

# Calibration of an embedded camera for driver-assistant systems

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**Abstract**—One of the main technical goals in the automotive industry is to increase vehicle safety. The European project SPARC (Secure Propulsion using Advanced Redundant Control) is developing the next generation of trucks towards this aim. The SPARC consortium intends to do so by providing the truck with active security systems. Specifically, by equipping the truck with different sensors, it can be made aware of its environment, such as other vehicles, pedestrians, etc. By combining all sensor data and processing it with internal proprioceptive information, the truck can advise, warn the driver or even override him in case of non-response.

Camera systems are particularly advantageous for sensing purposes, because they are passive sensors and they provide very rich information. Moreover, they can easily be software-reconfigured to extract new or additional information from the image. Typical information that SPARC aims to extract is the position of the vehicle within the lane, the presence and distance of other vehicles or obstacles and the identification of road signs. In this paper, a lane-detection algorithm will be presented and discussed.

Some of the resulting information needs to be given in world coordinates, as opposed to image coordinates. To carry out the necessary conversion, a previous calibration is needed. The challenge is to determine a procedure to calibrate a camera mounted on a truck to precisely determine the position of obstacles situated in a 100 meter range. The two-step calibration procedure presented here has been designed to simplify the calibration of the mounted cameras in the truck production line.

## I. INTRODUCTION

Passenger safety is one of the most important axes of research in the automotive industry. This goes beyond increasing vehicle reliability or equipping cars with passive security systems. Indeed, 95% of accidents are due to human behaviour and only 5% to defective vehicles [1]. Moreover, 80% of these accidents involve improper driving reaction, speed and U-turn manoeuvre [2]. Analyses of these accident scenarios show that more than 40% of the accidents might have been avoided if the vehicles had been equipped with a warning system. This level of safety could rise to 95% if the vehicle could autonomously engage a safety driving response in critical situations.

Therefore it is necessary to develop active security systems capable of sensing the environment where the vehicle is evolving and analyzing the situation in real-time. This driver-assistance system should further be capable of interacting with the driver, in order to inform or warn him of a potentially dangerous situation, and to act on the powertrain

and steering to avoid the accident should the driver not respond on time.

### A. European project SPARC

The European project "Secure Propulsion using Advanced Redundant Control" (SPARC) aims to build the new generation of driver-assistant systems for heavy goods vehicles. Trucks are particularly interesting for this project because compared to accidents with cars, heavy vehicles cause more than two times heavy damage, nearly two times more injuries and more than three times the number of persons killed. Furthermore, because of their driving distance, driving time and professional use, trucks stand out as pioneer for car technologies. To prove this principle, SPARC intends to demonstrate the scalability of the security systems by porting the developments made on trucks to a small passenger-car.

To achieve these aims SPARC is based on two concurrent developments. The first is the X-by-wire technology that enables the steering wheel of the driver to be mechanically disconnected from the wheels: as in the aircraft industry, the steering column is replaced by servomotors and the driver commands are sent through wires. This equipment has been successfully tested in the Powertrain Equipped with Intelligent Technologies project (PEIT, contract no.: IST-2000-28722), and allows some automatic controls to maintain drive stability and reduce braking distance in critical situations. The second development is the creation of a safety assistant or Co-Pilot to compute and decide truck behavior. This module is composed by the Human-Machine Interface (HMI) where the driver chooses the direction and velocity to apply to the truck. This information (or stimuli) can be characterized by a vector. In parallel, the Co-Pilot technology fuses all sensor information, and provides a redundant vector which expresses the safest vehicle behavior. Finally, the safety decision controller will generate a secure motion vector based on both previous vectors, and send this third vector to the powertrain in order to avoid accidents in case of driver failure (see Fig. 1).

