Road-marking analysis for autonomous vehicle guidance

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***Abstract*— Driving an automobile autonomously on rural roads requires knowledge about the geometry of the road. Furthermore, knowledge about the meaning of each lane of the road is needed in order to decide which lane should be taken and if the vehicle can do a lane change.**

This paper addresses the problem of extracting additional information about lanes. The information is extracted from the types of road-markings. The type of lane border markings is estimated in order to find out if a lane change is allowed. Arrows, which are painted on the road, are extracted and classified in order to determine the meaning of a lane such as a turn off lane.

***Index Terms*— Autonomous vehicle guidance, perception, classification**

I. Introduction

Driving a car autonomously on rural roads requires the perception of the environment. One of the fundamental information it needs, is knowledge about the road the car is driving on. Basically, this is the geometry of the road and the number of lanes. Since the vehicle should be able to execute maneuvers such as lane changing, collision avoidance, overtaking and turning off, it needs additional information about each lane. This includes knowledge whether a lane change can be applied and knowledge about the meaning of each lane, i.e. it has to be used for turning off.

The main contribution of this paper is the analysis of road-markings which provide the requested information. Road-markings can be divided into markings of lane borders and painted arrows on the road. The type of lane border marking determines if a lane change is allowed and the type of painted arrow reveals the meaning of a lane.

A lot of work exists in the field of lane detection, an overview can be found in [10]. Most approaches use edge elements (e.g. [9]) or regions (e.g. [3]). In most approaches, the estimation is done using Kalman-Filter [4] or Particle-Filter (e.g. [1]).

Only few works deal with the extraction and analysis of road-markings. In [5] a lane marker extractor is presented and the concatenation of these markings is used to estimate the course of the lane. The combination of road borders and road markers was used in [6] for lane detection. Another lane marker extractor is presented in [8]. Burrow et al. presented an overview of approaches for lane marker segmentation in [2].

This paper is organized as follows. First, our approach for lane detection is presented which is the basis for the road marking analysis. The analysis itself is divided into two parts. The estimation of the type of lane border marking is presented in section III-A. The classification of painted arrows is shown in section III-B. Results are presented in section IV.

II. Lane detection

Lanes are detected using a particle filter. A rule-based system handles the tracking of multiple lanes by deleting invalid lanes and creating new lanes if necessary. For each lane, a single lane tracker is used with minor adaptations.

The lane model used for estimating each lane describes the lane in front of the car and assumes that it is straight and flat. It consists mainly of two parallel, straight lines. The model is described by four parameters. The offset x_0 describes the lateral shift of the car's main (longitudinal) axis with respect to the middle of the lane. The angle ψ is the rotation between the car's main axis and the lane. The width of the lane is denoted with w. The last parameter is the tilt angle ϕ between the looking direction of the camera and the road plane. Figure 1 depicts the model of a single lane together with its parameters.

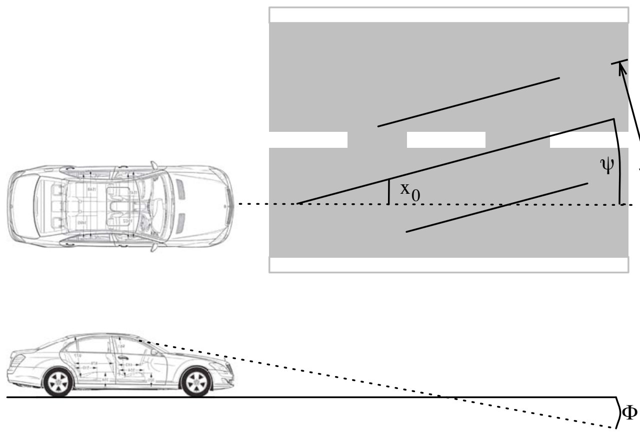

Fig. 1. Model of a single lane used for tracking.

