Auto-Quantification of Various Contributing Factors on LiDAR-Camera Modalities toward Autonomous Driving Environment

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ABSTRACT

This study proposes a framework to quantify various factors (including weather condition, luminance conditions, and over-under exposures) that will influence the performance of LiDAR and camera in detecting objects. The proposed framework comprises of the frequency-based and spatial-based image analysis algorithms, which have been tested to achieve the expected results.

INTRODUCTION

The rapid developments of imaging sensors and transistor count have revolutionized vehicle technology. The most common sensors to be utilized are camera (RGB and/or IR), and LiDAR, which have different characteristics, as the sensing mediums are not alike. As an image-based sensor, camera receives signal from the reflected lights that travel through; this condition infer that any airborne substance (e.g. water in fog or rain) with significant concentration may absorb the signal—thus reducing the image visibility [1]. Differ from camera, LiDAR is an active transducer that generates 3D point clouds that are created based on the time-of-flight of laser beams (ToF). Airborne materials during inclement weathers may affect the ToF; thus generating false point clouds [2].

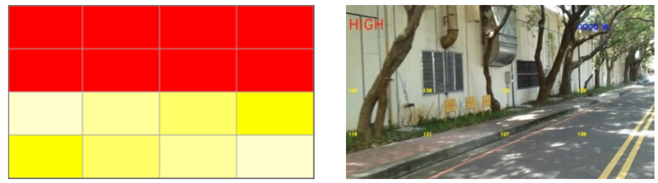
Another factor to be taken into the account is the luminance value. As a passive sensor, camera relies on the external light source to generate the reflected signals; therefore, the image quality (i.e. structure, contrast) will most likely to decrease in dim condition such as in the nighttime or shadowy regions [3]. Although this particular condition does not apply to LiDAR, this active transducer may suffer from signal inference from excessive exposures from light source that partially emits light with wavelengths near to infrared signal band [4]. Based on these contributing factors, the proposed framework quantifies the factors using both frequency and spatial-based analyses that can be used for improving the object detection algorithms.

PROPOSED FRAMEWORK

The proposed framework comprises of three algorithms that quantify the contributing factors of object detection using camera or LiDAR sensors, which can be specified as: a) lux detection and intensity measurement; b) weather detection; and (c) adaptive over-underexposures measurement.

A. Intensity Measurement and Lux Detection

To obtain the accurate representation of luminance, the luminance map (L) from the Lab color-space is utilized after transforming the input RGB image. Noise reduction in L map is performed using the Gaussian and Median filters that result in the $\bar{L}$ map, which is then segmented into blocks as in Fig. 1(a).



(a) (b)

Fig. 1. *(a) The segmentation map and (b) the sample result for the intensity measurement and the lux detection.*

The intensity measurement is performed over the region of interest (ROI) illustrated as the yellow-coded blocks in Fig. 1(a). The average luminance in each block is calculated from the $\bar{L}$ map, of which result is shown in Fig. 1(b). As for the lux detection, the average luminance is measured from the overall red-coded blocks in Fig. 1(a) and then compared with the average luminance from the overall yellow-coded blocks.

B. Weather Detection

During the inclement weathers, fewer object details can be obtained as the light signals are attenuated; thus increasing the low frequency data while decreasing the high frequency data. The L map is transformed from spatial to frequency as follows:

$$M = \mathrm{F}(L), \tag{1}$$

where F denotes the Fourier transformation and M denotes the magnitude of frequency map. From M, the low frequency information is removed using the high pass filter as:

$$\bar{M} = HPF(M). \tag{2}$$

From the high frequency map ($\bar{M}$), an adaptive binarization method is performed to generate the bitmap version of $\bar{M}$, namely T. Any sparse pattern detected in T in several consecutive frame is referring to the excessive presence of airborne material; otherwise, the weather is normal.

C. Adaptive Over-Underexposures Measurement

The over and underexposures are image-based phenomenon that occurs when there is excessive and inferior amount of light intensity, respectively, traveling to the corresponding sensor. The overexposure (O) can be mathematically expressed as:

$$O = (1 - S) \times L \times \left(1 - \frac{d}{dp} L\right), \tag{3}$$

where S denotes the color saturation map of the input image and p represents the pixel domain. On the other hand, the underexposure (U) can be mathematically expressed as:

$$U = S \times (1 - L) \times \left(1 - \frac{d}{dp} L\right). \tag{4}$$

Between (3) and (4), the O and U maps are generated based on the saturation, luminance, and contrast maps of the input image.

