between ”red” and ”pink”. Hammy can avoid that by conducting colour calibration based on HSV(Hue, Saturation, Value) colour space to classify different colours. It was proved that HSV is able to classify colours better than both CIELAB and RGB (Reg, Green, Blue) colour space (Paschos, 2001). Basic colours including Red, Yellow, Green, Blue can be converted from RGB to HSV by below equations(Saravanan, 2010):

With value of RGB in range [0,1]:

$$H := \begin{cases} 0, & \text{if } MAX = MIN \\ & \Leftrightarrow R = G = B \\ 60 \cdot \left(0 + \frac{G-B}{MAX-MIN}\right), & \text{if } MAX = R \\ 60 \cdot \left(2 + \frac{B-R}{MAX-MIN}\right), & \text{if } MAX = G \\ 60 \cdot \left(4 + \frac{R-G}{MAX-MIN}\right), & \text{if } MAX = B \end{cases} \quad (2)$$

$$\text{if } H < 0 \text{ then } H := H + 360$$

$$S_{\text{HSV}} := \begin{cases} 0, & \text{if } MAX = 0 \Leftrightarrow R = G = B = 0 \\ \frac{MAX-MIN}{MAX}, & \text{otherwise} \end{cases} \quad (3)$$

$$V := MAX \quad (4)$$

$$L := \frac{MAX + MIN}{2} \quad (5)$$

3.2 Sign Detection

The process of sign detection contains two steps: colour contour detection and shape detection. In order to extract the colour contour of the sign, a state of the art contour detector technique integrating both local and global cues was utilized (Maire et al., 2008). This technique was claimed to deliver best performance on the Berkeley Segmentation Dataset benchmark in 2008. Hammy would reduce the level of noise by Gaussian Blur(Nixon and Aguado, 2012) before activating contour detector on HSV colour space of the frame. A pre-defined range was adapted to prevent the system from wasting its resources on detecting unwanted colours. The center of colour contour must be specified so that our system can perceive the ROI and concentrate on it. This could be done by calculating the central moment (m_{ij}) and extrapolating the central coordinates from it (Yang and Albregtsen, 1996):

$$mu_{ji} = \sum_{x,y} (array(x,y) \cdot (x - x')^j \cdot (y - y')^i \quad (6)$$

where (x', y') is the mass center:

$$x' = \frac{m_{10}}{m_{00}}; y' = \frac{m_{01}}{m_{00}} \quad (7)$$

To classify the shape of a traffic sign, the captured frame was converted to grayscale(Saravanan, 2010) in an attempt to optimize resource utilization. Canny Edge detection (Canny, 1986) was implemented to highlight the captured sign contour. Subsequently, the Douglas - Peucker algorithm was integrated to count the numbers of vertices from the traffic sign's contour extraction. This algorithm would convert a curve created by multiple line segments into a similar curve with fewer vertices (Prasad et al., 2012). Therefore the shape of a traffic sign can be determined by counting the number of total vertices. With numbers of vertices equal to three, four and five the shape will be triangle, square/rectangle, and pentagon respectively. In case the numbers of vertices are considerably large, the shape would be assigned as circle (a circle is composed of vast numbers of line vertices).

3.3 Sign Recognition

In an attempt to interpret the sign, Hammy would access the pre-existing database associating to information extracted from the colour and shape of the traffic sign and execute template matching algorithm (Pereira and Pun, 2000). The database should contain images of traffic sign in which users want Hammy to recognize. The template T slides over the original Image I and gives a resultant matrix R which contains the pixel locations in terms of (x,y) where the pixels matched. If there are no pixels detected this matrix R would be null. In terms of visualisation, the matrix R is basically a black image except for the region where it matched, which would then be represented as a bright spot. If the same template may appear multiple times the image would then have multiple bright spots on the same dark image.

OpenCV library (Bradski, 2000) provides several equations to calculate the region where features of a template are matched. These equations perform the appropriate function between the template T and the original image I, which returns either the minimum or the maximum values based on the equation chosen. In this experiment the normalised coefficient correlation was used given by the equation below (Goshtasby et al., 1984):

$$R(x,y) = \frac{\sum_{x',y'} (T'(x',y') \cdot I'(x+x',y+y'))}{\sqrt{\sum_{x',y'} T'(x',y')^2 \cdot \sum_{x',y'} I'(x+x',y+y')^2}} \tag{8}$$

The resultant matrix in this case is of the shape of the original image with a value between 0 and 1 in each pixel position. A threshold is then used to determine the pattern location of the matching position. The higher of the threshold, the higher accuracy required for the template to match the captured images.

