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Hybrid AI road markings analysis from a retroreflector

Christophe Heinkelé, Colin Holler, Abdessamad El Krine, Aude Stresser, Valérie Muzet

Abstract—Road markings are essential for driving. Their characteristics are surveyed with dynamic retroreflectometers and are provided in an aggregated form to managers, usually averaged on 100 meter intervals. We have developed and tested a road marking analysis method that represents the measured signal as images and allows renderings at finer scales, such as the marking segment scale. To do this, we used several artificial intelligence methods. First, an architecture derived from U-Net was proposed for the automatic segmentation of marking elements. To check the consistency of the maps produced, we tested several techniques used in natural language processing with architectures such as LSTM and an attention mechanism derived from Transformers. Since there exist no annotated databases for this type of data, a Model-View-Controller software solution was developed to visualize, annotate and enhance the data. This led to the implementation of a processing chain as well as incremental learning methods. This paper presents both the software for processing data and visualizing the results, the methodology implemented and the first results obtained.

I. INTRODUCTION

Road markings provide both visibility and visual guidance for the driver. The characterisation of road markings follows standards [1], [2] based on the perception of a human driver. The most widely used road standard marking performance indicator relates solely to night-time visibility, known as retroreflection R_L , i.e. the reflection of headlights on a marking located 30 m from the driver. It is defined as the ratio $\frac{L}{E}$, where L is the luminance of the field of the road marking in the direction of observation and E is the illuminance perpendicular to the direction of the incident light. A dynamic characterisation of road marking performance is possible using retroreflector mounted on the side of a vehicle. They usually provide an average over a step of 100 m [3], 50 m or 30 m [4]. With the rise of the autonomous vehicle, these standards are being reconsidered, and criteria based on the luminance, also output by certain mobile retroreflectometers, can be used to characterize marking visibility in daylight conditions.

In this paper, we use a mobile retroreflector, Ecodyn3, which is capable of agglomerating R_L and luminance profiles to provide a global image of the daytime and nighttime photometric properties of the marking [5]. We introduce the global data exploitation methodology we have developed, based on artificial intelligence tools, and that we evaluated on real data. It provides road managers with a characterization of road markings, from the scale of individual marking segments to that of a route.

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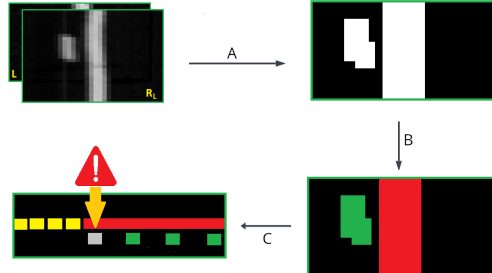


Fig. 1: Visual summary of the proposed road marking mapping process from raw R_L and L data (see text)

A visual summary of the process is shown in Fig. 1. From the raw retroreflection and luminance data, treated as images, we propose a modification of a U-Net model, which provides a segmentation of the marking elements (step A). The latter can be used to calculate parameters characterizing marking quality, but also to determine the typology of markings along a route using a shape recognition algorithm based on geometric criteria (step B). Finally, considering the marking segments as words of a language, we use natural language processing (NLP) algorithms to detect possible inconsistencies (in relation to standards) in the mapped marking scheme (step C). To implement this method, we have developed software based on the Model-View-Controller (MVC) paradigm.

The rest of the paper is organized as follows. In Section II, we review state-of-the-art pattern recognition methods that address the three issues under consideration (segmentation, identification and error detection). The used mobile retroreflector and the creation of a set of reference data for the learning and evaluation of the methods implemented is the subject of Section III. In the following three sections, we describe the proposed methods and their quantitative evaluation: segmentation (Sec. IV), identification (Sec. V) and consistency check (Sec. VI). Finally, Section VII concludes the paper.

