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# Road Marking characterization for ADAS Machine Vision Reliability

Abdessamad EL KRINE<sup>1</sup>, Joffrey GIRARD<sup>2</sup>, Maxime REDONDIN<sup>3</sup>, Christophe HEINKELE<sup>4</sup>, Aude STRESSER<sup>4</sup>, Valérie MUZET<sup>4</sup>

<sup>1</sup>*Cerema ENDSUM, 11 rue Jean Mentelin, 67035 Strasbourg, France. E-mail: abdessamad.el-krine@cerema.fr*

<sup>2</sup>*Cerema BEE, 23 avenue Amiral Chauvin, 49130 Les Ponts-de-Cé, France. E-mail: joffrey.girard@cerema.fr*

<sup>3</sup>*Institut VEDECOM, 23 bis allées des marronniers, mobilLAB, F-78000 Versailles. E-mail: maxime.redondin@vedecom.fr*

<sup>4</sup>*Cerema ENDSUM, 11 rue Jean Mentelin, 67035 Strasbourg, France. E-mail: firstname.lastname@cerema.fr*

The evaluation of the road markings visibility has been defined according to human needs, but shall now be extended to the needs of vision-based Advanced Assistance Driving Systems (ADAS). Several publications propose minimum levels of daytime or night-time visibility of the road marking and their contrast with the surrounding pavement, to ensure optimum detectability of Machine Vision systems. However, the calculation methodology is rarely indicated (the heterogeneity of the markings is not always taken into account) and very little information about the Machine Vision system is provided. In this study, a daily experiment was conducted on a small dry road section using a mobile retroreflectometer and a vehicle equipped with a Machine Vision system. Several statistical analyses are performed on the collected data at different study scales (punctual or global scale). They show that despite very low levels of marking retroreflection values and visibility contrast ratios, the road marking lines are almost always very well detected by the camera's algorithm. That demonstrates that the current indicators characterizing the marking visibility according to standards are not enough to fully understand the behaviour of Autonomous Vehicle cameras.

**Keywords:** Road marking, ADAS vision reliability, Photometry, Detection level, Retroreflection.

## 1. Introduction

The quality of road markings has always been a major issue in terms of road safety for users and of penal aspects for management authorities. The entire characterization of markings (visibility, color, etc) has been standardized, taking into account the perception of the human driver. Today, it is being completely challenged by the technological developments of Autonomous Vehicle (AV) sensors, which have a different perception of the road than the human eye. The road marking has to be legible throughout the day or night, in all weather conditions, for both drivers and vehicles equipped with ADAS (Automated Driver-Assistance Systems). It is through a detailed analysis of the performance of markings, carried out in conjunction with ADAS sensors, that it may be possible to propose new indicators.

### 1.1. Context and state of the art

The automated steering functions rely on algorithms to operate, some of which are applied to vision and detection devices, in particular cameras and LIDAR (or a combination of both). The Lane Departure Warning (LDW) ADAS sensors, which are the subject of this study, are typically cameras coupled with real-time road marking detection algorithms.

There is an abundance of scientific literature on road marking detection methodologies (Hiller et al. 2014; Liang et al. 2020), but very little information is reported on the intrinsic characteristics of the cameras installed in LDWs and generally there is no access to the raw data. Similarly,

the algorithms implemented in the manufacturers' vehicles are not detailed. Burghardt et al. (2020) furthermore insist on the lack of collaboration between scientists developing new Machine Vision (MV) technologies and researchers working on horizontal road markings. For the majority of the vision sensors used for LDWs, the algorithm provides a score (an integer between 0 and 3) that gives information about the quality of the detection of the marking line: the score 0 corresponding to a "Very Low" quality level of detection, and 3 corresponding to a "Very High" quality level of detection (Pike et al. 2018; Stacy 2019; Marr and Scott 2020). Classically in the literature, a descriptive statistical analysis is performed on the mean score value to examine if a road marking line is easily detected by the Machine Vision system or not. To our knowledge, the attribution of these numerical values (0, 1, 2 or 3) and notably the metric distance between the detection levels is however never justified.