The basic idea of tracking a single lane is to use a particle filter. Each particle represents one sample and the evaluation function determines the probability having the measurements given this particular sample. Each particle represents a particular parameter set of the lane model M_i, described by the four introduced parameters:

$$M_i = \{x_0^i, \psi^i, w^i, \phi^i\}. \tag{1}$$

The a-posteriori probability for each particle is calculated by evaluating different cues with each cue representing a specific hint about the observed scene. The cues used in this work are:

- Lane marker cue (LM), estimating the probability of having lane markings under the projected model.
- Road edge cue (RE), estimating the probability of having edge elements at the borders of the lane.
- Road color cue (RC), estimating the probability of having an area of road color under the projected area.
- Non-road color cue (NRC), estimating the probability of having an area of non-road color outside the projected area.
- Elastic lane cue (EL), evaluating the expected offset of the lane.
- Lane width cue (LW), evaluating the expected width of the lane.

Each cue gives a value between 0.0 and 1.0 and the overall rate of a particle $p(M^i)$ evaluates to:

$$\begin{aligned} p(M^i) &= p_{LM}(M^i) \cdot p_{RE}(M^i) \cdot p_{RC}(M^i) \cdot \\ &\quad p_{NRC}(M^i) \cdot p_{EL}(M^i) \cdot p_{LW}(M^i) \end{aligned} \tag{2}$$

The resulting estimation $p(\hat{M})$ is then given by the weighted sum of all particles. This value is compared with two thresholds in order to decide, if a lane was really tracked. Finally, all estimated lanes are stored in a list and a control component keeps track of all estimated lanes. A set of rules is used to start new trackers and to terminate outdated ones.

Figure 2 shows an example where all three lanes are tracked. The approach is described in detail in [11].

Fig. 2. Example of tracked lanes using the particle filter.

III. Road marking analysis

In order to classify road markings, two different types of information are analyzed. The first one is the type of lines, e.g. solid or dashed, and the second one are the arrows which are painted on the road. Fortunately, Germany has strict regulations for painting road markings [7] which can be used for the analysis. The guidelines describe the appearance of road markings and arrows as well as the position of each marking. For dashed lines, the distance between two markings is defined as well.

Basis for the analysis is the lane detection described in the previous section. The analysis does not depend on a particular lane model, since it uses only the lane borders and the middle of the lanes as search regions for line and arrow classification respectively. Therefore, it can easily be combined with other approaches for lane detection.

A. Classification of lines

The classification of the lines is divided into four steps. First, the lines are sampled using scanlines. In the second step, each scanline is classified, in order to extract the type of line it represents. The scanlines are than concatenated and outliers are removed in the third step. Finally, the series of scanlines is analyzed and the type of line (none, solid or dashed) is determined.

1) Sampling with scanlines: The classification of lines starts with the sampling of the painted lines using scanlines. A scanline is a straight line orthogonal to the painted road marking and it is represented in 3d-world coordinates in the vehicle coordinate system. Each scanline has a length of 1 meter in order to cope with errors of the lane tracking. The distance between two scanlines is set to 0.5 meter. This follows the german regulations for road markings and assures that all markings and gaps between markings are captured. The overall layout can be seen in figure 3.

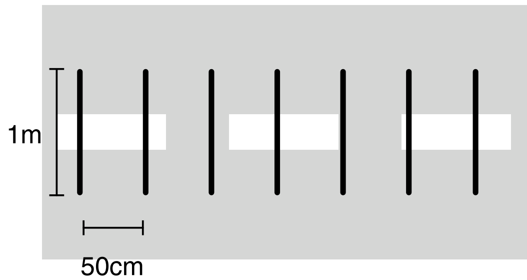

Fig. 3. Layout of scanlines for analysis.

For the image analysis, the scanlines are projected into the camera image using the projection matrix estimated by the detection of the lanes. A binarization along the projected scanline is performed in order to extract the road marking under the scanline. A global threshold cannot be used for the binarization of all scanlines since road surface and markings have different brightness at different distances.