II. STATE OF THE ART

For lane marking detection, methodologies based on convolutional neural networks (CNN) on images are frequently used nowadays [6]. The U-Net architecture is a CNN-based autoencoder first used in 2015 for the segmentation of medical images [7]. It is composed of three parts: an encoder that extracts features from the input image, which reduces dimensions down to a *bottleneck*. Then the decoder up-scales the feature maps back to the initial image dimensions, using skip-connections to add details and produce the segmentation

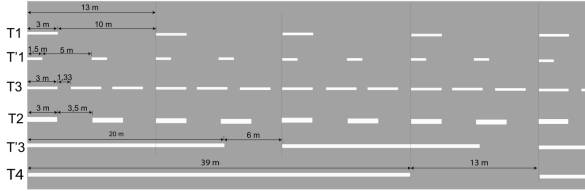


Fig. 2: Road marking nomenclature in France [10]

map (i.e. assign each pixel to a class). This approach seems appropriate for road marking segmentation since the data from a retroreflectorimeter can be seen as images [5].

The use of artificial intelligence methods requires large annotated databases to train the models, and very often public databases are used. In our application where the data do not come from cameras but from a mobile retroreflectorimeter, there are neither annotated data nor pre-trained models. In order to limit the tedious annotation phase as much as possible, we decided to create a database by incremental learning [8]. To do this, we used a Model-View-Controller (MVC) architecture as in [9].

Our second objective is to develop a robust methodology to automatically identify the type road markings from the segmentation results. Road marking follow a standardized nomenclature in all countries. In France for example, the length of a line segment and the length of the intervals between successive segments are defined according to IISR 7 [10]. A graphical representation of the french regulation is represented in the Fig. 2. With such standardized dimension, classical methodologies based on geometric criteria are particularly suitable to identifying the type of marking. If there is an error in the segmentation or if the marking is partially erased, then a marking segment may be truncated causing a wrong evaluation of its length and as a consequence, a bad identification. To detect such errors, and also inconsistencies resulting from the incorrect implementation of markings in relation to regulation, a methodology based on natural language processing (NLP) has been developed. It is based on an analogy between the succession of road markings types and the words of a sentence.

Recurrent Neural Networks (RNN) [11] are a family of neural networks specialized in the processing of sequential data. RNN share parameters from cell to cell, and each cell of the output is a function of the previous one. This approach translates the notion of recurrence and introduces the notion of memory within the neural network. However, classical recurrent neural networks are sensitive to the vanishing gradient problem, when updating weights in the backpropagation algorithm. Thus, long-term information can be lost. To overcome this problem, the Long Short-Term Memory (LSTM) [12], [13] architecture has been proposed. The LSTM is a cell composed of three gates: a forgetting gate, an input gate and an output gate. This allows the network to retain information that it has seen long before (unlike the classical RNN). We have also implemented and tested the attention mechanism from Transformers networks [14]. They

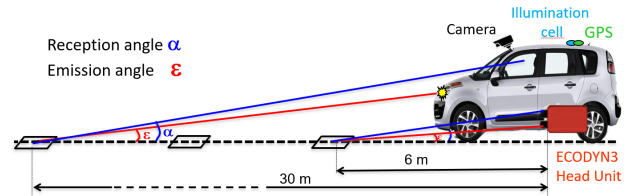


Fig. 3: Schematic drawing of the Ecodyn3 measurement geometry

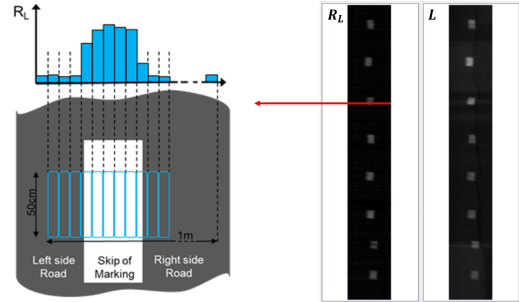


Fig. 4: Graphical representation of an Ecodyn3 acquisition and of the corresponding retroreflection (left). Generation of images corresponding to the Ecodyn3 measurements: one for retroreflection and the other for luminance (right)

are sequence-to-sequence neural networks like the RNN, but the heart of its architecture is the attention mechanism, which preserves the interdependence of words. The Transformer has the particularity of being parallelizable and of being able to focus on several elements of the input data, which is done via the number of heads.