The Co-Pilot builds an internal representation or map of the world surrounding the vehicle in order to select the best action to be taken to follow a safe trajectory. This action is then encoded as a *redundant vector*. It is redundant because usually the driver has taken that same action. In order to build this internal representation of the environment, the Co-Pilot relies on a set of sensors, such as radars, GPS or camera systems. No single sensor is capable of providing accurate, robust information in all weather or traffic conditions. Therefore, the Co-Pilot exploits the complementarity of sensors by fusing their information.

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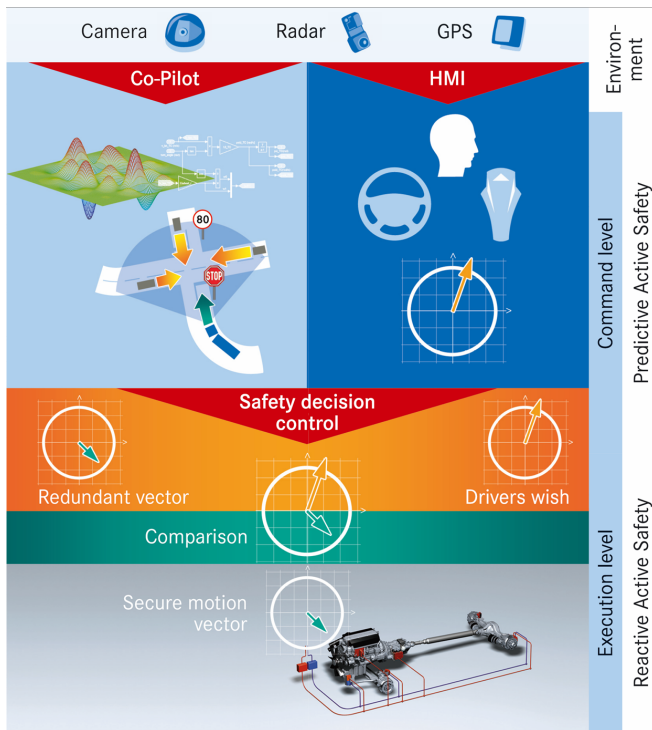


Fig. 1. SPARC system diagram: The safety decision controller receives the driver command through the Human-Machine Interface (HMI), and from the Co-Pilot a sensor-based redundant command vector. The safety controller decides which one is more reliable and acts accordingly on the powertrain using X-by-wire technology.

### B. SPARC camera system

Camera systems are particularly advantageous for sensing purposes, because they are passive sensors and they provide very rich information. However, the amount of information provided by the camera is too much to be processed with traditional automotive electronic control units. To this end, an embedded platform for image analysis is being developed within the SPARC project. The goal of the vision platform is to extract from the image the relevant information in each situation and provide it to the Co-Pilot.

Information that has been identified as relevant for most traffic scenarios is

- Position of the car relative to the current lane
- Width of the lane
- Radius of curvature of the lane
- Obstacles and objects on lane and immediate neighboring lanes
- Time of contact, or time that will elapse before the impact with the objects
- Roadsigns contents and position

Some of the resulting information, such as lane width or obstacle distance, needs to be given in world coordinates, as opposed to image coordinates. This is necessary either because it only has sense in physical coordinates or because this information is to be correlated with other sensors and thus a common metric is needed. To carry out the necessary conversion from image to world coordinates, a previous

calibration is needed.

Thus, we will initially present the lane detection principle and then, in section III, we will introduce a method that can be used to calibrate the camera directly at the end of the production line. This approach tries to minimize the effort to implement the calibration process while minimizing the measurement error. Then, the section IV will highlight the experimental results that are obtained with such a calibration method. Finally a conclusion based on these results will be described.

## II. LANE DETECTION ALGORITHM

The task of detecting and tracking road limits or lane marking is particularly difficult. Mainly because the evolving scene is a complex blend of elements, with a high level of changes and variability in which the system has no control. To be able to avoid building a system that works only in specific situations, which will not fulfill the SPARC objectives, the algorithm will implement several approaches to detect the desired lane. Thus, as described in [3], the algorithm will use multiple hypothesis of detection which will track to multiple models of lanes. This method will then fuse the result of all the tested model, and provide the solution with the higher level of confidence.