A marking is constituted of a main layer composed of a binder, fillers, pigments and additives (paint, cold coating, thermoplastic strip, etc.). To ensure visibility at night (retro-reflection of light waves from vehicle headlights), glass microbeads are generally added above the main layer. Pavement marking standard (EN 1436 2018; ASTM E1710 -18 2018) and guidelines (CIE 144 2001) define several physical quantities to evaluate the performance of road markings from the human driver's point of view. To assess the visibility of the marking in night-time conditions, the retroreflection coefficient  $R_L$  is used as a reference indicator. It corresponds to the ratio of the luminous luminance of the headlight reflection on a marking located

30 m from the driver, over the illuminance at the surface measured perpendicular to the direction of the incident light (expressed in  $\text{mcd.m}^{-2}.\text{lx}^{-1}$ ). To evaluate the visibility of the marking during the day, the luminance quotient  $Q_d$  is considered, defined by the luminous luminance reflected by diffuse lighting (corresponding to an overcast sky) on the marking at 30 m, over the horizontal illuminance at the marking (also expressed in  $\text{mcd.m}^{-2}.\text{lx}^{-1}$ ). Daytime visibility can also be evaluated by calculating the CIE luminance  $\beta$ , which is defined for a vertical viewing geometry and  $45^\circ$  illumination. These marking visibility performance are expressed independently of the surrounding pavement characteristics. The COST331 (2000) report proposed a model to characterize the visibility of markings. In this model, the various indicators to be reported ( $R_L$ ,  $Q_d$ ) are considered to be homogeneous for both the pavement and the markings. According to the European report (Eurorap 2011), a marking (with a minimum width of 15 cm) is considered sufficiently visible to a driver if its retroreflection is at least  $150 \text{ mcd.m}^{-2}.\text{lx}^{-1}$  on dry roads and  $35 \text{ mcd.m}^{-2}.\text{lx}^{-1}$  on wet roads.

With the development of systems for the guidance of AV, several studies like (Marr and Scott 2020; Pike et al. 2018; Eurorap 2011) investigated whether these indicators of road markings visibility were still relevant. For a given indicator of visibility  $X$  ( $R_L$ ,  $Q_d$  or CIE  $Y=100\beta$ ), it appears that the contrast ratio between the road marking and the surrounding pavement is more revealing of the visibility interpreted by the MV systems. This contrast ratio  $Cr_X$  (Pike et al. 2018) is usually defined by :

$$Cr_X = \frac{X_{mean}(\text{marking})}{X_{mean}(\text{pavement})} \quad (1)$$

With  $X_{mean}$  the mean value of  $X$  on the considered scale of analysis. At the moment, this relative indicator is not defined or recommended by the standards.

Based on the results of marking line detection by specific camera algorithms, some studies (Pike et al. 2018; Stacy 2019; Marr and Scott 2020) have tried to link marking detection scores to a characterisation of the marking/pavement combination. By testing different experimental conditions, they estimated the contrast thresholds of the different physical indicators ( $R_L$ ,  $Q_d$ , or CIE  $Y$ ) to ensure a good level of detectability of the marking lines by the camera (i.e. a score above 2). To have a good confidence rate of detection of markings in night-time conditions, Pike et al. (2018) recommend a  $R_L$  contrast ratio greater than 2.5 on dry road and a mean  $R_L$  value of the marking line higher than  $34 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ . Stacy (2019) found that to get a detection score greater than 2 in night-time conditions, the retroreflection should be greater than  $200 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ . Both studies characterized the marking with static devices. Other studies, in which mobile devices have been used to evaluate the performance of road markings, have shown different results. In Lundkvist and Fors (2010), they found that a minimum retroreflectivity of  $70 \text{ mcd.m}^{-2}.\text{lx}^{-1}$  is necessarily in dry night-time conditions. In an Austroads report, Marr and Scott (2020) suggest that camera systems can detect marking when the  $R_L$  contrast

ratio is between 5 and 10. According to Carlson and Poorsartep (2017), a  $R_L$  contrast ratio of 3 is sufficient at night and ADAS camera generally detect marking with retroreflectivity of at least  $100 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ , but do not necessarily provides the strongest detection.

For a good daytime detection of marking lines, Pike et al. (2018) advocate a CIE  $Y$  contrast ratio greater than 1.6, while Marr and Scott (2020) recommends a  $Q_d$  contrast ratio greater than 3. Probably due to the difficulty of dynamic measurement of daytime indicators, the studies are not necessarily performed on the same physical quantity.

Moreover, Stacy (2019) failed to find a good correlation between the average pavement marking quality score assigned by the ADAS machine vision camera and different indicators of marking like retroreflection,  $Q_d$ , CIE  $Y$  and associated contrast ratios.

The results of all these studies are quite different. These discrepancies are partly due to the small amount of available information on the ADAS MV systems and also to the different measuring devices, protocol and data analysis used. The statistical methods for characterizing the indicators are not very detailed and it is likely that, as in the COST331 report (2000), an assumption of homogeneity of the marking's characteristics is made. The same applies to the pavement surrounding the marking, which is also assumed to be uniform.