The distribution of the image intensities along the projected scanline is mainly influenced by three road regions: the road marking, the road surface, and the roadside. Therefore, we assume three peaks in the distribution which are estimated using k-means clustering. The optimal threshold is than the medium value of the second and third peak.

2) Classification of scanlines: After the segmentation, all pixels of the lane marking are set to 1 whereas the rest is set to 0. The width of the marking is estimated using pixel positions A to D as shown in figure 4. The backprojection of these pixel coordinates into the vehicle coordinate system gives the 3d-position of the transitions $A \rightarrow B$ and $C \rightarrow D$. Thus, the width of the road marking is between $\overline{BC}$ and $\overline{AD}$.

Road markings follow strict regulations in Germany. A width of 12 cm is used for small markings and signals normal lane boundaries whereas 25 cm wide markings which are used to indicate turning lanes or emergency lanes. The distances $\overline{BC}$ and $\overline{AD}$ are compared to these widths. This yields a classification of the marking into the classes “no marking”, “small marking” or “wide marking”.

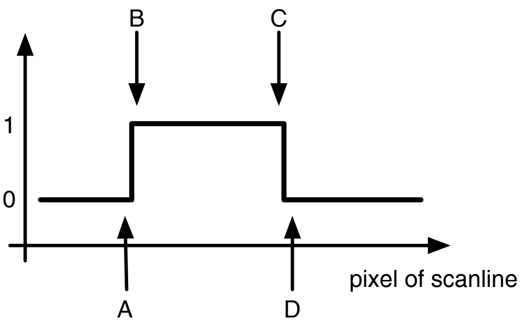

Fig. 4. Sample points for estimating the width of the road marking.

3) Concatenation of scanlines: So far, each scanline is assigned a type of line marking. The aim is to separate the road marking into segments of solid and dashed lines. Therefore, the next step is to concatenate the scanlines in order to identify these segments.

For concatenation of a scanline, its successor and its predecessor are taken into account. In order to decide if a scanline can be connected, the positions of the transitions $A \rightarrow B$ and $C \rightarrow D$ within each scanline are compared with the corresponding positions of its successor and predecessor. If the position of either the upper or the lower transition are similar, the scanlines can be concatenated. As can be seen in the left of figure 5, the middle scanline can be connected, because the position of the upper as well as the position of the lower transition are similar. In the right of that figure, the segmentation of the marking has errors which lead to a wider marking. Nevertheless, the connection is established because the position of the upper transition fit.

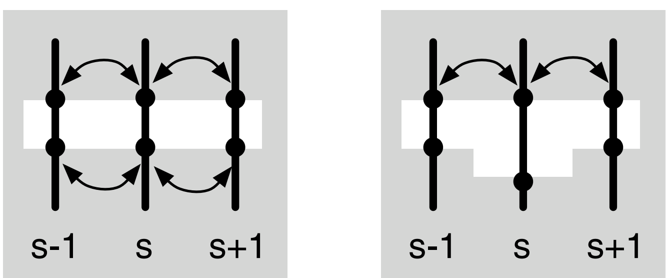

Fig. 5. Concatenation of scanlines because the position of the transitions fit.

In the second example in figure 6, one can see a solid road marking on the top and the scanlines are connected. In the right of that figure, a second line starts. Thus, scanline $s+1$ containes two roadmarkings. The upper one is already connected and the lower one is not connected with scanline s, because their positions are different.

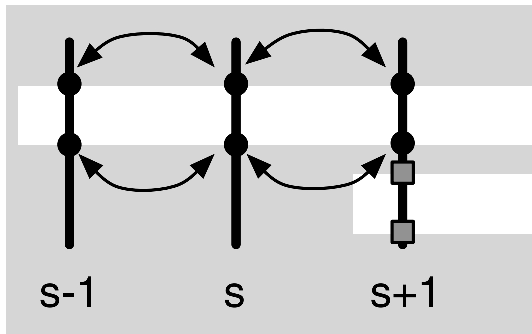

Fig. 6. Case where the position of the transition does not fit.