III. DATA ACQUISITION AND ANNOTATION

A. Ecodyn3 device

We used a Cerema vehicle equipped with the Nextroad mobile retroreflectorimeter Ecodyn3 [15] that measures both the retroreflected luminance coefficient R_L and the luminance L of road markings according to the standard geometry [1], i.e. with an observation angle of 2.29° and an illumination angle of 1.24° . Since the Ecodyn3 head unit is mounted on the bottom of the vehicle chassis, the measurement is taken at 6 m instead of 30 m (see Fig. 3). The dimensions of the measurement area of the Ecodyn3 are 0.5 m long and 1 m wide. This area consists of 32 measurement channels of approximately $0.03 \text{ m} \times 0.5 \text{ m}$ (see Fig. 4).

With the Ecodyn3, since we have access to the raw data, the outputs are not averaged values on 50 or 100 m as with other retroreflectorimeters. The data are treated in the form of digital images by considering each measurement channel as a pixel according to patent [5]. It is then possible to generate two images [16], one for the retroreflection signal and the other for the luminance signal with each acquisition forming one line of the generated image (see Fig. 4). Each line of the image is composed of 32 columns (matching the 32 measurement channels), and the distance between two lines corresponds to a longitudinal distance of 0.4 m.

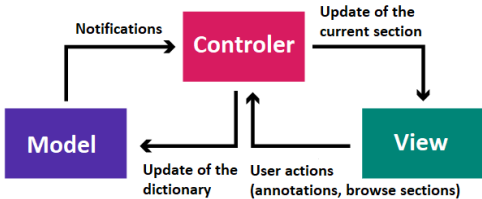


Fig. 5: The MVC architecture used for the labellisation

B. Databases and labellisation process

We measured, under circulation at normal speed, 437 km of roads by day on the French road network. There was mostly highways and local roads and some urban areas.

High-quality databases are essential for all types of supervised learning methods. As the data used here are not conventional images but the physical characterization of the marking and the surrounding pavement, which are both retroreflection R_L and luminance L , no prior labeled learning database is available. Representing the data as images as shown in Fig. 4 allows visual analysis for the operator and facilitates manual entry of road markings in order to perform data labeling. Incremental learning is used to increase both the quality and the size of the database through successive learning processes. Instead of carrying out the labelling from scratch, which is time-consuming, we use the previously trained models, for both the segmentation and identification steps, and the operator only corrects the model prediction errors. These can be either segmentation mistakes or inconsistencies in the identification of the type of marking.

To conduct all this process, we have developed a specific software package, called VTEcodyn. This software is based on an MVC (Model-View-Controller) architecture as described in Fig. 5. The main idea is to store the user action performed on the viewer (the human-machine interface) in the model through a set of control functions contained in the controller. This means that the user works on images but labels raw data. The developed software facilitates the tedious task of labeling (with incremental learning and ergonomic tools to automatically fill regions or assigning the same label to all shapes in a batch), calls the trained models and present their outputs.

The interface of the software developed for road marking annotation and data processing is shown in Fig. 6. It presents:

- raw data visualization ①② and contextual image ④;
- U-Net models inference visualization with a colored representation of markings types ③;
- path diagram location ⑤, with the inconsistency detected by the NLP model;
- manual error correction, which allows the generation of new reliable training data ⑥;
- data exports of marking characteristics (retroreflection, luminance and contrast with the neighboring road) at different scales of analysis: pixel, marking module or a chosen distance ⑦.

IV. SEGMENTATION OF ROAD MARKINGS

A. Early fusion and binarization with U-Net

The learning technique is based on an *early fusion* method, because we use both R_L and L , which are two physical measurements of the same surface conducted simultaneously. The training takes as input a two-component image, which is a tensor where

- x -axis has always $2^5 = 32$ points, corresponding to the transversal resolution of the device
- y -axis is the length of a batch (usually 2^k with $k \geq 2$), in our case $k = 5$ to have squares as inputs
- the depth is of size 2, one for R_L , second for L .

Before the learning process, normalisation to $[0, 1]$ is conducted on each batch for R_L and L .

The U-Net architecture has been adapted to the specific format of Ecodyn data. The input tensor has a depth of two, which is constituted of a two-channel picture with normalized data. Fig. 7 represents the architecture of our modified U-Net network. Several tests and an optimization process were achieved in order to find the ratio between high Precision/Recall and the number of parameters of the U-Net network, especially the depth of the bottleneck. In the output of the U-Net, we have a binarized image where each pixel is associated either to the marking class or the background class (that corresponds to the pavement).