## 1.2. Objectives

In this context of road markings visibility by Machine Vision systems, the French project SAM (Safety and Acceptability of Autonomous Mobility) consists in developing knowledge to build a technical and regulatory framework to facilitate the circulation of Autonomous Vehicles on the French road network. One of the tasks of this project is to evaluate the detection of road markings by camera-based driving assistance systems, by varying different parameters, both on the state of wear of the markings but also on the state of the road. The objective is to propose a characterization of the couple marking/pavement that is more relevant to what is perceived by MV systems (the entity in charge of driving), and thus to propose a characterization that would be more relevant to the AV. To compare ADAS system performance and more quantitative measurements, one shall define indicators but also consider a suitable scale of analysis.

A first experiment was carried out on a section of a circulated road around the city of Rouen. Two instrumented vehicles drove on this road to collect measurements allowing to characterize the road marking lines. There were both a reference device of the mobile retroreflectometer type (ECODYN3) capable of measuring retroreflection as well as luminance and a vehicle equipped with AV cameras (MOOVE). In this study, a cross-analysis of the measurements collected by the two mobile devices is performed to compare the characterization of the marking lines both from the point of view of the current standard and a computer vision system. A discussion of these results is finally conducted, allowing a comparison with those of the literature, and also to suggest some perspectives.

## 2. Material and method

### 2.1. Itinerary

The experiment was carried out on a circulated road near the city of Rouen. This itinerary was composed of different types of road, including a departmental (DR 13) and a national road (NR 138) and therefore, the speed of traffic could vary up to 90 km.h<sup>-1</sup>. In this study, only the axial marking line (on the left of the right traffic lane) was analyzed respectively on one section of the DR 13 and of the NR 138. Different types of white axial lines, which characteristics are all described in the French regulation IISR (2011), were present on these road sections. On the DR 13 section, there was a T1 dashed line (a 3 m long skip followed by a 10 m long void) and a solid line, while on the NR 138 section there was first a T1 dashed line, followed by a T2 dashed line (a 3 m long skip followed by a 3.5 m long void gap). The markings showed highly variable degrees of wear and tear. The road surface was a bituminous pavement of variable characteristics along the itinerary. All the measurements were performed on dry road pavements by day, under sunny conditions with the potential presence of clouds.

### 2.2. Mobile acquisitions of big data about real world driving

The MOOVE project is the result of a collaboration between VEDECOM institute and French car manufacturers (Bonic et al. 2017). Its main objective is to drive on European roads and acquire a maximum of data to create a database of the parameters defining real life driving situations. Each MOOVE vehicles are instrumented as a 360° vehicle perception. The main standard sensors used here are two onboard cameras, two lidars front rear, one long range radar front, four short range radar corners and a Global Navigation Satellite Systems (GNSS). In this study, we only focused on the data collected by the Real World camera (associated to the GNSS) concerning the road markings detection.

When it circulates, MOOVE device can simultaneously analyze four road marking lines in its traffic lane. The real world camera records images and provides a result file with a set of data at 25 Hz, all composed of:

- A quality level of the marking line detection. It is a rating with four different graduations: “Very Low”, “Low”, “High” or “Very High”;
- A confidence level in the detection quality, between 0 % and 100 %. A level of 100 % means that the camera’s algorithm is sure to detect the road marking line, whereas a level of 0 % means the algorithm did not detect any road marking line.
- Further intrinsic characteristics like the type of the line (solid, dashed or double), the road marking color (white, yellow or invalid) and the line marking width.
- A polynomial model describing the curve of the marking line on a validation distance in meter.

For a given image, the collected data for each marking line are geolocated and saved in a database. Except these informations, very few details about the Real World camera are provided.

### 2.3. Mobile measurements of marking performances

The Cerema vehicle equipped with the mobile retroreflectometer ECODYN3 (see Fig. 1) measures in accordance with the geometry of standard EN 1436 (2018) both the retroreflected luminance coefficient  $R_L$  and the luminance  $L$  of a road marking. The vehicle is also equipped with an environmental camera, a GPS sensor and an illumination cell. An acquisition corresponds to the realisation of a series of measurements located and geo-referenced every 0.4 m. These acquisitions are triggered by an odometer located on the vehicle. The dimensions of the measurement area of the ECODYN3 are 0.5 m long and 1 m wide. This area is divided into 32 measurement channels.