4) Line type classification: For the classification of the line type, the series of scanlines is transformed into a series of symbols, where each symbol represents a particular type of lane marking. Each scanline has 0, 1 or 2 markings and the symbol of a scanline is derived by looking at the neighboring scanlines.

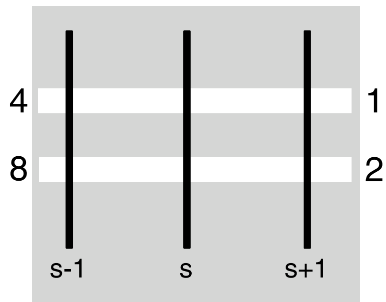

Fig. 7. Deriving the symbol of scanline s by looking at scanlines $s-1$ and $s+1$.

Figures 7 shows, how the symbol for scanline s is derived. For each neighboring scanline (left and right) and each line marker position (upper and lower), a value is generated and the resulting symbol is the sum of these values. If a marking for a neighbor at a position exists, the value as depicted in figure 7 is assigned, otherwise it is set to 0. For example, if the right neighbor has a lower marking, a value of 2 is used.

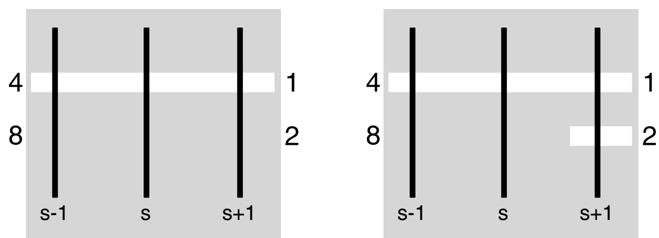

Fig. 8. Example for deriving the correct value for scanline s.

Consider the examples given in figure 8. In the left part, both, the left and right neighbor have an upper marking and the value of scanline s is $v_s = 5$ $(1+4)$. In the right part, again both neighbors have the upper marking. Additionally, the right one has a lower marking and thus the value $v_s = 7$ $(1+2+4)$. Figure 9 shows a complete sequence of symbols where the road marking is a dashed line.

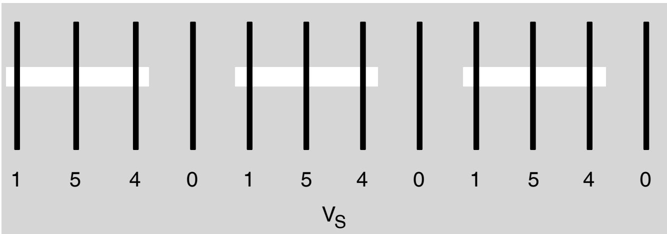

Fig. 9. Resulting sequence of symbols for a dashed marking.

The resulting sequence of symbols can be seen as a string and regular expressions are used to extract the different segments of the road markings.

B. Classification of arrows

Painted arrows on the street provide the second type of information which can be used to derive the meaning of a lane. Shape and position of arrows are regulated as well as the painted lines.

The order of processing for classifying arrows is as follows. First, for each lane, a region within the image is determined where an arrow is expected. A segmentation of this region takes place in order to extract the arrow in the second step. The bounding box of the extracted arrow is than used for template matching with known arrows.

Fig. 10. Overlaid search region for arrow detection.

Arrows are painted in the middle of a lane. Together with the information from the lane detection, a region in world coordinates is defined and projected into the camera image for each detected lane.The size of the region corresponds to the size of the biggest arrow plus a tolerance to cope with noise from the lane detection. The resulting image region is shown in figure 10.