B. Evaluation of the segmentation

The data available are Ecodyn3 measurements conducted in France. There are separated in two blocks: 313 km of roads for the learning set and 124 km for the test set. The trainings were run with the Adam optimizer [17] with a learning rate of 0.001, a batch size of 32 and a number of epochs of 200. The metrics used to measure the performance of the model are the classical classification metrics, such as Mean Square error (MSE), precision, recall and F1 score, as well as the inference time. The incremental learning method has been used with the modified U-Net network, in order to reach the best performance in terms of precision and recall, or in F1-score. Figure 8 illustrates the improvement of these indicators with the increase of the learning set size.

Two U-Net architectures were trained to make the two-class segmentation, using either 4 depth layers (resulting in 135 407 parameters) to a simplified model with only one depth layer (resulting in 26 066 parameters). The results of both approaches are presented in Table I.

TABLE I: Evaluation of different U-Net architectures

U-Net depth	MSE	Precision (%)	Recall (%)	F1 (%)	Param. numbers	Time (s)
4	0.0406	97.37	94.99	96.46	135 407	0.062
1	0.0296	96.37	95.01	95.69	26 066	0.026

The results are slightly better with a depth of four layers. However, a depth of one layer is sufficient for our application because it has fewer parameters, and is therefore less



Fig. 6: Labellisation process on raw data

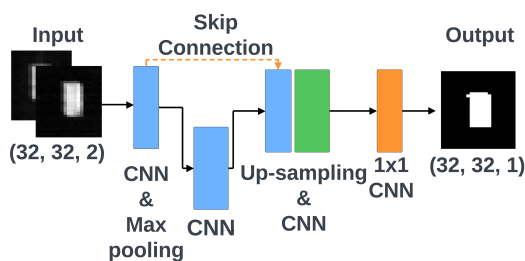


Fig. 7: U-Net architecture for road marking segmentation

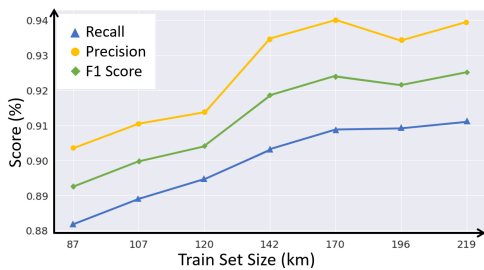


Fig. 8: Impact of the increase of the database size on the performance indicators (precision, recall and F1-score)

vulnerable to over-fitting. Moreover, it is really faster and still has an F1-score of 95.7%.

An example of the segmentation results is shown in Figure 9 for three very different types of road markings. The results are quite relevant, with a very good accordance between the ground truth and the prediction.

V. IDENTIFICATION OF ROAD MARKINGS

Since our aim is both to provide a fine characterization of the road marking (on the scale of a road marking segment for example) but also a methodology to detect inconsistencies at the scale of a route, after the binarization step it remains essential to identify the type of marking.

A. Identification from the nomenclature

First, a classification of the type of marking (see graphical representation of the french regulation in the Fig. 2) was

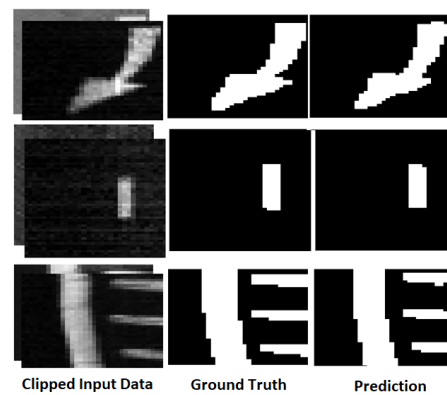


Fig. 9: Example of U-Net prediction obtained with a depth of one layer

TABLE II: Confusion Matrix of the identification: ground truth (lines) and results of the geometric classification (columns)

