# Application of a Stereovision Sensor for the Occupant Detection and Classification in a Car Cockpit ${ }^{*}$ 

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#### Abstract

. In this paper, we present recent methods that we have proposed to deal with the occupant detection and classification in a vehicle. The aim of this work is to provide information about the passenger presence and location within the vehicle, from stereo data. The results of this classification will be used for an active airbag control: the inflation could be activated, depovered or deactivated with respect to the seat configuration. The paper will focus on the extraction of a 3D global representation of the seat area, from a 3D image, and on the classification performed using this global description.


Keywords: Intelligent vehicles, Classification, Occupant detection, Stereovision.

## 1. Introduction

To improve safety in vehicles, in the last years, automobile industry has introduced a lot of new components in the vehicles (intelligent cruise control, rain detection, etc.). Is this interest, which has been cause of a massive introduction of airbags. Nevertheless, it has produced new problems, followed of governments regulations and consumers demands, in order to control the airbags deployments.

Nowadays the airbags firing is controlled only by an accelerometer. When an impact is detected the airbag is automatically deployed at speeds up to 200 mph . And mainly, the passenger seat is where this force can injured a passenger in a wrong position, or
in some cases, if the passenger is a child or a baby, it is possible to cause him/her the death [2].

Occupant detection and classification of passenger seat configuration open up new ways to control the airbag firing. At first, some simple sensors (optical barriers, ultrasonic sensor, ...) have been tested for the passenger detection, but these methods are not sufficient to detect some complex configurations. Vision systems offer the opportunity to improve the vehicle safety. An active stereovision system (a camera and an illuminator) has been evaluated [7], but the resolution of the 3D image acquired by this method, is too weak (typically, between 200 and 400 3D points).

An exhaustive analysis of the seat occupancy configurations, requires an higher resolution; we use a stereovision sensor mounted close to the inside rear mirror. Passive stereovision has been also applied for the airbag control, in [3] and [5]; but in these papers, only partial classifications are proposed. 3D data is obtain by a pixel-based stereo matching algorithm: from these 3D data and the known movement constraints of the seat, its location (previously unknown) can be estimated. From this, the occupied zones on the seat are characterized, what us allow to detect and classified the seat occupancy.

An overview on the 3D-vision system [2][3] is given in the section 2. The seat position and orientation is found applying some known movement constraints and from the 3D points which belong to the seat external surface: the section 3 deals with the recursive algorithm proposed to find this external surface. In Section 4 we describe the seat occupancy representation and the case-based classification algorithm. Finally in section 5 we show the current

[^0]- This research has been funded by the PREDITprogram of the french Ministry of National Education and Research.
results of our method, evaluated from images acquired in a vehicle.


## 2. The Stereovision method

Our 3D-vision system [4] is based on a pair of cameras mounted in a car, close to the inside rear mirror; pixel-based stereo matching algorithms provide 3D data. The performances of our stereovision method are good enough to fulfil the requirements of the airbag application: (1) the complete algorithm is executed in 250 ms on $128 \times 128$ images, so that we can tackle weak real-time constraints; now, we are optimising our stereo algorithm using a multi-resolution approach, so that we could acquire a 3D image at 15 Hz . (2) Our stereo method provides a 3D dense reconstruction on the passenger area (typically, between 3000 and 5000 3D points) so that a large variety of situations (e.g. passenger with a child on the knee, or in advanced or extended position, different objects,...) could be sufficiently characterised to provide good inputs for a classifier, and (3) we obtain an accurate reconstruction. For this application, the accuracy is not a major requirement, but if a passenger is detected, an accurate positioning of the head within the cockpit, must be performed within a centimeter range.


Figure 1a: left image acquired in the car
Several matching criteria have been evaluated for this application, and we show in [4] that the nonparametric criterion proposed in [6] (the matchings are searched on the Census transforms of the initial images) is better than the classical ZNCC or SSD correlation criterion.