In a preprocessing step, the brightness of the pixels inside the region is analyzed and the classification is applied if the brightness is above a predefined threshold. The segmentation of the region into pixels belonging to the arrow and to the road is done by using binarization. It uses the same k-means clustering technique for estimating the optimal threshold as it is done for the line analysis. Connected component analysis is applied in order to extract the biggest component which is the candidate for arrow estimation.

The extracted component is than backprojected into the vehicle coordinate system and the region for template matching is generated by extracting the bounding box of the backprojected component. The bounding box is scaled to the size of the templates and the sum-of-squared-differences (SSD) between template and extracted region is used for determining the correct type of arrow. Figure 11 shows on the left a template used for classification and an extracted and scaled region which is to be classified.

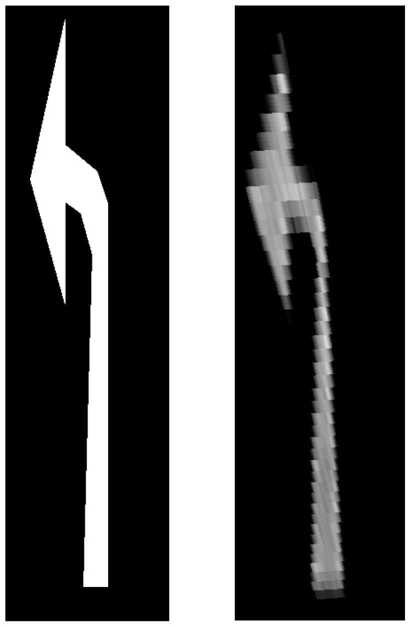

Fig. 11. Template of left arrow and extracted component.

IV. Results

For testing our approach, different image sequences were evaluated which contained country roads. Within the sequences several intersections appear which contain arrows for possible turning directions. A maximum of three lanes are visible at the same time at these intersections. The sequences were recorded with a standard DV-video camera at 25 Hz and an image resolution of 720x576 pixels. They were processed off-line and thus the processing time was not evaluated.

			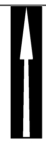			total
occurence	2	6	6	3	5	22
found	2	5	6	2	5	20
classified	2	5	6	2	5	20

TABLE I
CLASSIFICATION RESULT OF ARROW ANALYSIS.

The tracking of the lanes is the basis for the analysis of the road markings. The tracker shows convincing results, since in all frames the lane of the vehicle is correctly tracked (see figure 12). Only the left outermost lane within an intersection is lost in a few situations, because only few road markings are available or the lane is partially occluded by another vehicle (see figure 13, the red marked lane on the left signals an tracker loss).

Fig. 12. Tracking of multiple lanes within intersection.

Fig. 13. The outermost left lane is temporarily lost due to lack of road markings.

Figure 14 shows the output of the line classification. The scanlines are drawn with orange bars and the extracted road markings are overlaid with short red bars. The green lines display the result of the lane tracker module. The image overlay in the upper left corner shows the reconstruction of the recognized line markings from a bird's eyes view. The type of the borders of both lanes are correctly classified. For the right lane, the right border is classified as a solid line marking and the left border is classified as solid, too, for the first 15 meters in front of the vehicle. This holds also for the borders of the left lane.

Nevertheless, two things need to be pointed out. First of all, the width of the left border of the left lane is incorrectly classified as being a wide line marking (with a width of 25 cm). This stems from insufficient image resolution at larger distances and is difficult to handle in general. Fortunately, this is a less serious problem, since this marking is less important for the understanding of the road.

The second speciality is the space between the two lanes. It contains additional road markings which indicate this space as a blocked region. These markings are extracted, too, but the concatenation of scanlines prevents to take these markings into account for line classification.

Fig. 15. Example of classified arrows.

The classification of arrows is very convincing. Figure 15 shows the classification result of the arrows on the right and the middle lane. We did a frame by frame analysis of two image sequences with a total of 941 frames. In total, 22 arrows appear in the images and 20 were detected and correctly classified. One arrow was not detected because it was occluded by a vehicle. The other one was not detected because the lane was not found. All classifications were correct. Table I summarizes the classification results for each type of arrow.