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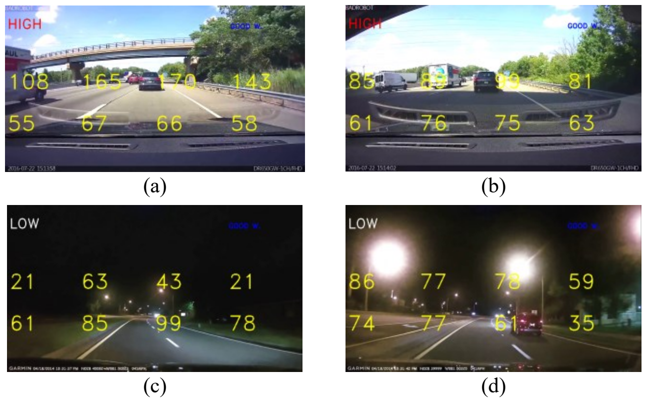

Fig. 2. *A result montage of the intensity measurement, time detection and weather detection on (a)-(b) a sunny and bright highway environment and (c)-(d) a clear and night suburban environment.*

Table I Assessment on the Proposed Weather and Lux Detection

Video	Weather Detection		Lux Detection	
	Ground Truth	Result	Ground Truth	Result
1	Good	Good	Low	Low
2	Good	Good	High	High
3	Bad	Bad	High	High
4	Good	Good	Low	Low
5	Bad	Bad	High	High
6	Good	Bad	High	High
7	Good	Good	High	High
8	Good	Good	High	High
9	Bad	Good	Low	Low
10	Good	Good	Low	Low
Accuracy	80%		100%	

EXPERIMENTAL RESULTS AND DISCUSSIONS

To objectively evaluate the performance of the proposed framework in delivering the aimed functions, each of the proposed algorithms is tested on 10 videos with different combination of scenarios including inclement (i.e. rain, fog or haze) and normal weather, day and night time, open-space and tunnel environment, as well as various over and underexposures condition from different light sources (i.e. sun or street lamps). The ground truth data are manually provided based on the perceived condition that can be inferred by human from the corresponding video. Subjective evaluation is performed specifically for the assessment of intensity measurement.

Firstly, the algorithm for intensity measurement is assessed using subjective evaluation based on its robustness in representing the dynamicity of luminance level across different conditions modeled in the tested scenarios. According to Fig. 2(a)-(b), the proposed intensity measurement is subjectively able to quantify the luminance level as demonstrated with the high intensity values during the bright condition and then achieved lower intensity values during the dim condition. Similarly, the proposed intensity measurement is also subjectively able to quantify the intensity values during the dim condition with variations of bright exposures from car headlights and street lamps during a clear night environment illustrated in Fig. 2(c)-(d). Furthermore, Fig. 2 also briefly demonstrates the robustness of lux detection and weather detection in different conditions including night and daytime with the expected results.

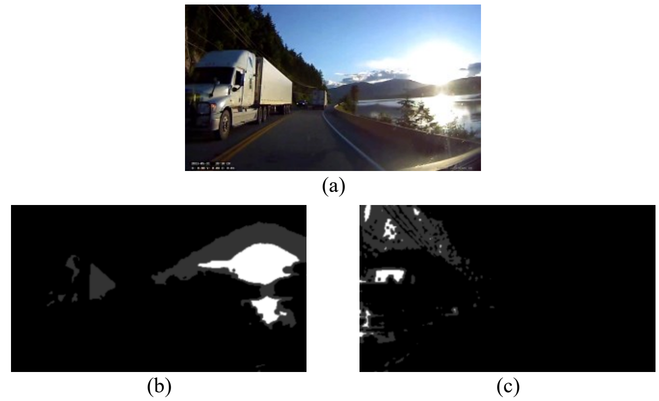

Fig. 3. *(a) The input image with result sample of the (b) over and (c) under-exposures measurement. The brighter pixels represent higher confidence for representation of the corresponding exposures.*

Table 2 Assessment on the Proposed Over-Underexposure Measure

Metric	Sørensen–Dice (Q)	Jaccard (J)
Underexposure Measure	0.914	0.842
Overexposure Measure	0.954	0.913
Average	0.934	0.878

The proposed weather and lux detection algorithms are evaluated objectively based on the ground truth data, which are presented in Table 1. According to Table 1, the accuracy rate of the proposed weather detection tested on 10 videos with different scenarios reaches an average score of 80%. In the test videos, various weather conditions including haze, rain and fog are incorporated within the test data. This result demonstrate the robustness of the proposed weather detection for different weather conditions. In addition, Table 1 also shows the average accuracy rate for lux detection that achieve a score of 100%. Therefore, with other dependent variables the proposed lux detection can robustly estimate the global luminance value.

To evaluate the performance of the over and underexposure measure algorithms, the *Sørensen–Dice* and *Jaccard* index are used to understand the overlap ratio between the ground truth and resultant maps (illustrated in Fig. 3) as follow:

$$Q = \frac{2TP}{2TP + FP + FN} \text{ and } J = \frac{TP}{TP + FP + FN}, \qquad (5)$$

where *TP, FP,* and *FN* denote the number of true positive, false positive, and false negative between the ground truth and resultant maps, respectively. According to Table 2, the over-underexposure measurements can achieve high O and J scores, which demonstrated the robustness of the proposed algorithm.

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