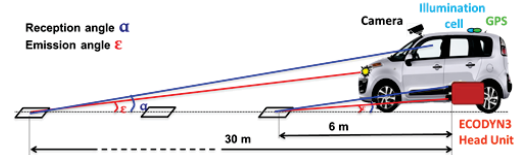


Fig. 1. Presentation of the ECODYN3 vehicle with a schematic drawing of the ECODYN3 measurement geometry.

Cerema has registered a patent (Guillard et al. 2013) on the use of data in the form of digital images by considering each measurement channel as a pixel. An extraction of markings is performed using a segmentation method. All statistical analyses are then carried out on the basis of the segmented images. It is then possible to characterize the marking at different scales, from punctual or over defined length like a marking skip for example.

### 2.4. Statistical analysis

Since the two devices do not have the same measurement areas, it is difficult to directly compare the data collected by the two devices. In order to conduct a robust analysis, different study scales were defined. They could correspond either to a global scale (e.g. on the length of a road section or a marking skip), or to a more local scale (e.g. a punctual measurement).

First, a descriptive statistical analysis was conducted on the detection by the MOOVE’s real world camera of the road marking lines (quality level and confidence level). Concerning the quality level of the marking line detection, we decided to keep the « verbal description » given by the algorithm (“Very Low” to “Very High”), rather than interpreting it as an integer between 0 (for the level “Very Low”) and 3 (for the level “Very High”). Converting to an ordinal numerical scale and making averages implies that the distances between each level are identical and equal to “1”. Since this hypothesis is not justified in the literature, it was not assumed in this study. Each road section was then divided into successive areas according to its quality level of marking line detection assigned to each of them by the camera’s algorithm.

Several statistical analyses were conducted on ECODYN3 data. The segmented images were used to characterize quantitatively the performance of the road marking line, using either retroreflection or luminance

measurements. For the punctual measurements (each 0.4 m long on the marking elements), the median value was used to characterize both the road marking and its surrounding pavement, since it is less sensitive to outliers and thus it leads to a more robust indicator. When a marking element was present, a median contrast ratio was computed every 0.4 m according to Eq. (2).

$$Cr_{x\_median} = \frac{X_{median}(marking)}{X_{median}(pavement)} \quad (2)$$

At more global scales (for example a marking skip or an area defined by the MOOVE statistical analysis), box-plot representations were used to visualize the disparity of the  $R_L$  values and of the  $R_L$  and  $L$  contrast ratios. Since the luminance values are very sensitive to environment parameters and meteorological conditions, it cannot be used alone to characterize the day marking visibility. However, the  $L$  contrast ratios are relevant because the road and marking are measured on the same conditions. In addition, the  $L$  contrast ratios are used to approach the  $Q_d$  contrast ratios. The box-plot representations allow to show the lower and upper quartiles (respectively labelled  $Q_{low}$  and  $Q_{up}$ ), and also the outliers data. This provides a robust representation of the marking line and road characteristics, taking into account the big amount of available data provided by actual mobile retroreflectometers.

A cross analysis was conducted between the two devices, considering the areas characterized by the quality levels of detection obtained by the MOOVE device. For these different areas, a confrontation was conducted between the confidence level of the line detection (associated to the quality level found by the MOOVE device) and the different statistical indicators ( $R_L$  values, and  $R_L$  and  $L$  contrast ratios) obtained with the ECODYN3 device. A last detailed analysis, both quantitative and qualitative, is then conducted for each identified area.

### 3. Results

#### 3.1. Results for the Machine Vision system of MOOVE

The left line is described by a total of 5948 set of data collected by the Real World camera on the two road sections considered. Road markings were all perceived white by the algorithm. Only two quality levels of the marking line detection were found by the camera's algorithm: the level "Very Low" in 9 % of cases or the level "Very High" in 91 % of cases. From the macroscopic analysis, the two infrastructure sections were then divided according to the quality level of the marking line detection, associated to the average confidence level of detection. Fig. 2 shows the cartographic representation and Table 1 the average results (with standard deviation SD for the confidence level) on each Area.

The confidence level was analyzed for each area because it is an indicator of the reliability of the marking line detection provided by the algorithm, which is not necessarily considered in the literature. The first 1200 m long of DR 13 have a quality level "Very High" of the marking line detection, with an average confidence level equal to  $97 \pm 11$  %. Just after, the confidence level sharply

decreased to exactly 0 % for 70 m, with a marking line quality level "Very Low", before becoming again "Very High", with a confidence level of  $86 \pm 22$  %. Similar results were found on the NR 138 section for the two quality levels detected by the Real World camera.



Fig. 2. Representation on *OpenStreetMap* website of the cartographic delimitation of the five Areas according to the quality level.

