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## Multi-sensor fusion method for crop row tracking and traversability operations

**Bernard Benet, Roland Lenain**

IRSTEA, UR TSCF, 9 avenue Blaise Pascal, 63178 Aubière, France

Email : [bernard.benet@irstea.fr](mailto:bernard.benet@irstea.fr)

### Abstract

Precision agriculture vehicles need autonomous navigation in cultures to carry out their tasks, such as planting, maintenance and harvesting in cultures such as vegetable, vineyard, or horticulture. The detection of natural objects like trunks, grass, leaf, or obstacles in front of vehicle in crop row is crucial for safe navigation. Sensors such as LiDAR devices or Time Of Flight cameras (TOF), allow to obtain geometric data in natural environment, using information of an Inertial Measurement Unit (IMU), for measurement accuracy. Fusion of geometric information with a color camera data improves the natural object identification, using some color classification technique, such as Support Vector Machine (SVM), considering two object classes, either solid objects such as crop or tree branch, and other elements like grass, leaf and soil. Agricultural vehicles can use these geometric and colorimetric data in real time, to follow crop rows and detect obstacles while executing various precision agriculture operations. In this application, perception sensors embedded on a light mobile robot were used to detect and identify natural objects in agricultural crops, working in various fields, with or without soil perturbation, with different speeds and several vegetation levels to achieve crop row tracking tasks, from a desired lateral deviation between robot and crop line, or traversability operations which consisted to take a decision in vehicle navigation, according to the size and nature of the detected objects, in front of vehicle. The vehicle could cross or avoid the object, or it must stop, for big solid obstacles.

**Keywords:** sensor fusion, crop row tracking, traversability, mobile robot navigation

### 1. Introduction

The development of Precision Agriculture, with respect to social needs, requires proposing new tool for food production, especially in the fields. Progresses achieved in robotics permitted to consider mobile robots as a promising solution to actually apply new methodologies. Nevertheless, in order to be fully autonomous, such device needs to be accurately and safely controlled, while using relatively low cost sensors. This problem is particularly pregnant considering the crop row tracking operations, obstacle detection and avoidance in natural environment. Autonomous vehicle guidance to perform farming operations such as planting, maintenance and harvesting in cultures such as vegetable, vineyard, horticulture, can be achieved using many kinds of sensors which can locate some crops and other natural objects, either in absolute mode with GPS devices or in relative mode using sensors like LiDAR or Camera device. Research works about automatic guidance for agricultural vehicles were achieved (Keicher and Seufert, 2000) and (Ming et al., 2008). As example, robotic technology evolution, with the use of these absolute or relative perception sensors for detecting and locating weeds could reduce dependency on herbicides, improving sustainability and reducing environmental impact. Various automatic systems have demonstrated the potential of this technology in the field, for various crops. GPS and machine vision fused together, and also with others technologies, are the trend for agricultural vehicle guidance systems. As most crops are cultivated in rows, an important step towards this long-term goal is the development of a row-recognition system, which allows a robot to accurately follow a row of plants. About GPS sensors, losses of GPS signal, as example if the vehicle penetrates in an environment with many trees, prevent to perform autonomous tasks with accuracy. In many applications, acceleration data given by an IMU device is used, to correct GPS signals, during a short time (Takai et al., 2014). For different crops, like for example citrus groves, the tree canopy frequently could block the satellite signals to the GPS receiver. So, in this case, perception relative sensors, such as LiDAR or Camera device, embedded on a vehicle such as a tractor, can be employed, to detect and follow crop rows (Subramanian et al., 2006). Among relative perception sensors, Time of Flight cameras (TOF) or LiDAR 3D, such as the celebrated Velodyne (Haselick et al., 2012), permit to get 3D information, in order to obtain environment maps, for terrain classification, with detection of various objects such as crop, grass, leaf, soil, but the cost of some of them does not appear to be compatible with the design of agriculture tool. As a consequence, cheapest sensors have to be used, even if they provide less accurate data. To get information of a set of crops, to realize a crop row tracking operation, a simple LiDAR 2D associated or not with a camera, can be sufficient for this task. Both LiDAR sensor and vision systems used separately or in fusion mode, permit to achieve many crop row tracking tasks, for sugar beet (Åstrand and Baerveldt, 2002), cotton crops (Billingsley and Schoenfisch, 1995) or rice rows (Choi et al., 2015).

