Road scenes analysis in adverse weather conditions by polarization-encoded images and adapted deep learning

R. Blin[1] S. Ainouz[1] S. Canu[1] F. Meriaudeau[2]

[1] Normandie Univ, INSA Rouen, UNIROUEN, UNIHAVRE, LITIS, 76000 Rouen, France
[2] University of Burgundy, UBFC, ImViA, 71200 Le Creusot, France

rachel.blin@insa-rouen.fr

1 INTRODUCTION

Road scene understanding is a vital task nowadays because of the development of driving assistance systems. Currently, in ideal cases (i.e. good weather and good visibility), road scenes obstacles are well detected. However, when there is a variation of illumination or adverse weather conditions leading to unstable appearances in road scenes, most of the methods of the literature implying conventional vision sensors fail to efficiently detect road objects.

We aim in this paper to combine the power of polarization to discriminate objects and deep neural networks to detect road scene content even in poor illumination conditions. The idea of using deep learning is motivated by our previous work that show how polarimetry may contribute efficiently to road scene analysis [1]. We constituted our own dataset in different weather conditions to show the positive impact of the combination of polarimetry and deep neural networks.

2 POLARIZATION FORMALISM

When an unpolarized light wave is being reflected, it becomes partially linearly polarized. That reflected light wave can be described by a measurable set of parameters, the linear Stokes vector S = [S_0, S_1, S_2] where $S_0 > 0$ is the object total intensity whereas S_1 and S_2 describe roughly the amount of a linearly polarized light.

The relationship between the Stokes parameters and the intensities, for each $(\alpha_i)_{i=1:4}$, measured by the camera is given by :

$$I(\alpha_i) = \frac{1}{2}[1, \cos(2\alpha_i), \sin(2\alpha_i)].[S_0, S_1, S_2]^T \quad .$$

For this work, our camera provides $(\alpha_i)_{i=1:4} \in \{0°, 45°, 90°, 135°\}$ as in [1]. The Angle (AOP) and Degree (DOP) Of Polarization can be determined from the obtained Stokes vector by :

$$AOP = \frac{1}{2}\tan^{-1}\left(\frac{S_2}{S_1}\right) \quad , \qquad DOP = \frac{\sqrt{S_1^2 + S_2^2}}{S_0} \quad .$$

The $DOP \in [0, 1]$ refers to the quantity of polarized light in a wave. The $AOP \in \left[\frac{-\pi}{2}; \frac{\pi}{2}\right]$ is the orientation of the polarized part of the wave with regards to the incident plan.

3 METHODOLOGY

As available polarimetric data are scarce, it was decided to acquire some new polarization images. The acquisition were made while driving to get the more realistic and diverse possible images scenario. The training data were acquired under sunny weather conditions whereas the testing data were taken under foggy conditions. Each image was labelled by means of bounding boxes and 4 categories of object (car, person, bike, motorbike) were used. Table 1 sums up the dataset properties.

Class name	Training set	Testing set
Images	2221	509
car	11687	9265
person	1488	442
bike	4	12
motorbike	21	0

TABLE 1 – Number of labelled instances in the database

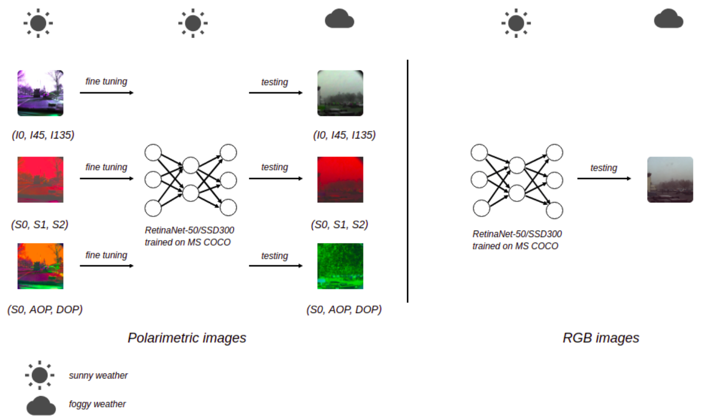

FIGURE 1 – Methodology

4 EXPERIMENTS

To remind the experiments conditions, a model of RetinaNet-50 [2] pre-trained on the MS COCO dataset [3] was used. It was then fine tuned on the polarimetric database. Figure 1 summarizes up the methodology.

5 RESULTS AND DISCUSSION

The *mAP* was computed for each of the polarization channel combination using the updated weights for each one of them. For RGB, the *mAP* of the detection from the RetinaNet-50 trained on the MS COCO dataset was used.

Entries	Class name	AP no FT	AP FT
RGB	person	0.8254	X
	car	0.6639	X
	mAP	0.6706	X
(I_0, I_{45}, I_{135})	person	**0.8556**	**0.9079**
	car	0.6064	**0.7290**
	mAP	0.6177	**0.7371**
(S_0, S_1, S_2)	person	0.6945	**0.8969**
	car	0.4114	**0.7375**
	mAP	0.4243	**0.7448**
$(S_0$, AOP, DOP$)$	person	0.0166	0.3585
	car	0.1265	0.6050
	mAP	0.1215	0.5938

TABLE 2 – Comparison of the detection with RetinaNet-50.

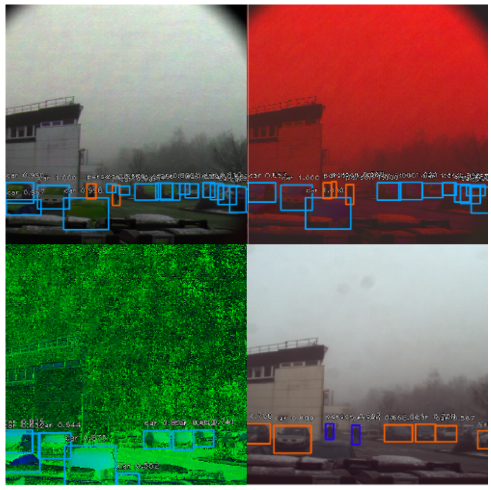

FIGURE 2 – Comparison of the detection in foggy weather. On top left (I_0, I_{45}, I_{135}), on top right (S_0, S_1, S_2), on bottom left $(S_0$, AOP, DOP$)$ and on bottom right RGB.

After fine tuning (AP FT), the detection with RetinaNet-50 in two polarization channels combinations ((I_0, I_{45}, I_{135}) and (S_0, S_1, S_2)) overcome the classical RGB detection as well as the detection without fine tuning (AP no FT) when it comes to car and pedestrian detection as it is shown in Table 2. Figure 2 illustrates as well the detection improvements and by the way the added value using polarimetric images.

6 CONCLUSION

This paper proves that polarimetric imaging is a real added value in the field of object detection in road scenes. Polarization images associated with deep networks efficiently detect objects in the scene especially in adverse weather conditions.

Références

[1] F. Wang and et al., "Polarization-based car detection," in *2018 25th IEEE ICIP*.

[2] T.-Y. Lin and et al., "Focal loss for dense object detection," *2017 IEEE ICCV*.

[3] ——, "Microsoft coco : Common objects in context," in *ECCV*, 2014.