V. CONCLUSIONS

In this work, an approach for road marking analysis was presented. The analysis is divided into two parts: lane border markings and painted arrows. As long as the lane detection provides correct information, lane border markings as well as painted arrows are correctly extracted and classified.

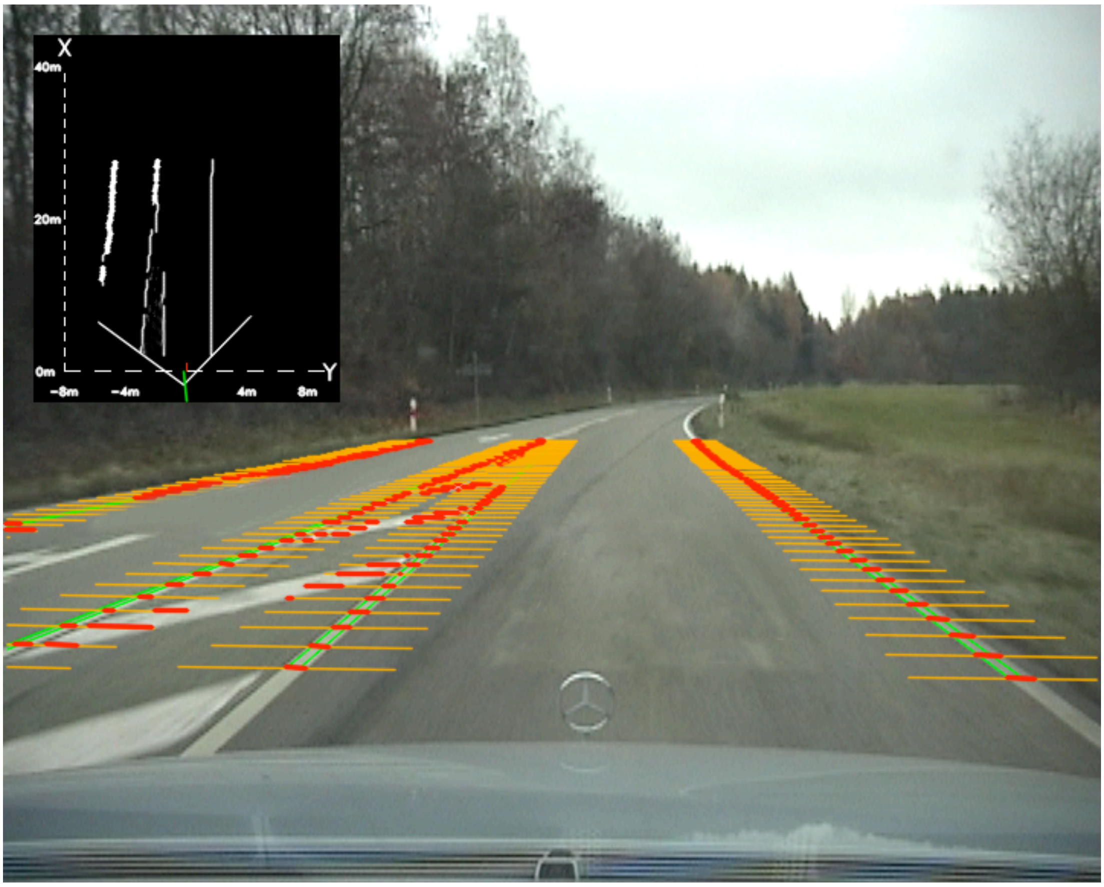

Fig. 14. Output of the road marker line classification.

There are two main directions for future work. The first one is to extend the analysis itself in order to extract additional information given by arrows which are part of the middle lane marking and the blocked regions. The second direction is to feed back the information about the lane markings into the lane detection process in order to increase the robustness of the lane tracking.

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