Finding guidance information such as known crop row spacing is a solution for achieving accurate control of the vehicle (Han et al, 2003). In the application presented in this paper, a LiDAR device, a TOF camera, a IMU sensor and a color camera, were used in a fusion mode, to get the natural object positions, in real time, in various crops. Sensors were embedded on a light mobile robot. Soil perturbations affected the autonomous navigation in cultures. In a first stage, IMU data permitted to correct position of LiDAR or TOF points detected in robot environment. Then a fusion method was applied between these corrected points and a color camera, in order to identify and classify each point. Using a color database corresponding to two pixels classes (class crop and others (grass, leaf, soil), identification with the Support Vector Machine classic algorithm (Hyeran and Seong-Whan, 2002), permitted to identify objects and carry out some measurements on these ones. For crop row tracking task, from identified crop points, after removing noise, two methods were tested and compared, Hough method and Least Square (LS) technique, to obtain geometric information on the line, in order to choose the most adapted for crop row tracking tasks, to get the best ground truth. Automatic control/command operations were then applied to follow crop rows, after setting a lateral distance between the vehicle and the crop row. Various applications use fusion methods between LiDAR and a color camera device, for example for detecting tree trunks (Shalal et al., 2013), or for autonomous tractor guidance in some crops (Garcia-Alegre et al., 2011). The aim was to develop a system able to track crop rows, with accuracy, working in different fields, in various working conditions: soil perturbations, different speeds, various vegetation levels. For traversability operation, the estimation of 3D information in front of a vehicle, was investigated through the fusion between one sensor giving geometric information in the environment such as a low cost LiDAR 2D or a TOF camera and a color camera which brings color information on natural objects. The measurement achieved on detected objects, were used to take a decision in robot navigation. The vehicle crossed or avoided the obstacle in front of him, or must stop for big ones. In various applications, TOF camera and color cameras are used to make measures on agricultural products, for plant recognition to achieve robotic weeding (Gai et al, 2015), and for mobile robot locomotion (Joachim et al, 2008). The fusion algorithm proposed aims at controlling an autonomous robot in crop row and detecting the presence of obstacle in order to preserve safety (for both robot and environment). Such a point of view permits to achieve several kind of task, such as environment monitoring tasks, planting, maintenance or harvesting, with accuracy, in agricultural environment, from detection, localization and physical characterization information obtained on naturel objects, in various cultures. From these geometric and colorimetric data given by TOF camera, LiDAR devices and color cameras, in fusion mode, the farmers can achieve agricultural tasks, either in real time, like for example weeding, taking into account the data for each crop, or in differed time, using the recorded databases for a culture. These information can also be used to detect and locate some illnesses in crops, or to make comparisons between natural objects in cultures.

## 2. Materials and methods

### 2.1. Mobile robot and sensors

The light mobile robot used in the experimentations is presented in Figure 1. Four sensors were embedded on this vehicle, to acquire and compute data, in order to achieve traversability or crop row tracking operations in fields, in various crops: a TOF camera (IFM PMD O3M151), a GigaEthernet camera, with a resolution of 1022x1022 pixels (Baumer VLG 40C), a LiDAR device (SICK TIM551), an Inertial Measurement Unit (IMU) (Xsens).

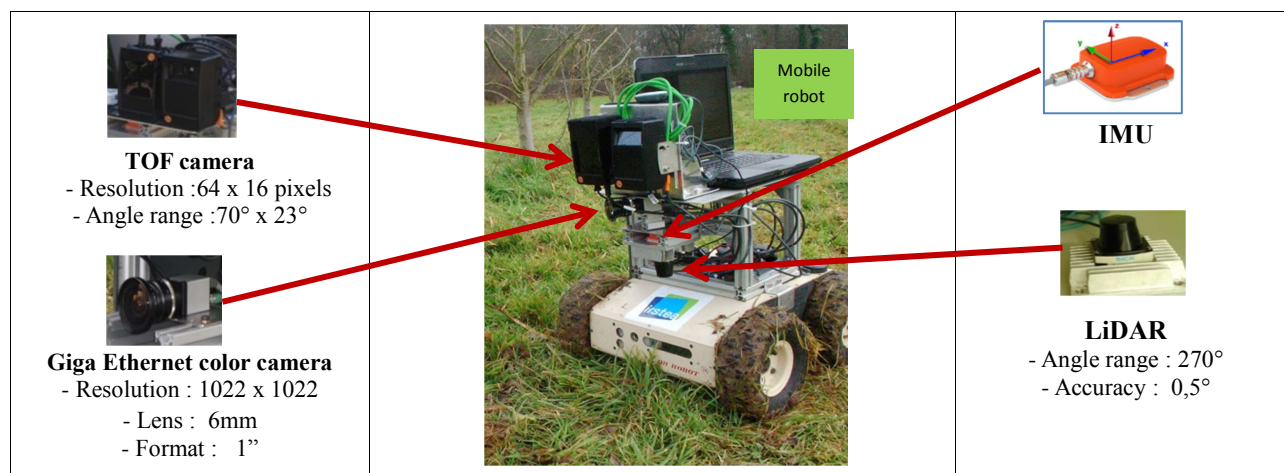


Figure 1. Mobile robot and embedded sensors

The TOF camera model chosen is insensitive to brightness variation, so it can be used for outdoor applications, in agricultural fields, in various lighting conditions, to make 3D geometric measures, unlike other 3D cameras, such as Kinects models, which can only be used in indoor conditions. Comparative studies for TOF cameras were conducted to analyse the measures accuracy, the sensitivity to lighting conditions (Piatti and Rinaudo, 2012). This camera was used in various mobile robotics applications (Hussmann et al, 2009), including the monitoring of borders (Montella and all, 2012). It can be used to produce map scenes both inside and outside, using the fusion mode with a color camera to identify objects. Figure 2 presents examples of outdoor data acquired with this camera: (a) 3D map in a crop field and (b) detection and identification of crop points (red color), by fusion with color camera data.