4 EXPERIMENTS AND RESULT

The frame of Hammy was designed with CAD software and then fabricated with 3D printer. A rechargeable 5V-2A power bank with storage of 20,000 mAh is mounted inside the frame. During experiments with all processing unit, motors and sensors operating continuously, Hammy could last up to 5-6 hours. The operating duration can be extended by replacing Jetson Nano with Raspberry Pi 3, yet the difference was insignificant. Hammy weighs approximately 1kg and has the dimension of 140x190x120mm. Fig. 3 illustrates the physical prototype of Hammy which was conducted in our research.

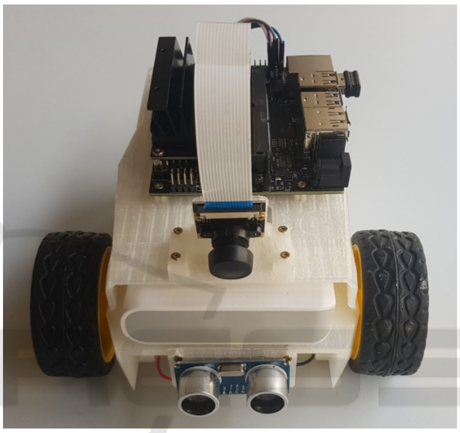


Figure 3: Prototype of Hammy.

To evaluate the performance of our algorithm, an urban scenario consisting of Hammy and a traffic sign stationed along the road was constructed (Fig. 4). The system was installed on both Jetson Nano and Raspberry Pi 3 Model B+ and tested in different lighting conditions: lack of illumination (dark - 2 Lux), natural illumination with daylight (ambient - 64 Lux) and indoor illumination with artificial light (lighted - 197 Lux). An experiment is considered successful when the rover stops before the sign and behaves accordingly to the indication demonstrated by traffic sign. From recorded data, the temporal performance, as well as the responsiveness of our system, were evaluated.

4.1 Accuracy Performance

As mentioned in the methodology section, our system depends heavily on the colour contour extraction and shape recognition. One of those processes that does not function properly will lead to the break of the whole system. We tested our system on a set of 200 image samples similar to Fig. 5 and recorded

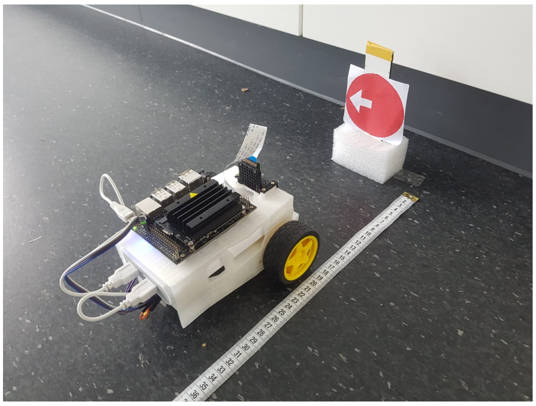


Figure 4: Testing the temporal performance and system responsiveness on Hammy.

the certainty of our system on Table 1. The result illustrates that while the accuracy of sign detection was relatively high (around 90%), this value on sign recognition was noticeably lower as less than 81%, especially in dark condition. Fortunately, our system architecture does not depend on a single data to deliver the decision. Conventional cameras usually record 24 frames per second, which means in one second Hammy can access and predict a collection of 24 images. Obviously, it is not efficient to process all images in one frame throughout, thus a portion of each image collection in one second is gathered for the process. The control unit of Hammy could also be intervened to orient the visual angle of camera, therefore new data can be collected in case previous data is challenging for decision making. Fig. 5a and Fig. 5b demonstrates the result after applying sign detection and sign recognition on an image.

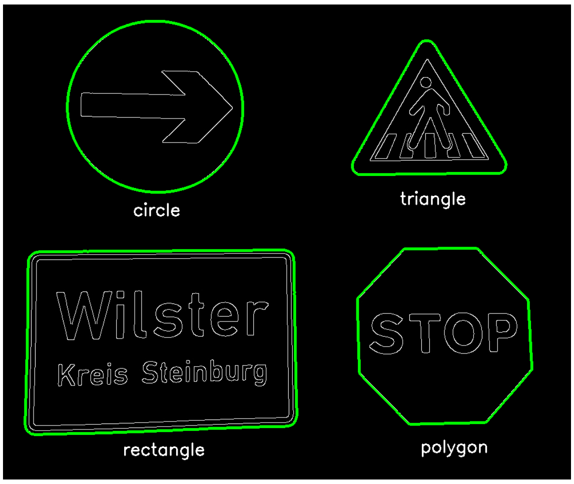
Table 1: Accuracy performance of sign detection and sign recognition on 200 samples.