As an example, we present on figure 1a, an image acquired in the car by the left camera of the stereo pair; the figure 1 b shows a 3D display of the resulted 3D image: a triangular mesh has been built from the 3D points and the image intensity is restored on each triangle. The cloud of points presented on figure 3 has
been provided from this 3D image, after some filtering method to delete 3 d points, which are on the door or on the dashboard.


Figure 1b: 3D reconstruction

## 3. Estimation of the seat configuration

An important requirement for this application is that the seat position is unknown: no dedicated sensors are mounted on the seat (in fact, such sensors exist now, on expensive cars, but will not be installed on cheap ones). So, a first step consists in estimating the seat position and orientation. It is very important in order to determine invariant attributes required characterizing the different seat configuration.


Figure 2. Seat position restrictions.

### 3.1. Restrictions

The figure 2 presents the following restrictions on the seat position: a) the horizontal and vertical translations of the seat sitting are limited, and also b) the rotation angles for the seat back. We consider that all the 3D points are on the seat or in front of it, because in our configuration, the cameras are mounted close to the rear mirror, and it is quite impossible to have points behind the seat back. Due to this assumption, the external surface (on the right on
the figure 3) of the cloud of 3D points provided by one stereo acquisition, is located on the seat. We consider this surface as a constraint for the seat position.

In order to find the minimum number of points that define this external surface, we propose a recursive algorithm which consists, in the initial step, in (1) the construction of a triangle defined from the extreme points (the faraway from the dashboard and the lower one), and (2) the search on the 3D image, of the nearest point to the point $\mathbf{M}_{\mathbf{0}}$ (figure 4a); this point belongs to the external surface. From this point, in the second step, two new triangles are defined (Figure $4 b$ ), and the same algorithm is applied again to find two other points of the external surface (Figure 4c); the algorithm is recursively applied until all points have been detected.


Figure 3. Cloud of points 3D

### 3.2 Seat localization.

The seat sitting and the seat back positions are then approximated separately by two planes, using the minimisation of an energy function; a simple leastsquare fitting is not adapted for this application, in order to be less sensitive to false 3D points included on the external surface of the seat.

The list of the points located on the external surface is divided in two lists, one for the seat sitting, the other for the seat back. We describe only the seat back approximation: an initial estimate of the $\theta$ angle is firstly defined as the extreme position (almost horizontal position of the seat back). At each iteration, we compute the energy for every point on the surface,
as a function of the distance between this point and the current estimate. The potential, which produces this energy, depends of the position of the point w.r.t. the current plane (behind or before equation 1). Then the $\theta$ estimate is updated so that the total energy is minimized the seat back is attracted towards the detected external surface. The energy minimisation is performed with dynamic programming [1].

$$
f\left(\mathbf{L}_{i}\right)=\left\{\begin{array}{l}
\left\|\mathbf{L}_{i}-\mathbf{I}_{i}\right\|, \mathbf{L} i \text { in front of seat back }  \tag{1}\\
\left\|\mathbf{L}_{i}-\mathbf{I}_{i}\right\|^{2}, \mathbf{L}_{i} \text { behindthe seat back }
\end{array}\right.
$$

## 4. Classification

The estimation of the seat position and orientation (figure 6a) allows the definition of invariant attributes. As a first attempt, a global occupancy description is built from the percentage of 3 D points in the 3D image that belong to some interesting areas of the cockpit.

### 4.1 Attributes

We select 3D areas as boxes (parallelepiped volumes figure 6 b ) and we count the number of 3D points in these areas.


Figure 5. Definition of the critical zones.

- Two areas are defined according to an emerging normalization, about the critical volume close to the dashboard (figure 5): the Critical Out Of Position area (COOP) and Out Of Position (OOP). The only criterion for the definition of these critical areas, consists in the distance to the dashboard (invariant w.r.t. the seat position).


Figure 4. Recursive algorithm for the search of points in the external surface.