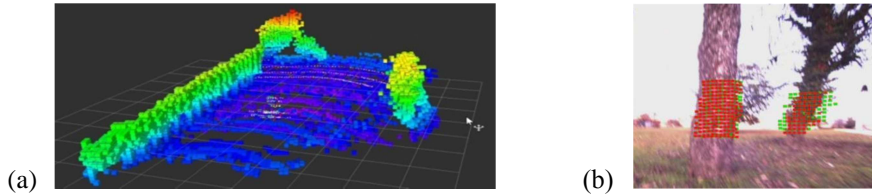


Figure 2. Outdoor data with IFM PMD O3M151 TOF camera

In the field of agricultural machinery, this type of sensor can be used to perform automated steering operations in different cultures to realize various applications such as the monitoring board, the harvesting, recognition swath, self-monitoring line cultures, in particular in the vineyard, to ensure the automatic steering along a vine row.

### 2.2. Model of mobile robot with sensors

LiDAR device and TOF camera enabled to obtain 3D points in the environment. These ones were corrected using pitch ( $\beta$ ) and roll ( $\alpha$ ) angular data given by IMU device. Figure 3 presents the robot model, with different geometric parameters, considering only LiDAR device positioning (T).

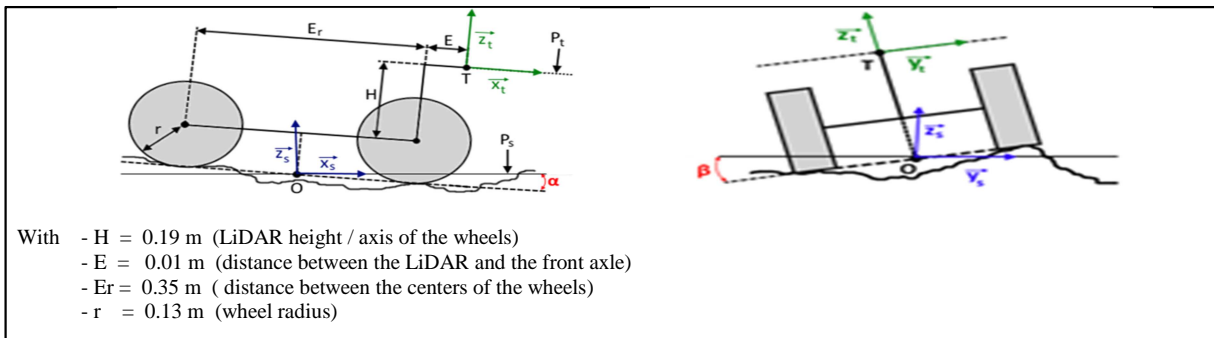


Figure 3. Robot model

### 2.3. Fusion Imu/(LiDAR and TOF)

The aim was to compute the point coordinates  $P_{LiDAR}(x,y,z)$  and  $P_{TOF}(x,y,z)$ , in environment, taking into account IMU data angles (roll ( $\alpha$ ), and pitch ( $\beta$ )). Figure 4 a) and b) present, respectively, the equation to obtain  $P_{LiDAR}$  corrected points, from LiDAR data points ( $(\rho, \Theta)$ ), and  $P_{TOF}$  corrected points, with the application of both rotations with (roll ( $\alpha$ ) and pitch ( $\beta$ )) angles. From corrected points, it was so possible to remove all points outside a desired search place, particularly points situated under a height limit. As example all points situated under a grass height parameters eg 100 mm) were eliminated.

$$\begin{aligned}
 \text{(a)} \quad P_{LiDAR} \quad & \begin{cases} x = \rho \cdot \cos(\theta) \cdot \cos(\beta) - (E + 0,5 \cdot E_r) \cdot \cos(\beta) + (r + H) \cdot \cos(\alpha) \cdot \sin(\beta) \\ y = \rho \cdot \sin(\theta) \cdot \cos(\alpha + \pi) + (r + H) \cdot \sin(\alpha) \cdot \cos(\beta) \\ z = \rho \cdot (\sin(\theta) \cdot \sin(\alpha + \pi) + \cos(\theta) \cdot \sin(\beta)) - (E + 0,5 \cdot E_r) \cdot \sin(\beta) + (r + H) \cdot \cos(\alpha) \cdot \cos(\beta) \end{cases} \\
 \text{(b)} \quad & \begin{bmatrix} \cos(\beta) & \sin(\beta) & 0 \\ -\sin(\beta) & \cos(\beta) & 0 \\ 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} \cos(\alpha) & 0 & \sin(\alpha) \\ 0 & 1 & 0 \\ -\sin(\alpha) & 0 & \cos(\alpha) \end{bmatrix} \rightarrow P_{TOF}
 \end{aligned}$$

Figure 4. Computation of corrected LiDAR and TOF points

### 2.4. Calibration Camera/(LiDAR and TOF)

Figure 5 presents the geometric model of the robotic system, with sensor position, which enabled to calibrate the complete sensor device, necessary for fusion operations. From these sensor positions, computation of distance between robot and detected natural objects, in front of vehicle, in fields, and also height of these objects, could be achieved.