Table 1. Average results of the five Areas

Area number	1	2	3	4	5
Road	DR13	DR13	DR13	NR138	NR138
Quality level	Very High	Very Low	Very High	Very High	Very Low
Data number	3116	208	876	1416	332
Distance (m)	1200	70	160	900	220
Average Confidence level $\pm$ SD (%)	$97 \pm 11$	0	$86 \pm 22$	$99 \pm 7$	0
Dashed line (%)	100	100	1	95	100
Solid line (%)	0	0	99	5	0

Fig. 3 represents the confidence level of the left road marking line detection on the different areas (DR 13 section at the top and NR 138 section at the bottom). In agreement with the average results on Table 1, the Fig. 3 confirms that the confidence level has two distinct evolutions. In all the "Very Low" identified areas (Area 2 and Area 5), the associated confidence level is always 0 % and corresponds to a dashed line. The "Very High" Areas are rather associated to high percentage of the confidence level detection (above 86 %). The Areas 1 and 4 are also similar in term of type of line (both dashed line) and average confidence level of the line detection (respectively  $97 \pm 11$  % and  $99 \pm 7$  %). However, on the Area 3, the left marking line was detected with a lower confidence level ( $86 \pm 22$  %). The confidence level of detection of the marking line on Area 3 is more variable than on Area 4, with strong fluctuations,



although the quality level is “Very High” for both Areas. Consequently, these results demonstrate that the level of quality should not be the only factor to consider, and it must be completed by the confidence level of marking line detection.

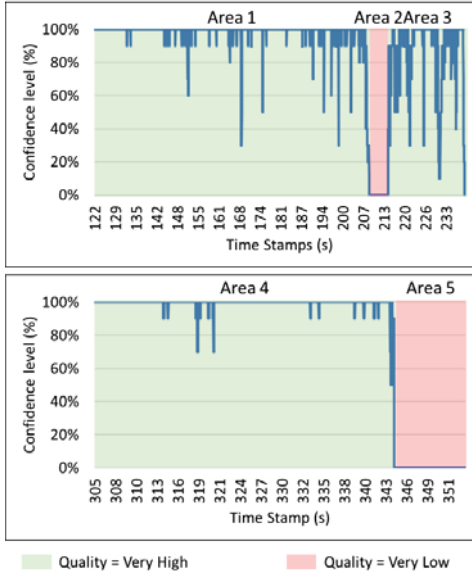


Fig. 3. Confidence level of the road marking line detection according to the quality level. Results along the DR 13 section are at the top and those along the NR 138 section are at the bottom.

3.3. Cross analysis between the ECODYN3 and MOOVE

For the cross analysis between MOOVE and ECODYN3 devices, a comparison was conducted at the scale of the five Areas identified by the MOOVE’s algorithm according to the quality and confidence levels of the marking line detection (see Fig. 3 and Table 1). For each Area, four graphics are presented in Fig. 4. The first three present boxplots, respectively for the  $R_L$  values of the marking line and the  $R_L$  and  $L$  contrast ratios (between the marking line and its surrounding pavement) calculated all along the Areas. The fourth is a cumulative bar of the confidence levels found on each Area by the MOOVE’s Real World camera.

The median  $R_L$  value of the marking line on the Area 5 is very low: around 23  $\text{mcd.m}^{-2}.\text{lx}^{-1}$  (with an upper quartile  $Q_{up}=37 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ ), which could explain the “Very Low” quality level and the null value of the confidence level. On the other hand, despite low median  $R_L$  values on Area 1 (median  $R_L$  value equal to 53  $\text{mcd.m}^{-2}.\text{lx}^{-1}$  with  $Q_{up}=66 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ ) and on Area 4 (median  $R_L$  value equal to 18  $\text{mcd.m}^{-2}.\text{lx}^{-1}$  with  $Q_{up}=42 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ ), the marking line was detected with a “Very High” quality level and a high average confidence level (respectively equal to 97 % and 99 %).