- Five areas are defined relatively to the current seat configuration: two for the seat area (boxes which envelop the seat sitting and the seat back) and three for the passenger area (one just above the seat sitting, two along the seat back; the higher one could contain points acquired on the passenger head; the lower one has a variable height which allows us to distinguish between adults and child).


### 4.2 Learning step

We have defined eight classes that cover the principal problems as described in the next table:

| Class | Definition |
| :---: | :--- |
| 0 | Case Undetermined |
| 1 | Empty seat |
| 2 | Rear face baby seat |
| 3 | Front face baby seat or object |
| 4 | Adult in correct position |
| 5 | Child with or without booster |
| 6 | Something on the COOP area |
| 7 | Adult with something in the OOP area |

Table 1. Classes definitions
An example of an image for each class is showed in the figure 7.

The classification is made by the method of the K nearest neighbours, from the results of the attributes learnt in a database built from a set of images (300 images at this moment).

### 4.3 Evaluation step

The results for an evaluation data set, given from 50 stereo images, is showed in the next table (2). By
now, we are refining this evaluation using a larger data set.

|  | Found classes |  |  |  |  |  |  |  |  |
| :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: | :---: |
|  |  | 0 | 1 | 2 | 3 | 4 | 5 | 6 | 7 |
|  | 0 | 4 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
|  | 1 | 0 | 6 | 0 | 0 | 0 | 0 | 0 | 0 |
|  | 2 | 2 | 0 | 0 | 0 | 0 | 0 | 0 | 0 |
|  | 3 | 0 | 0 | 0 | 2 | 0 | 2 | 0 | 0 |
|  | 4 | 0 | 0 | 0 | 1 | 4 | 6 | 0 | 0 |
|  | 5 | 0 | 0 | 0 | 6 | 1 | 10 | 0 | 0 |
|  | 6 | 3 | 0 | 0 | 0 | 0 | 1 | 0 | 0 |
|  | 7 | 0 | 0 | 0 | 0 | 0 | 2 | 0 | 0 |

Table 2. Confusion matrix
As we can see in the confusion matrix, the empty seat class as the undetermined position are classified correctly. But it exists serious problems with the other ones, for example: the class 2 (rear facing baby seat) $s$ not recognized, because some images of an out of position passenger give attributes very close to a rear facing baby seat. We have tested 11 images of adults in correct position (class 4) but as we can see, 6 of they are classified as a child and one as an object.


Figure 6: a) Seat position, b) 3D boxes defined, c) points 3D in boxes.

In order to solve some problems we proposed to use the information about the points density. Again due to our configuration (the cameras close to the interior rear mirror), the points density will be greater in the surfaces closer to the stereo system. Once identified the regions of higher density (figure 7), we can (1) apply a segmentation method based on an adaptive threshold and (2a) either characterize the curvature of these high density zones (convex, concave or flat), so that we could recognize the passenger head, or ( 2 b ) it is also possible to compute the position of this segmented zones, with respect to the seat position and to the dashboard.

With these new attributes, we can determine if there is a person or not, and discriminate between an adult and a child, even if he/she is in an advanced position.

## 5. Conclusions

The contributions of this work are mainly: (a) the evaluation of the stereo in a vehicle cockpit, (b) an algorithm for the detection of points in the external surface of the seat, and a method proposed to estimate the seat position and orientation (method based on the minimisation of an energy function) and (c) the classification of the passenger seat configuration using at first, a global occupancy representation to recognize simple situations, and then density or curvature attributes to deal with the head detection.

These contributions made the definition of areas in the passenger seat, invariant and good ones for the classification. Some preliminary experimental results have been presented on the learning and classification steps: an on line evaluation of this method is on the way, using a low cost dedicated stereo sensor mounted in a car.

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Figure 7: a) Undetermined case, b) empty seat, c) rear face baby seat, d) front face baby seat or object, e) adult, f) child with or without booster, g) something on the COOP area, h) passenger adult with something in the OOP area.


Figure 8: a) d) Original images, b) e) density images, c) d) segmentation images.


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