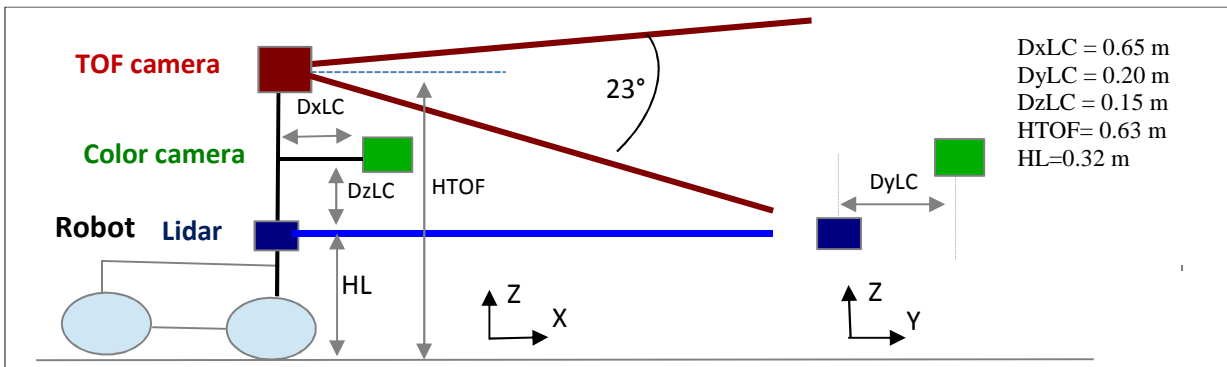


Figure 5. Calibration Camera / (LiDAR and TOF)

### 2.5. Fusion Camera/ LiDAR and TOF

The camera calibration, taking into account its characteristic parameters, and the information about relative position of LiDAR, TOF and color camera, embedded on robot, permitted to get intrinsic and extrinsic parameters of the multi sensor device, in order to realize the fusion between sensors, In our application, after fusion with IMU data, two sensor fusion types were considered: a first one between LiDAR device and color camera and a second one between TOF camera and the color camera. Figure 6 shows the mathematical method used to compute the geometrical position of points given by LiDAR and TOF device, inside a color image.

$$\begin{pmatrix} su \\ sv \\ s \end{pmatrix} = \begin{matrix} \text{intrinsic parameters} \\ \begin{bmatrix} k_u & s_{uv} & c_u \\ 0 & k_v & c_v \\ 0 & 0 & 1 \end{bmatrix} \end{matrix} \begin{matrix} \text{extrinsic parameters} \\ \begin{bmatrix} f & 0 & 0 & 0 \\ 0 & f & 0 & 0 \\ 0 & 0 & 1 & 0 \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{bmatrix} R_{3 \times 3} & \begin{matrix} t_x \\ t_y \\ t_z \end{matrix} \\ 0 & 0 & 0 & 1 \end{bmatrix} \begin{pmatrix} X \\ Y \\ Z \\ 1 \end{pmatrix} \end{matrix}$$

Figure 6. Mathematical model for positioning LiDAR and TOF points inside color image

Figure 7 shows the positioning of LiDAR points (a) and TOF points (b) inside a color image, by fusion. For each point, to take into account the inaccurate information provided by LiDAR and TOF devices, a window (10 x 10 pixels) was considered around each point on color image, to determinate, in a next step, the class of each point (crop, grass,...).