Actually several models are tested and implemented in experimental vehicle. These models rely on the following specific hypothesis:

- The relative height of the gradient versus its neighbourhoods, defines a hypothesis that the roadside have to contain a big contrast. Indeed, in most conventional situations the road and the side lanes have completely different pixel value.
- The road or lane width is a quite known value, thus the distance between left and right lane cannot vary too much during two consecutive images. Moreover, this value must be contained in a given interval of possible road width.
- If the acquisition time between to successive images is short, then the distance between two successive road limits detection have to be small.
- The line width can also be found by analysing two similar peaks at a given distance. If a given width is found, we are quite sure to have detected a road line.
- Line color can also be a reliable data. However, the user must be aware that illumination changes can have severe influence on this value. Thus, a solution can be found by using a relative value, between center of line color and road color.
- As the field of view of the camera has to deal with road perspective, the algorithm will have difficulties to found reliable data objects that are far away. Thus, as the density, in image plane, of objects situated far away is big, it increases the possibility of finding a transition that has no direct relation with the lane. Thus, the points that are close to the top of the image must have a bigger uncertainty than the bottom ones.

- Finally, after having estimated the road-side, it is possible to compute the gradient of the image along this estimator. The relative value of this gradient along the lane estimation can help to qualify and improve the road boundary.

This last hypothesis has a severe influence on lane detection performance. Indeed, all the other assumptions are local and could not use the globality and continuity of the lane limits (see Fig. 2).

### III. CALIBRATION PROCESS

It is not only necessary to detect the lane where the vehicle is evolving, but also to provide quantitative information about it. For instance, the radius of curvature is necessary to decide if the vehicle is entering a curve too fast. Other information, such as the distance between the truck and the closest obstacle, require the vision platform to be calibrated.

Through calibration, we intend to relate pixel-based information read by the camera, to scene information. The dimensional analysis of a 3D scene with a single, fixed camera forces the user to constrain the supplementary degree of freedom of the system. Indeed, although a point in the scene has three degrees of freedom, the same point in the camera has only two. In order to constrain the system, we suppose that the road is completely flat. It is clear that this supposition is a theoretical model of road, and that physically constructed roads, match only partially this hypothesis. Moreover, the calibration procedure supposes the camera orientation and position to be fixed, which is particularly false when a camera is embedded in a truck. Indeed, the pitching of its cabin will largely modify the position and orientation of the camera, which will increase the error of the dimensional estimation. Several solutions can be proposed to eliminate, or decrease this behavior. The first one is to attach accelerometers to the cabin to estimate its actual position. Thus, it is possible to correct the calibration of the camera by taking into account the modification of its position and orientation. A second approach could consist in estimating the pitching of the cabin based on a model containing the steering angle, load and speed of the vehicle. These methods can be used to increase the behavior of the calibration method, but will not be further detailed because they are not the aim of this article.

If we have to define an imaging system [4], we can say that it collects radiation emitted by objects for future processing. This emitted ray (particle flow, magnetic, or acoustic wave) is projected on a sensor that is constituted by small sensitive surfaces. Thus, the basic concept of calibration is to link the coordinate of three-dimensional emitting points with their corresponding ones in the image coordinate defined by the sensor. Classical calibration methods take at least one picture of a calibration pattern. This calibration pattern can be a chessboard, a pattern of full round circle, or whatever, but the calibration method will rely on these specific points as the chessboard corners or the center of the circles. The 3D coordinate of these points have to be perfectly known because they will be linked to the same point in the image.

#### A. Calibration technique overview

There are several calibration algorithms described in the computer vision literature. They differ mostly by their scope, precision and requirements for their application. Some algorithms [5] [6] require a good initial guess of some parameters, typically the focal length and imager geometry. This implies an a priori knowledge that has to be given by the user. Other algorithms require a non-coplanar calibration pattern [7] or two different calibration patterns [8], implying a longer calibration procedure. Concerning the attainable precision, algorithms based on linear systems do not consider lens radial distortion [9] [10]. This introduces significant errors when working with short focal length optics. Only algorithms with nonlinear optimization [11] can handle radial distortion.