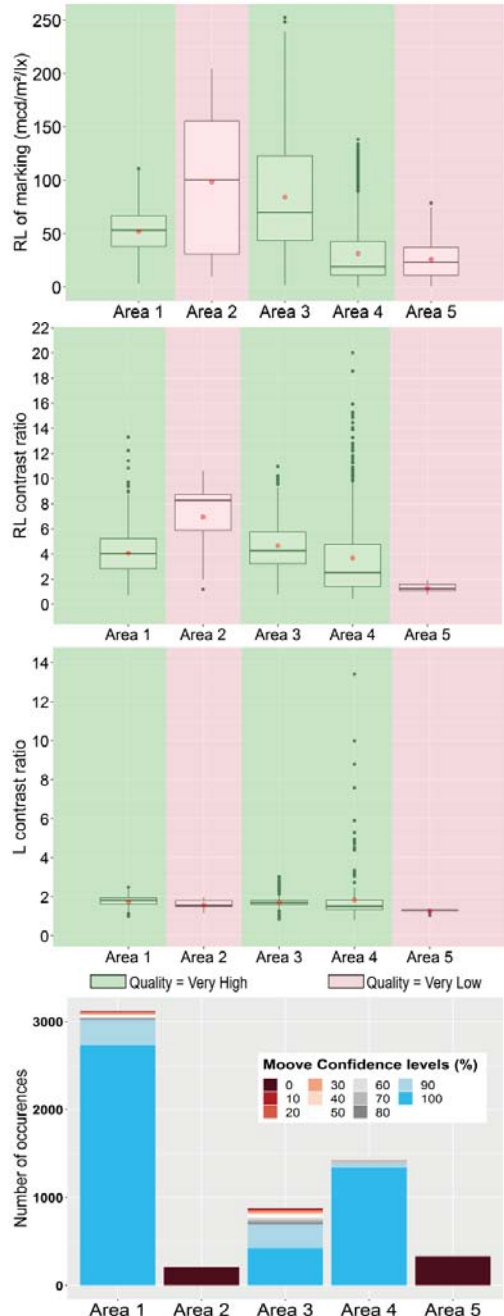


Fig. 4. Cross analysis of the five identified areas with different quality levels of detection. From top to bottom, boxplots of  $R_L$  values, of  $R_L$  contrast ratios, of  $L$  contrast ratios and cumulative histogram of the real world camera’s confidence level of marking detection.

It is also the case for the “Very High” Area 3, with a higher disparity of the  $R_L$  values around the median value (median  $R_L$  value is equal to  $69 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ , with  $Q_{low}=43 \text{ mcd.m}^{-2}.\text{lx}^{-1}$  and  $Q_{up}= \text{mcd.m}^{-2}.\text{lx}^{-1}$ ), even if the cumulative bar of the confidence level is more contrasted. Moreover, the median  $R_L$  value is the highest on Area 2 (around  $100 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ ), whereas its quality level is “Very Low” with a confidence level always equal to 0 %. As expected, the  $R_L$  representative of the night-time visibility of the markings does not make it possible to account for the visibility of the markings during the day seen by an AV.

The boxplot representing the  $R_L$  contrast ratios shows that for the three Areas with a “Very High” quality level, the median ratio values are between 2.5 and 5 (it is the same range for the mean ratio values). This could suggest that an Area where the marking line has a median  $R_L$  value at least 2.5 times higher than the median  $R_L$  value of its surrounding pavement is enough to be very well detected by the Machine Vision system. However, this result is not confirmed with the Area 2, where the median  $R_L$  contrast ratio is the highest and close to 8.2. These results indicate that the retroreflection ratios of the marking line alone is not sufficient for the needs of AV systems during the day. The boxplots on the  $L$  contrast ratios do not provide much information, because the median values are very close for the five Areas, with a very small disparity of the data. However, it is noticeable that the median  $L$  contrast ratio of Areas with a “Very High” quality level is between 1.5 and 1.8.

In order to better understand the obtained results, a focus is conducted on the Areas 2, 3, 4 and 5.

On the small length of Area 2 (only 70 m long), the marking line was detected with a “Very Low” quality level, despite high values of  $R_L$  contrast ratios (above 5). The marking line on this area is composed of a continuous line and a folding arrow. We suppose that the MOOVE’s camera is not able to interpret the presence of both the marking line and arrow.

On the Area 3, the marking line is continuous with the presence of zebras at the beginning and the presence of a pavement separator at the end (see Fig. 5). Despite the relative low values of  $R_L$  for the continuous marking line (below  $150 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ ), the Real World camera was able to detect a marking line with a “Very high” quality level associated with an important variability in the level of confidence (see Fig. 3). The real world camera probably interpreted the solid line and the zebra as a single marking line. That could explain the variability of the confidence level related to the variability of the road marking line.



Fig. 5. Photographs of the marking line on Area 3. On the left, beginning of the line with presence of zebras; on the right, end of the line with presence of a pavement separator.



Fig. 6. Photographs of the Area 4 with a changing of type of pavement on the left side and the output of a tunnel on the right side.