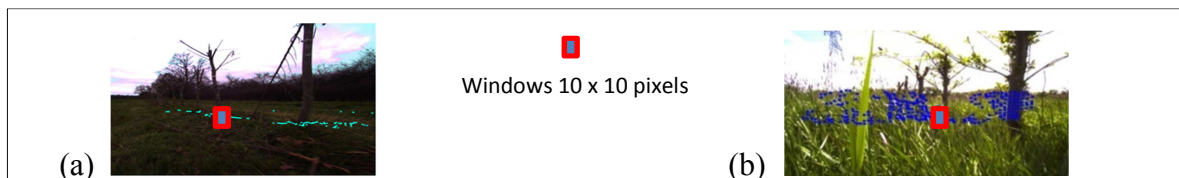


Figure 7. Positioning of LiDAR (a) and TOF (b) data on color images

### 2.6. Pixel classification and identification

Merging 3D LiDAR systems with camera was the subject of various works by identifying points or 3D zones in the environment for different classes of color properties (Laible et al, 2013). Point classification by SVM methods (Support Vector Machine) was carried out focusing on two element classes: solid objects such as crop, or tree branch, and noise such as grass, leaf, soil, working in different lighting conditions, in environment. The aim was to compute the mean color in windows associated to each point (Figure 8), in order to classify each point, after applying a SVM method which consisted to determinate a hyperplane for separating both classes, from databases corresponding to RGB color of both classes. Figure8 presents some color samples for both selected color classes for our application. Pixel identification stage consisted to work in every window around the geometric points detected with the TOF camera (PT) and LiDAR (PL), and classify each point using the SVM method, taking into account the mean color inside windows.

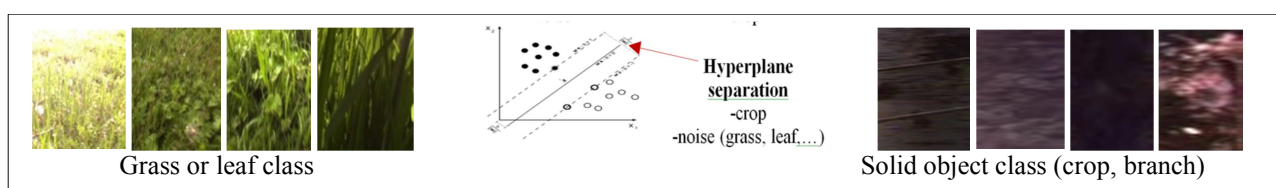


Figure 8. Selected images for object classification by SVM method

Examples of SVM classification results, to discriminate both object classes, are presented in figure 9, in white and black color, respectively for grass and solid object classes.



Figure 9. SVM classification result

### 2.7. Crop row tracking operation

The chart below (Figure 10) shows the various stages carried out to realize the crop row tracking task. First, LiDAR device enabled to obtain 3D points in the environment. These ones were corrected using data given by IMU device. All the geometric points situated outside a desired region, were eliminated. Then a second fusion operation between corrected LiDAR data and color camera information enabled to get the desired color points, corresponding to objects that must be tracked by robot. For vineyard, the aim was to detect trunk points and to eliminate the green ones corresponding to grass and leaf. One method like Hough or LS technique was then applied to obtain at the end, the line geometric information used for crop row tracking operation. Finally, the robot control algorithm was launched, using the line information, the desired lateral deviation and taking into account also the robot angular deviation, the temporal aspect, and the variable spacing between natural objects in crop rows.

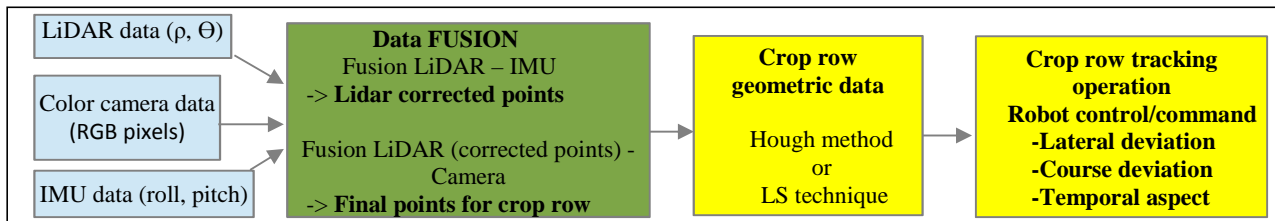


Figure 10. Crop row tracking operation

For each  $P_{LiDAR}$  point (called  $G_i$  in Figure 11), if this point, was identified as a crop point, with SVM method, then the  $P_{LiDAR}$  point was kept in next stage (final points  $F_i$ ), for obtaining, in next stage, the geometric parameters of the crop line. Otherwise,  $P_{LiDAR}$  point was eliminated.

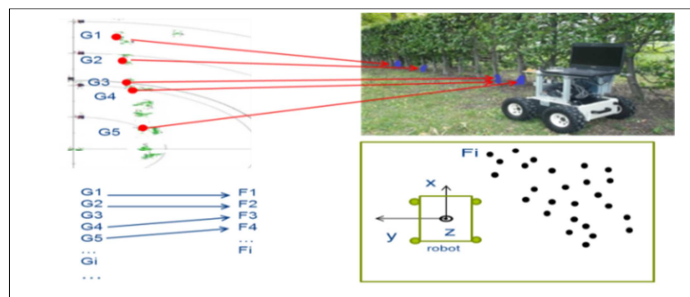


Figure 11. Detection by fusion of crop row points

Two methods were tested to obtain, from the final points  $F_i$  obtained by fusion methods, the crop row geometric information used for tracking operation (Figure 12): the LS technique with the crop line computation presented in (a) and the Hough method (Duda and Hart, 1972) (b). Hough method consisted of working in  $(r, \theta)$  space in which a point characterizes a line, and to increment a matrix accumulator, considering all points  $F_i$ , and with variations of both variables  $r$  [ $r_{min}; r_{max}$ ] and  $\theta$  [ $\theta_{min}; \theta_{max}$ ]. The maximum value of the matrix corresponded to the desired crop line.