#### B. Calibration technique

To calibrate a camera mounted on a truck the logical choice would be to place the calibration pattern on the surface where most measurements will be carried out: the road. However, this is not practical because road flatness is difficult to be guaranteed. Moreover, the area covered by the calibration pattern in the image would be very small and calibration would only be effective in this area. The original contribution of this project is to use a vertical calibration plane, placed in front of the camera and covering most of the image, and then to virtually rotate this plane to fit the road surface (see Figs. 3 and 4).

The aim of this research is not to develop a new calibration algorithm but to use an existing one to calibrate the camera against this vertical plane, and then use simple geometry to recover the position of objects on the road placed in front of the truck. This approach is particularly advantageous for calibrating trucks at the end of the production line, because it only requires a vertical plane aligned to the cabin frame.

The first step of our calibration technique will start by calibrating the vertical plane with the vision system. We could extract several benefits to use the Tsai's calibration. Indeed, this method computes the image distortion if the calibration pattern covers a large size of the image, it does not need any initial guess for the different unknowns and it needs only 7 points to compute the calibration. Moreover, this algorithm can deal with coplanar calibration plane and has one of the best calibration accuracies (see [12]). The calibration procedure extracts the following unknowns:

- Extrinsic parameters: the rotation matrix (3 by 3 matrix with 3 unknown angles) and translation vector (3 unknowns)
- Intrinsic parameters: focal length, radial lens distortion (2 unknowns), and scale factor.

The second step of our calibration technique is to retrieve the points located on the road by using the extrinsic parameters of the previous calibration.

- $c = O(x|_c; y|_c; z|_c)$  describes the coordinate system of the camera, where  $x|_c$  increases from the top left to the top right corner of the image, and  $y|_c$  is the axis that starts from top left to bottom left.



Fig. 2. Lane detection without (left image) and with (right image) cumulated gradient along the lane. Using this global hypothesis, the algorithm succeeds in situations where the contrast of one street side (left one) is not constant and the other side (right one) has no particular marking.

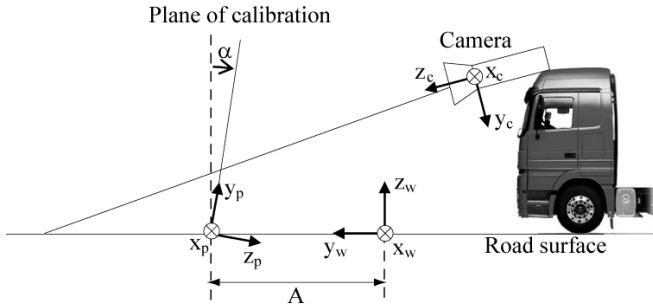


Fig. 3. Sketch of camera geometry with the different coordinate systems (projection of scene on the left-side of truck).

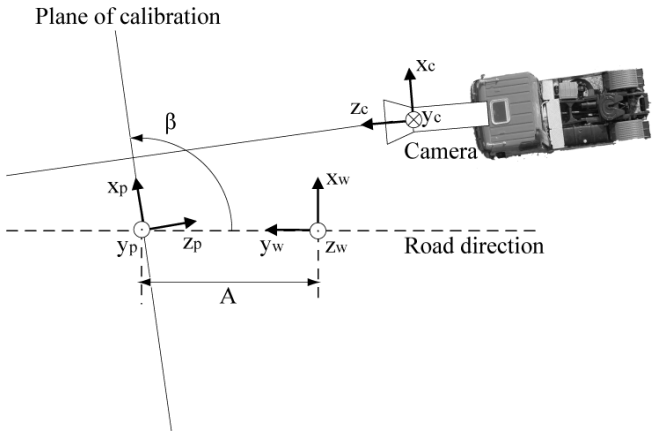


Fig. 4. Sketch of camera geometry with the different coordinate systems (projection of scene on the floor of the road).