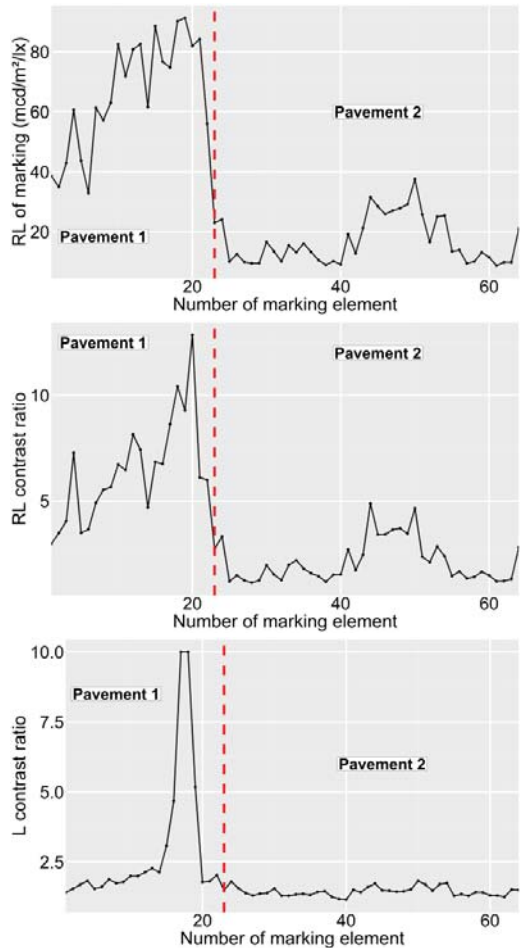


Fig. 7. Results of the Area 4 presented at the scale of a marking skip for the median  $R_L$  values (at the top),  $R_L$  contrast ratios (at the middle) and  $L$  contrast ratios (at the bottom).

On the Area 4, the road marking line is detected with a good level of confidence, even if the marking skip  $R_L$  values were low (always under  $100 \text{ mcd.m}^{-2}.\text{lx}^{-1}$  and often below  $50 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ ). The nature of the pavement was not the same all along this area: the first 264 m long were composed of an old light asphalt pavement (labelled “Pavement 1”), whereas a darker asphalt pavement (labelled “Pavement 2”) constitutes the next 476 m long (see Fig. 6, left). The Fig. 7 represents the evolution of the dashed marking line

retroreflection as well as the  $R_L$  and  $L$  contrast ratios all along the Area 4. For a given graph, each point corresponds to the median value computed at the scale of one marking skip. The retroreflection values of the marking skips were better on the Pavement 1 than on the Pavement 2, resulting in higher night contrast ratios (see Fig. 7, at the middle). There was also a very short tunnel just before the type of pavement changing (see Fig. 6, right), which affected the measurements of all the used devices. The environment camera of ECODYN3 was saturated at this location: the luminance measurements sharply increased, resulting in an increase of the day contrast ratios (see Fig. 7, at the bottom). The visible influence on the Real World camera was punctual lower confidence level down to 70 % (see Fig. 3, at the bottom). Excluding the tunnel, the day contrast was low, less than 2.5, all along the Area 4.

On the Area 5, the ADAS sensor was not able to detect the road marking line with a high quality level. These results are not surprising. First, the retroreflection of the marking line was quite low (below  $50 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ ), as well as the associated  $R_L$  and  $L$  contrast ratios (see Fig. 4). Secondly, there was a lot of traffic on this area during the measurement session, associated to a changing lane. In these conditions, the Real World camera does not seem to well interpret the dashed marking line (which delimits an insertion lane).

#### 4. Discussion

The goal of this research is to propose a characterization of the couple marking/pavement that is more relevant to what is perceived by Machine Vision systems. This study presents a first analysis, based on a daily experiment conducted on a small road section using a mobile retroreflectometer and a vehicle equipped with one type of AV camera. We conducted several statistical analyses at different study scales, in order to characterize the road marking performance according to the EN 1436 specifications, and to try to understand how the Machine Vision system behaves.

The retroreflection and luminance values of the marking and its surrounding pavement were collected with a mobile device allowing punctual and global analyses. To characterize the marking performance, the median value is used instead of the classically used average value because it is less sensible to outliers. The  $R_L$  values of the marking elements widely suggest that they were quite old, and below the recommendation of  $150 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ . Median contrast ratios were deduced from these median  $R_L$  and  $L$  values, in order to take both the marking and its surrounding pavement into account.

The road marking detection performance of the MOOVE's real world camera was generally excellent along the two road sections considered. Only two small Areas were detected with a "Very Low" quality level by the camera's algorithm. In these Areas, the associated confidence level of the marking line detection was always equal to 0 %. It was also noticed that this very low detection appeared when there was a sudden change on the road: a narrowing of the roadway or a change of pathway. We have shown that the use of the quality level of detection alone

shall be completed by the analysis of the confidence level to better understand the performance of a Real World camera used to detect road marking.