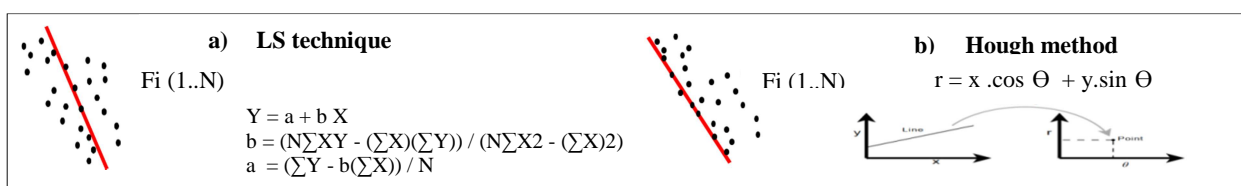


Figure 12. Crop row detection

Finally, the robot control algorithm was launched, using the line information ( $Y=a+ bX$ ), the desired lateral deviation (DELat) and taking into account also the robot angular deviation and the temporal aspect (Figure 13), in order to avoid high robot movements, during navigation.

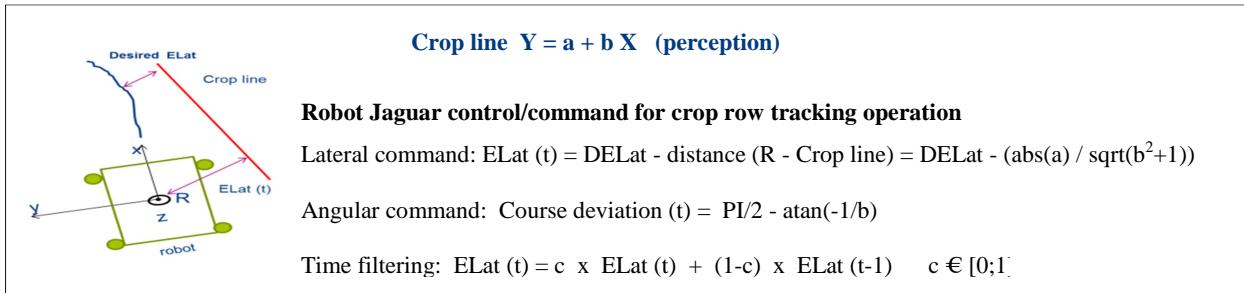


Figure 13. Robot control for crop row tracking

### 2.8 Traversability principle

The aim was to detect objects at a distance between 0 and 5 meters from robot, and take a decision in the robot mobility control. LiDAR device gave planar information with high resolution (one point each  $0.5^\circ$ ) whereas with TOF camera used, a low resolution image ( $64 \times 16$ ) was obtained. TOF cameras can be used for traversability operations in different environments, such as PMD Camcube camera model embedded on farm vehicles, civilian or military (Balta et al, 2013). Detecting solid obstacles such as trees, relatively large is an easy task to achieve with TOF cameras and facilitates autonomous navigation of mobile robots. In our application, solid objects, in front of vehicle, such as branches or trees were considered as obstacles to avoid, while grass-type objects were traversable objects. The charts below (Figures 14 and 15) show the various operations carried out to obtain the final decision stage, for a traversability application in a culture. In real time, the mobile robot, according to the data obtained with three sensors (color camera, TOF camera and LiDAR) adapted its mobility. Grass and solid objects were considered separately. In real time, the Grass (G) and Solid (S) point numbers above two height values Gheight and Sheight, respectively for grass and solid objects, were computed. These points could be obtained with LiDAR or TOF camera. For these point numbers, the maximum value obtained with both sensors was taken into account for traversability decision. The distance values between robot and objects were also considered in this operation, respectively DGrass and DSolid for grass and solid objects. According to the information obtained for grass and solid detected objects, the vehicle could move at normal speed, at reduced speed, must avoid solid objects or must stop, if obstacle was very near it. Several thresholds values T1...T5 were defined for traversability decision.