- $p = O(x_{|p}; y_{|p}; z_{|p})$  describes the coordinate system of the calibration plane. To perform Tsai [12] calibration,  $z_{|p} = 0$ .
- $w = O(x_{|w}; y_{|w}; z_{|w})$  describes the coordinate system of the road in the 3D world, indeed the straight road is expressed by  $x_{|w} = cst$ . Moreover, a critical hypothesis of algorithm is to define that road is perfectly flat, i.e.,  $z_{|w} = 0$ .
- $\alpha$  defines the inclination of the calibration plane with a

perpendicular to the road surface

- $\beta$  defines the angle between the direction of road and the normal of the calibration plane
- the length  $A$  is the offset in the straight forward road direction between 3D world coordinate  $w$  and calibration plane system  $p$

Thus, the coordinate system of the 3D world is assigned by the knowledge of the calibration plane system, the angles  $\alpha$  and  $\beta$ , and the distance  $A$ .

### C. 3D world reconstruction after plane calibration

After having calibrated the camera against the calibration plane, we can recover the extrinsic and intrinsic parameters of the system. Then, it is possible to construct the different transformations that link the different system of coordinates. The second step is to compute the projection of the point situated on the calibration plane to the road surface.

1) *Coordinate transformations*: Now, using the extrinsic parameters, we know explicitly

$$\vec{x}_{|c} = R_{pc} \cdot \vec{x}_{|p} + \vec{T}_{cp} \quad (1)$$

$$\vec{x}_{|p} = R_{pc}^{-1} \cdot \vec{x}_{|c} - R_{pc}^{-1} \cdot \vec{T}_{cp} \quad (2)$$

which describes the relationship between the camera coordinate model and the calibration plane system. This transformation can be summarized by a rotation matrix  $R_{pc}$  from coordinate system  $p$  to  $c$ , and a translation vector  $\vec{T}_{cp}$ .

Following a similar approach, the relationship between the systems  $w$  to  $p$  can be written

$$\vec{x}_{|p} = R_{wp} \cdot \vec{x}_{|w} + \vec{T}_{pw} \quad (3)$$

with  $R_{wp} = \begin{bmatrix} s\beta & -c\alpha \cdot c\beta & -s\alpha \cdot c\beta \\ 0 & -s\alpha & c\alpha \\ -c\beta & -c\alpha \cdot s\beta & -s\alpha \cdot s\beta \end{bmatrix}$  and  $\vec{T}_{pw} = A \cdot (c\alpha \cdot c\beta; s\alpha; c\alpha \cdot s\beta)^T$  where  $s\alpha$  stands for  $\sin(\alpha)$ . Thus, the position of points situated on the calibration plane and expressed in  $w$  coordinates is defined by

$$\vec{x}_{|w} = R_{wp}^{-1} \cdot (\vec{x}_{|p} - \vec{T}_{pw}) \quad (4)$$

2) *Reconstruction of road model*: This problem is solved by stating that the object position expressed in  $w$ , its projection onto the calibration plane and the optical center of the camera are aligned. Thus, using simple geometry manipulation, it is possible to extract the estimated position of the object onto the modeled road by the knowledge of the two other points. The projection onto the calibration plane  $\vec{x}_{p|w}$  is directly given by applying successively (2) and (4). The position of the focal of the camera had to be extracted from (2), which gives  $\vec{x}_{c|p} = -R_{cp}^{-1} \cdot \vec{T}_{pc}$  when expressed in  $p$  system. Thus, with the help of (4) it is possible to extract the position of the optical center of the camera in  $w$ , denoted  $\vec{x}_{c|w}$ . Finally, if the estimated position onto the road is described by  $\vec{x}_{r|w} = (x_{r|w}; y_{r|w}; z_{r|w})^T$ , then

$$x_{r|w} = \frac{x_{p|w} - x_{c|w}}{z_{p|w} - z_{c|w}} \cdot (z_{r|w} - z_{c|w}) + x_{c|w} \quad (5)$$

$$y_{r|w} = \frac{y_{p|w} - y_{c|w}}{z_{p|w} - z_{c|w}} \cdot (z_{r|w} - z_{c|w}) + y_{c|w} \quad (6)$$