	T ₁	T ₂	T ₃	T ₄	T ₃ '	LC	ARROW	UNK
T ₁	7155	112	44	1	0	11	3	221
T ₂	23	5226	92	1	4	1	14	12
T ₃	50	87	5379	0	0	0	55	56
T ₄	0	0	0	460	6	3	2	40
T ₃ '	0	3	0	0	131	0	1	11
LC	13	20	69	2	23	152	82	124
ARROW	1	9	0	0	0	0	139	1
UNK	19	175	174	0	2	27	196	63

conducted according to geometric criteria. After the segmentation process, since the size of a pixel is $0.03 \text{ m} \times 0.5 \text{ m}$, it is possible to estimate the dimensions of the related components. For the assignment of segmented marking elements in the different types of marking, intervals were defined considering the middle of each standardized size. On a given route, the barycenter of each component is then marked with its GPS coordinates and with its type. An unknown class (noted UNK) is added for markings that do not appear in the nomenclature of the regulation.

B. Evaluation of marking identification

For the evaluation of the geometric marking type identification, we used 212 km of data. To measure the performance of this algorithm, a confusion matrix was constructed. When going through the related components of the road, a parallel between the operator ground truth and the output of the algorithm is made and the results are presented in Table II. The results are very satisfying for the highly represented markings such as T_1 , T_2 , T_3 or T_4 with over 90% recall and accuracy. However there are still identification problems for continuous lines (LC). Since the length of continuous line is not defined, they could have the same length as a T_1 during a discontinuity to signal at small intersection, such as a field entry. Unknown markings (UNK) are also poorly identifiable as they can result from several factors, poor segmentation, degraded or missing markings. However, it is better for the algorithm to classify a marking as UNK than the inverse because the user can classify problematic markings even better than with NLP classification methods.

VI. CONSISTENCY CHECK USING NLP

Once the detected road marking elements have been assigned a type, we aim at checking that these assignments are consistent with the standard. This can be used to detect (and therefore correct) any processing errors, or to highlight faults in the marking implementation.

A. Semantic description

A semantic description of the French nomenclature is defined both to reduce the dimension of the identification results and to put them in a form compatible with natural language processing methodologies. Each marking-space couple becomes a kind of word and their succession can be considered as a kind of sentence.

The semantic description is defined as follows :

- A letter $A_{marking}$ corresponding to the different possible length of a line segment. In France it could be M_1 for 3 m, M_2 for 20 m, M_3 for 39 m, LC for continuous line and UNK for a non standardized length or a rare road markings;
- A letter E_{type} for the possible length of gaps between consecutive segments. It could be either BG_T_1 for 10 m, BG_T_2 for 3.5 m, BG_T_3 for 1.33 m, BG_T_4 for 13 m, $BG_T'_3$ for 6 m, BG_x_y when there is a transition between two markings of type x and y , BG_UNK for a non standard background length, and at least BG_LC if there is no marking

Since the annotation was conducted both for the segmentation and marking type identification, a solid database is available to learn the succession of markings. In France, some marking lines are made up of a continuous marking and segments of adjacent markings. In order to deal correctly with such mixed lines and their succession along a route, our methodology introduces three channels : one (central) for the continuous line and two (on either side) for adjoining broken lines, as illustrated in Fig.10. Each channel is used as an input for the architectures used in NLP. In our application, a

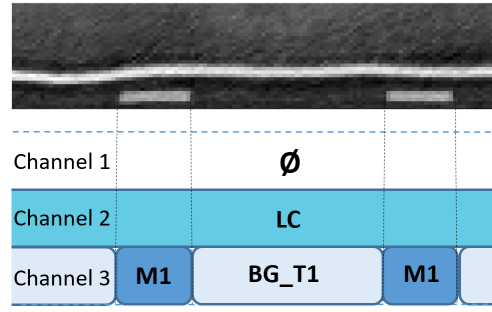


Fig. 10: Raw data (above), modelisation with a division of the signal into 3 channels for semantic analysis (below).