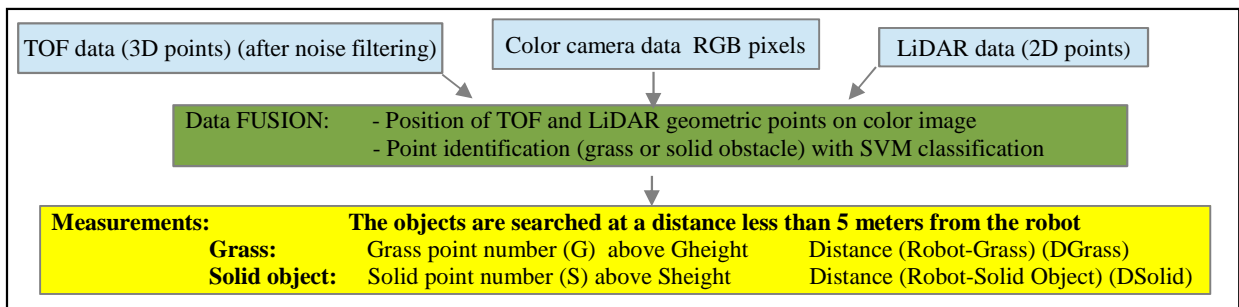


Figure 14. Data acquisition and measurements for traversability

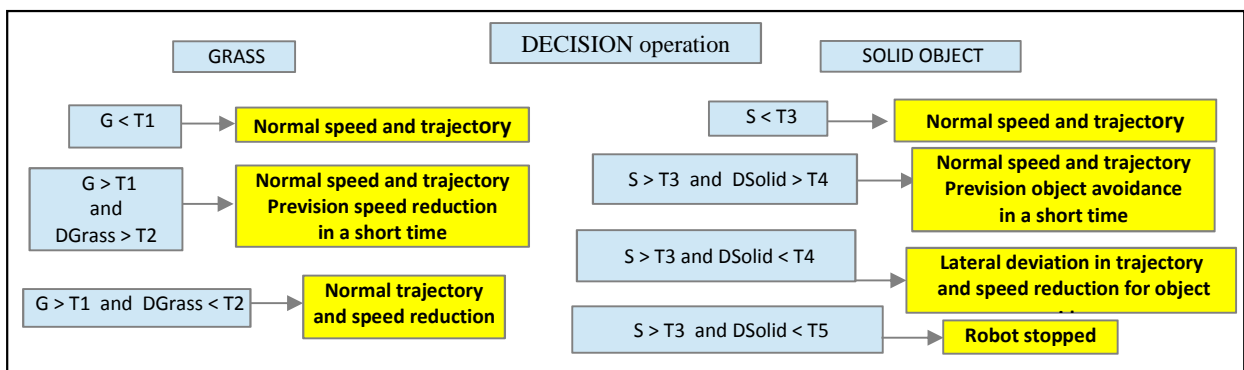


Figure 15. Traversability decisions

### 3. Results and discussion

Experimentations were achieved in different crops (Figure 16), particularly in vineyard environment, in order to study the capability of the developed fusion method, to realize crop row tracking operations, with accuracy, working with various robot speeds between 1 and 3m/s, various vegetation levels and ground perturbations such as holes, bumps, or mud. For traversability operation, various grass heights and solid obstacles, in these fields, in front of vehicle, were taken into account, to realize some measurements in order to take some traversability decisions, for robot navigation, to modify speed and trajectory of mobile robot.



Figure 16. Test fields for crop row and traversability operations

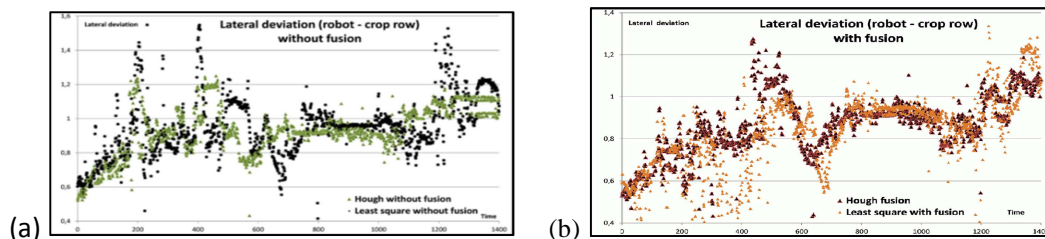
#### 3.1. Crop row tracking operation

Figure 17 presents results images with the LiDAR points put on images. Black and red color points are respectively the crop points that will be tracked by vehicle and noise points corresponding to either points which have not crop color (grass, leaf, soil,...) or points outside the desired place, where we are looking for tracking points. The colorimetric discrimination achieved with SVM method enabled to eliminate noise, to keep only, finally, crop elements (set of points characterized by geometric position in 3D environment).



Figure 17. Fusion result for crop points detection

A study was carried out to compare two methods (Hough and LS) to get, from crop points, the crop line geometric parameters which must be tracked by vehicle. The standard deviation differences, between both methods, in lateral deviation values, presented in Figure 18 (manual navigations, working without (a) or with (b) fusion mode with camera, near a crop line), showed that Hough method was less sensitive to noise, gave more stable information and permitted to get less oscillation, in the robot navigation than LS technique.



	Without fusion		With fusion (camera)	
	Hough method	LS technique	Hough method	LS technique
Standard deviation of lateral deviation	0,145 m	0,209 m	0,143 m	0,172 m

Figure 18. Comparison between LS technique and Hough method

Hough method with fusion (LiDAR, IMU and Camera) was the most stable, to detect and follow crop rows, particularly in a noise environment. Anyway, Hough method is much slower (processing time) than LS technique, so for high speed applications, with a few noise points detected by LiDAR device in one crop, it could be better to use this last one.