#### IV. EXPERIMENTAL RESULTS

This chapter presents the initial tests that have been performed in order to characterize the robustness of the approach. The different experiments depicted here use a camera with a vertical resolution of 400 pixels and a focal length of 6.49 mm. As the camera has to be mounted in cars and trucks, it was decided to place it at a height of 1.15 m. The orientation of  $c$  was also set to car conditions with an angle of  $8^\circ$  around  $x_{|c}$ . The calibration plane has been placed with  $\beta \cong 90^\circ$  and  $A = 1.148$  m.

The calibration process has been done using the coplanar algorithm of [12], on a target of three by five patterns. These 15 points are used to calibrate the camera, and hence to find its intrinsic and extrinsic parameters. In order to correct the radial distortion, the calibration target covers the whole image taken by the camera.

After having performed the calibration, we moved a test target between 2.8 and 11.5 m. The distance has been measured with a laser that has a precision of  $\pm 2$  mm, and a repeatability of 95%. Then, the computational procedure described in section III has been applied.

The results are summarised in figure 5, which shows that the factor  $\alpha$  has a severe influence on results. Indeed, if the calibration plane is supposed to have  $\alpha = 0^\circ$ , we can see that the relative estimation error seems to rapidly explode (more than 55% of error for an object placed at 11.5 m). Replacing  $\alpha$  by  $-1.3^\circ$  results in a mean error of  $-2\%$  when computed on the whole range of measured distance. Moreover, by setting  $\alpha = -3.0^\circ$ , the relative error tends to be quite constant.

As shown in figure 6, by subtracting the mean of measurements error (with  $\alpha = -3^\circ$ ), the precision reaches less than  $\pm 1\%$  in the distance range of [2.8 m; 11.5 m]. This method requires several measurements to be able to compute the mean of experiments. An alternative solution is to average the errors at the range limits. In this case the maximum error was found to be 1.4%.

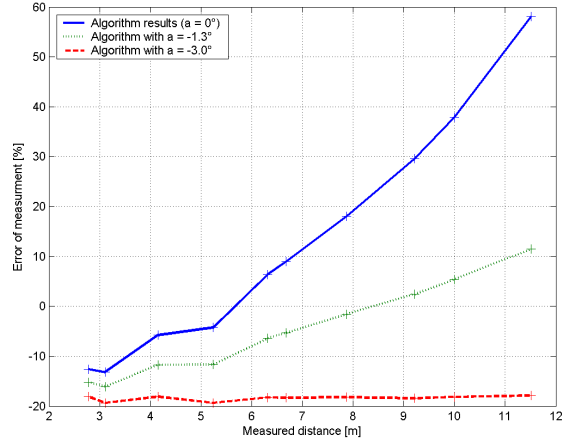


Fig. 5. Result of calibration method relative error. The graphics highlight that the influence of parameter  $\alpha$  is critic to have a perfect reconstruction of road model. By supposing a perfect verticality of calibration plane ( $\alpha = 0^\circ$ ), the reader can see that an error of more than 55% at 11.5 m could take place in this particular example. However, if  $\alpha = -3^\circ$ , the relative error of measurement is quite constant on the whole range of measured distance.