Based on all these results, a cross analysis was conducted between the two devices. Due to a lack of information concerning the measurement area of the Real World camera, the analysis scale was decided according to the MOOVE quality level segmentation. Thus, all the measurements collected by ECODYN3 on the marking line within the considered Area were considered. Several results have been shown. Except for the case of changing lanes or lane reductions, the tested ADAS camera was able to detect the marking lane with a "Very High" quality level, even if the retroreflection of the marking line was very low. During the day, the line detection was very good, even with a median  $R_L$  at 20 or  $30 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ . These levels correspond to classical road pavement retroreflection, showing that there were no glass beads left on the marking. This confirms that  $R_L$  values of markings are not sufficient to fully understand the detection of the Machine Vision systems. However, the retroreflection is the classic factor used to define maintenance policies (Redondin et al. 2019), especially because it is easily measured dynamically, contrary to the  $Q_d$  factor or  $\beta$  factors, which characterize the daytime visibility. The  $R_L$  contrast ratio could be a better indicator because it takes both the characteristics of the markings and its surrounding pavement into account. At the scale of a given Area length, it was shown that the Real World camera was able to detect the road marking line with a "Very High" quality level when the median (or mean) contrast ratio was less than 5 for the retroreflection and less than 2.5 for the luminance. These values are lower than most of the thresholds given in the literature. Although the Real World camera was still able to make a very high detection of the continuous marking line panned in front of the zebras (see Area 3), the presence of zebras introduces more variability in the detection level of confidence of the AV vision sensor. When the AV camera was not able to detect the road marking (characterized by a null confidence level of detection), it was only in the cases of changing lines or at a track narrowing zone.

We tried to propose an analysis of the road marking performance at different scales: on a skip length or on a road section length. This opens up new perspectives. Thus, an indicator of the quality of the implementation of a marking taking into account heterogeneity could be proposed. It could also be interesting to use this kind of new indicators to update the preventive maintenance models (Redondin et al. 2019).

The day contrast ratio was here based on luminance values collected with the ECODYN3 device, with an observation at  $2.29^\circ$ . It was unfortunately not possible to measure neither the  $Q_d$  factor, nor the  $\beta$  factor to make a comparison with the literature as in Pike et al. (2018) for instance. Moreover, the luminance contrast ratios were very similar from an Area to another, with most of the values between 1.5 and 2 and a small dispersion. Thus, it was difficult to deduce something from this factor in our study.



More work is needed to test this contrast ratio with other conditions.

Contrary to most of the literature, where studies are conducted on test tracks (Pike et al. 2018; Stacy 2019), our study was conducted on a circulated road with sunny conditions and a dry road. Thus, we could not control all the markings characteristics and visibility conditions. It is not possible to propose some thresholds (of  $R_L$  values or  $R_L$  contrast ratio) with this research. However, it is possible to compare our measurements with the thresholds published in the literature. All the  $R_L$  values of the three Areas with a “Very High” quality level are below  $150 \text{ cd.m}^{-2}.\text{lx}^{-1}$ , which is not consistent with Stacy (2019), who suggested  $R_L$  values above  $200 \text{ mcd.m}^{-2}.\text{lx}^{-1}$  to have at least a “High” quality level. On one of these Areas, the  $R_L$  values of the line marking could even be below  $30 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ . Thus, it is not consistent with the findings of Pike et al. (2018) (threshold of  $34 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ ) and Lundkvist and Fors (2010) (threshold of  $70 \text{ mcd.m}^{-2}.\text{lx}^{-1}$ ). That confirms that the  $R_L$  value is not the best indicator to make a link between the quality of the road markings and their detection by the Machine Vision systems. Considering our  $R_L$  contrast ratios, the median values were between 2.5 and 5, which is rather consistent with the threshold of Pike et al. (2018) and the one of Carlson and Poorsartep (2017), but not with the range given by Marr and Scott (2020).

To conclude, we confirmed that the comparison between a quantitative analysis of road marking and an AV Machine Vision system is complex. Since the technical specifications of AV Real World camera are not known and the used algorithm are protected, the researchers only have access to the systems outputs. In our study, several methodologies were proposed to compute a local day and night local contrast ratio. Since our results are based on a single experiment, conducted by day, we shall comfort it with more data based on several experimental conditions. In the SAM project we will create a marking pattern on a test track with different types of pavements. It will thus be possible to have several different controlled conditions.

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