	Dark	**Ambient**	**Lighted**
Sign detection	87.5%	90.5%	92.5%
Sign recognition	75%	80.5%	80.5%

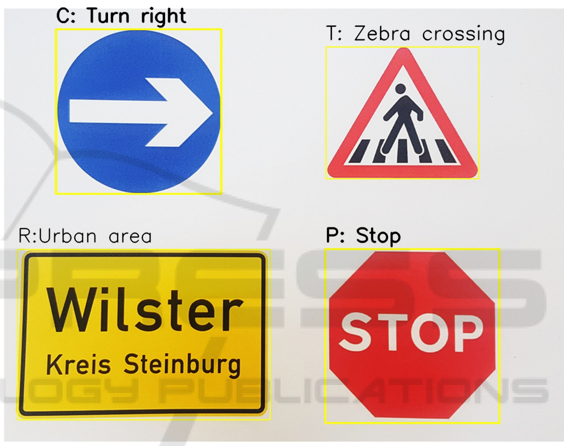
4.2 Temporal Performance

As can be seen in Fig. 2, Hammy perceives the final result of traffic sign through consecutive steps: *Colour recognition, Sign recognition* and *Threshold filter*. To measure the temporal performance of our algorithm, a python module called *timer* was implemented with a starting point and a end point set before the first step and after the last step respectively. The results are summarised in Fig. 6.

It is evident that the algorithm achieved the best performance in lighting condition when the process-



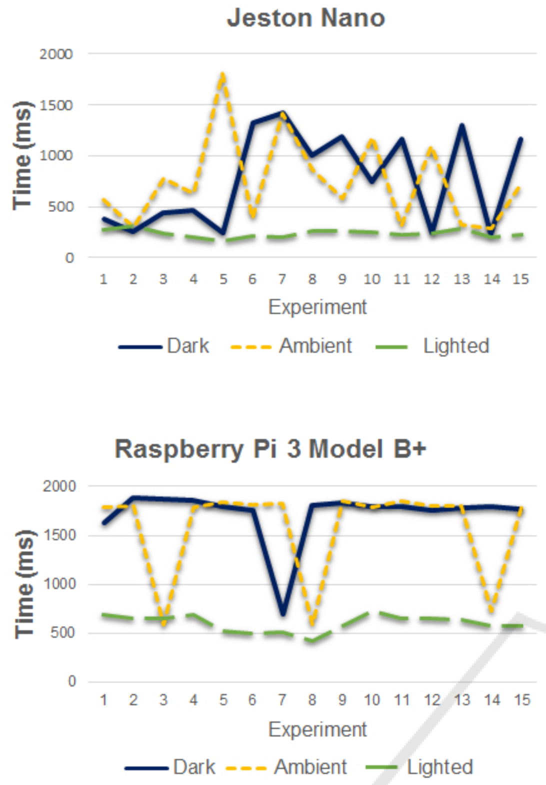
(a)



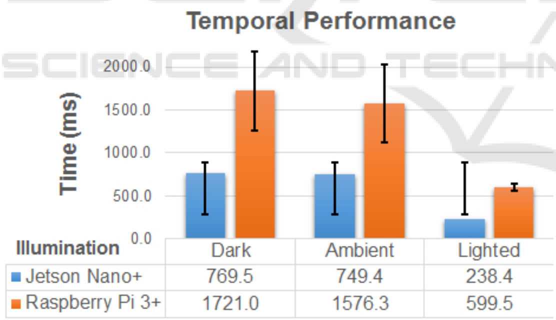
(b)

Figure 5: a) Shape extraction and classification of traffic signs. b) Template matching following the database's hierarchy tree.

ing time fluctuated evenly around 238.4ms on Jetson Nano and 599.5ms on Raspberry Pi 3 Model B+. The standard deviation was also the smallest among three conditions, which indicates the system works most stable in lighting condition. Meanwhile in dark and ambient condition, it showed poorer performances as approximately double on Jetson Nano and triple on Raspberry Pi 3 . The results indicate that our method depends heavily on the lighting condition since colour region and sign edges can contrast better to the background. In addition, Jetson Nano delivers better performance in comparison to Raspberry Pi 3 thanks to its integrated 128-core Maxwell GPU, yet this difference is not significant. With processing time less than 2s for all three conditions, the system performance on both of them satisfied our requirement in the ability of real-time operation. Nevertheless, it should be no-



(a)



(b)

Figure 6: a) Temporal performance in three different illuminating conditions. b) Comparison of the temporal performance between Jetson Nano and Raspberry Pi 3 Model B+.

ticed that the system normally breaks if the sign is affected by external factors (hidden by obstacles, discolouration, deformation, etc) since its features can not be exposed to fit with the template extracted from the database. Such problems can be solved by conducting Machine Learning methodologies including SVM (Greenhalgh and Mirmehdi, 2012) and Neural Networks (Zhang et al., 2017) (Zhu et al., 2016) (Eykholt et al., 2017). Those methods was proved to deliver reliably and precisely the prediction without the need of collecting all the features from the template. Regardless, Machine Learning methods usually are resource-intensive and require graphic processing unit (GPU) to increase the speed of their computation.