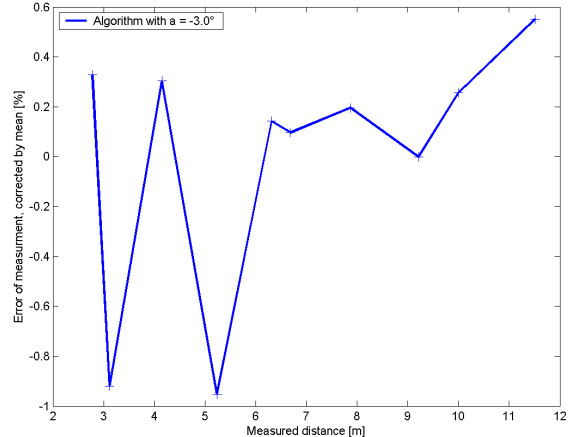


Fig. 6. Result of calibration method for  $\alpha = -3^\circ$  with suppression of relative error offset.

#### A. Calibration improvement

As it was exposed by experimental analysis, the measurement of angle  $\alpha$  is a critical step for calibration result. Thus, the solution will depend on specific situation:

- in the production process, the position of truck and calibration plane is perfectly mastered. Thus, the knowledge of angle  $\alpha$  can be measured with a precision of less than  $0.05^\circ$ . In this case, the environment can be changed to fit the requirement of the calibration method.
- for experimental tests, the method consists in a two-step calibration process. The first step has been largely described in previous chapter and will use the most precise measure, of the critical angle  $\alpha$ . This measure will largely depend on the tool that will be used to

determine the inclination of calibration plane. However, this measure need not be extremely precise, because the second step of calibration will be used to determine it much more accurately. Indeed, after the first calibration, we measure the distance to two objects, one situated in a close range, for example 3 m, and a second one in a far range 40 m. Having these two measurements, it is now possible to determine experimentally the angle  $\alpha$  to fit precisely these distances.

Both methods, not only afford to find the optimal  $\alpha$ , but they can determine the correction factor that could be applied to correct the shift in the estimation error.

## V. CONCLUSION

The SPARC project develops new technologies to improve drivers' security in the next generation of commercial vehicles. It states that there is no sensor from which it is possible to extract sufficient information to protect the driver in every situation that can occur on roads. Thus, different sensors of different physical principles are fused to reconstruct the 3D scene of the environment of the truck. This fusion has two advantages, the first one is to be quite robust if a single sensor become defective. Moreover, by fusing different data type, it is possible to obtain more robust and precise information.

One of these sensors is a camera that is connected to a vision platform that will extract the more useful information to achieve the security goal of SPARC. In this paper, we rapidly describe an algorithm to perform lane detection. The approach is based on a multiple lane model and multiple hypothesis of detection.

Based on these results, it is now necessary to determine the position of objects and obstacles on the road. For that, it is necessary to relate the pixel-based information of the camera to the 3D scene. This calibration process will also be useful for other algorithms, such as computation of lane curvature and width. This article presents a calibration method that can be used at the end of production line. Instead of performing the calibration directly on the road surface, which is particularly difficult to realize for space and cost reasons, this method performs the calibration on a vertical plane set in front of the truck. We present the transformation that can be applied to compute the calibration, and present the results of a car calibration. These results shows that the verticality ( $\alpha$ ) of the calibration plane is a critical parameter. Two solutions have been proposed, the first one is to control perfectly this angle with a precision of less than  $0.05^\circ$ . However, should the measurement of  $\alpha$  be difficult, a second method was proposed which does not require to know the exact inclination of calibration plane. Finally, the results show that a precision of less than  $\pm 1\%$  in the range of [2.8 m; 11.5 m] can be obtained with simple setup.

### A. Future work

It was observed in experimental results (see figure 5), that the relative error of measurements when  $\alpha = -3.0^\circ$

has an important offset. After the initial investigations, it could be pointed out that this bias was partially due to an inaccurate estimation in the camera position, which presents an error of about 13%. Moreover, further experiments show that the initial position of the calibration plane has a severe influence on this bias. However, this article describes several procedures to find and suppress this offset.

We have only describe the influence of  $\alpha$  because it is an angle that is difficult to measure and because it has the bigger impact on the calibration results. Since it is easier to determine the angle  $\beta$  of the calibration plane, we have neglected its error contribution. In the future we intend to point out the different influence of these two angles.

## VI. ACKNOWLEDGMENTS

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