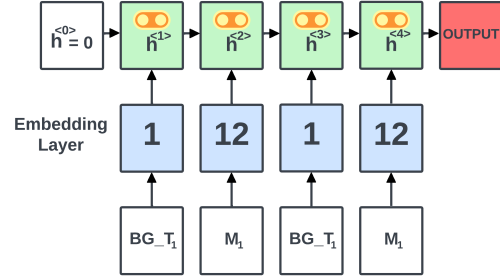


Fig. 11: Classical RNN Architecture

strictly positive sequence of size T composed of a succession of marking segments and gaps is defined as an ordered set of data. The idea is to divide the route into several sequences according to the geometric criteria and to classify whether they are correct or not, depending on the presence of logical errors. For example, an occurrence of a T_4 letter in a neighborhood of T_1 letters will indicate that the sequence is faulty. In our study, we chose a sequence size of 16, i.e. 8 marking segments and 8 gaps.

B. Implementation of LSTM and Transformers

The first natural language processing method implemented uses LSTM. The letters of our sequences are first associated to integers and then entered into an embedding layer, which is used to transform each letter into a vector of dimension N_e , $N_e = 32$ in our application, allowing the network to learn more about the relationship between the elements of the sequence and to process the data more efficiently. The output of the embedding layer is sent to the recurrent layer and as a final layer, a simple dense layer for classification is used (see Fig. 11).

For the analysis of the semantics of the route using transformers, only the encoder part of the architecture from [14] will be used. The two main features of this encoder are position embedding in addition to embedding layer, which allows for giving an order relation in the input sequence (implicit in the RNN method). The notion of self-attention, based on the similarity between two vectors via the scalar product allows for focusing on the most important words in a sentence while taking into account the words interdependence. Indeed, the attention mechanism is used to identify markings identification errors.

C. Evaluation of the NLP algorithms

The 212 km of data available are separated in two blocks: 137 km of roads for the training set and 75 km for the test set. As a reminder, the road output of the segmentation and geometric identification algorithm has been decomposed into several sequences and an operator annotated the sequences as true (correct) or false (faulty). These sequences and associated labels are input to the NLP architecture for training. An architecture with an LSTM layer with 32 neurons is used as well as two architectures using the attention mechanism of the Transformer (Trans₂ with two heads and Trans₁ with one head) with an encoder with 64 neurons followed by an Average Pooling layer and dense layers for classification. Training was carried out with the Adam optimizer with a learning rate of 0.001, a batch size of 32 and a number of epochs of 200. The results are presented in Table III. The model with the LSTM layer performs better in terms of precision than the architectures with attention mechanisms. However, we have better recall in the case of transformers. These results are promising and we expect them to exceed 90% in F1-score by enriching the data bases used for training. The best results are obtained with the transformer with one head.

TABLE III: Results for the consistency check

	MSE	Precision (%)	Recall (%)	F1 (%)	Number of parameters	Time (s)
LSTM	0.05657	86.74	88.17	87.45	15905	0.0155
Trans₂	0.0535	84.65	92.44	88.37	43 486	0.0711
Trans₁	0.0683	81.75	96.16	88.37	26 910	0.0301

VII. CONCLUSION

A method combining several deep learning architectures was implemented to enable an automatic analysis of Ecodyn3 retroreflectometer signals. This type of road marking data characterization being very specific, there were no available learning databases. In order to simplify the annotation task and increase more easily the database size, a software based on an MVC architecture has been implemented, which allows the use of incremental learning. The adaptation of the U-Net architecture to the automatic analysis of the markings reached performance metrics above 95%. Marking type identification is complemented by an automatic detection of inconsistencies, which focuses quickly on problematic cases, that could be either model mistakes or inconsistencies of marking implementation with respect to regulations. It could thus help both the annotator and the road manager to detect problems.

The VTEcodyn software developed incorporates all the methods presented in this paper and provides users with all these new functions. Its use does not require artificial intelligence skills. It has already been used to exploit Ecodyn3's data of the SAM project [15] (Safety and Acceptability of Automated Mobility) whose aim is to develop knowledge to build a technical and regulatory framework to facilitate the circulation of automated vehicles on the French road network. Although the results reported here are already of a

sufficiently high quality for this type of application, there is still a need for further training on larger databases, in particular to improve performance on less frequent markings such as arrows. Developments to date concerning identification are specific to French road marking standards. However, natural language methods obey a semantic that can be adapted to other countries. This presents no particular difficulty, although it will be necessary to relearn the rules of the country's nomenclature.

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