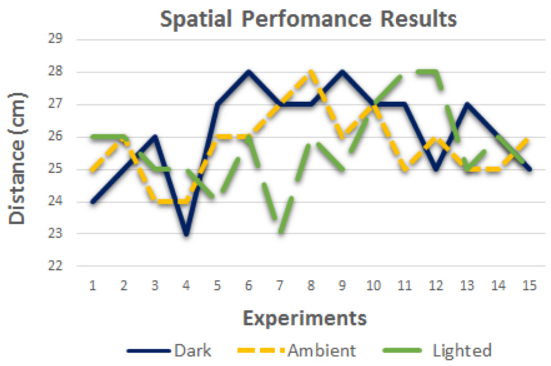
4.3 System Responsiveness

One of the most important characteristics of self-driving vehicles is the ability to rapidly respond to external factor in real-time. In this experiment, Hammy ran on a straight path with 65% maximum velocity and a turning sign was installed on its route (Fig. 4). As mentioned above, when Hammy approached closer to the traffic sign it would try to extract the colour region and the shape of potential traffic signs from the captured frame. When the confidence of the colour and shape recognition reached a defined threshold (calibrated 25cm in front of the traffic sign), Hammy would stop, access the database and extract the features of pre-existing templates based on the hierarchy tree. Subsequently, the rover made its decision by comparing the extricated features with sceptical ROI and selecting the best one. Similar to the temporal performance experiment, we tested Hammy in three different illuminating condition and plotted the data as can be seen in Fig. 7.

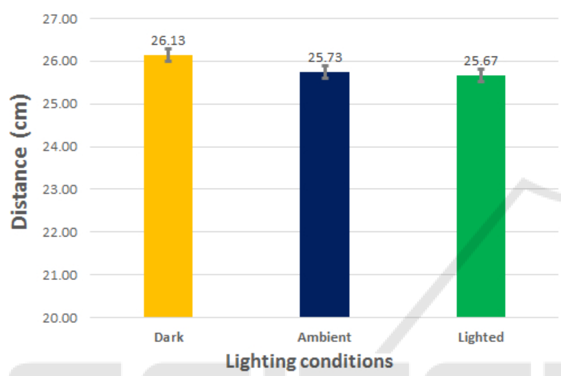
It can be observed that the stopping distance of Hammy fluctuates unevenly in the range of 23cm to 29cm in three lighting conditions. The tolerance compared to the desired stopping distance (25cm) is around $\pm$4cm. The average of responsive distance in dark condition is approximately 26.13cm while this number in ambient and lighting conditions are 25.73cm and 25.67cm. The experiment results show that the lack of illumination might deteriorate Hammy's ability to detect and recognise traffic signs. However, this tolerance is acceptable since the deviation ($\pm$4cm) is relatively small and can be compensated by Hammy's controller.

5 CONCLUSIONS

In the last decade, many researches in the field of traffic sign detection and recognition have been developed, still few of them have indicated an effective real-time solution for self-driving rovers which can be implemented on small, affordable single-board computers. Therefore, we presented a system for traffic sign detection and recognition which is cost-effective and compatible with two of the most popular embedded boards: Jetson Nano and Raspberry Pi. The idea is to formerly detect and classify colour and shape of



(a)



(b)

Figure 7: a) Spatial performance result among three illuminating conditions. b) Average of spatial performance.

the traffic sign, then use this information as correlated conditions to go deeper into the database branches where sign templates are stored. In the next step, features of all templates are extracted and compared with ROI from video stream and those which have the highest similarity will be selected. The advantage of this methodology is that it consumes a limited amount of computational power due to the hierarchical structure of the algorithm. Yet, this system depends heavily on the subtle changes in the external environment and the sufficiency of the database. For example, the colour can be misclassified if the real sign discolours over time, or the system will not able to recognise shape contour if the sign is hidden by obstacles. The system shows potential in areas which do not consist of too many appearance-affecting factors such as hospitals, factories, schools, laboratory, indoor areas, etc. It can also be implemented as an assisting module running parallel with other modules on an embedded system to perform multi-tasks, especially when this system has limited computational resources.

Future work should focus on algorithms that can reduce the affection of external environment factors to the sign detection and recognition process. Additional sensors can be equipped to improve the accuracy of decision such as colour sensor or LIDAR (Light Detection and Ranging) (Zhou and Deng, 2014).

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