Figure 19 presents crop row autonomous tracking result examples, without (a) and with (b) soil perturbations. In these tests, Hough method was carried out, the fusion with IMU and Camera was used, the control/command speed was 1m/s and the navigation distance was 50 meters. The c coefficient for temporal filtering was 0,8. The desired lateral deviation value (DELat) was 1.5 m.



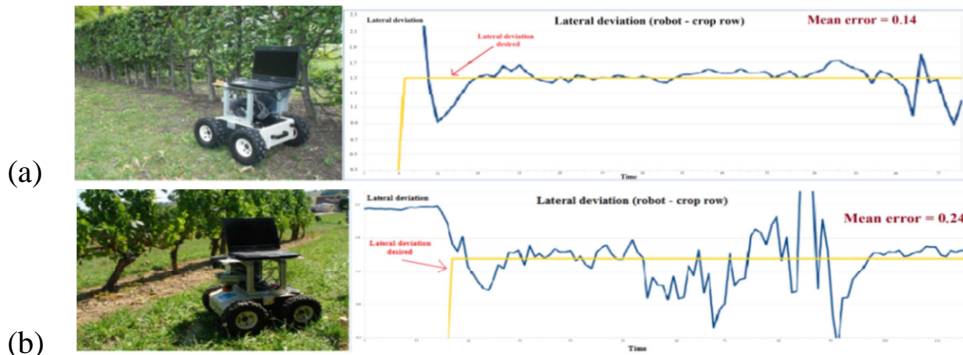


Figure 19. Crop row tracking on soil without and with perturbations

For all tests carried out, the mean error for lateral deviation between robot and crop row, varied in the range [0.1 - 0.2m] and [0.2 – 0.3m] respectively for soil without and with perturbations such as vines. Figure 20 presents crop row autonomous tracking result examples, without (a) and with (b) soil perturbations (vines), working with a speed of 1.5m/s. As example, the difference between mean absolute error for two robot speeds 1m/s and 1.5m/s, was about 0.06m and 0.11m, respectively for tests without and with soil perturbations, working in the same crops, modifying only speed value. For many tests, mean error for lateral deviation was about 0.25 m and 0.4m, respectively for soils without and with perturbations, with a speed of 1.5 m/s.

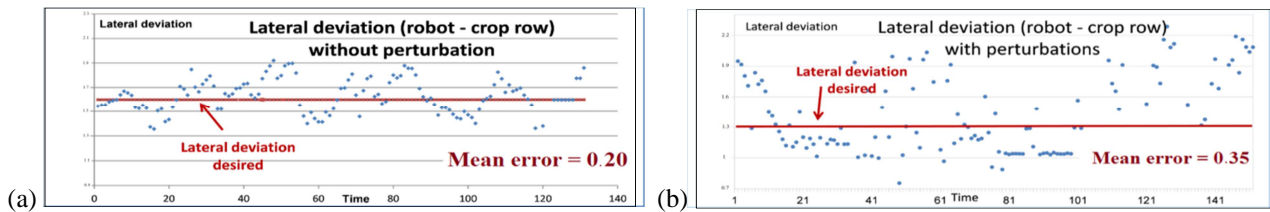


Figure 20. Speed influence on crop row tracking accuracy

### 3.2. Traversability operation with LiDAR and TOF device

The fusion method consisted to put the LiDAR and TOF data inside the color image, and to make some colorimetric and geometric measurements on the detected objects in front of the vehicle, for identifying these ones. For each image, the computation of grass and solid point numbers (G and S), above respectively the threshold values chosen for grass height (Gheight) and for solid objects height (Sheight), and the mean distance between robot and these objects (DGrass and DSolid) characterized the height and position of these ones. From this information, some decision could be taken in the traversability operations, for crossing or avoiding objects, and in extreme case the robot must stop, if a solid object was in front of it, near it. In the experimentations, the aim was to detect grass points above  $G_{height}=0.32m$  (=HL) and Solid points above  $S_{height}=0.25m$ . The threshold values chosen for traversability decision were the following:

$T1 = 100$  points,  $T2 = 3$  m,  $T3 = 100$  points,  $T4 = 4$  m,  $T5 = 1$  m

In Figure 21 and 22, grass and solid objects detected by LiDAR and TOF device, in front of robot, were put by fusion on color image. Pixel classification results by SVM are presented in red and blue color, respectively for grass and solid objects, for LiDAR device (A) and in green and red color, respectively for grass and solid objects, for TOF camera (B).

Measurement results and traversability decisions, taking into account the nature and size of detected objects are presented under each image. For LiDAR, object were detected at fixed height (HL=0.32m from the ground).




<p>A</p>	 <p><math>G = 27 &lt; T1</math>    <math>S = 20 &lt; T3</math></p>	 <p><math>G = 133 &gt; T1</math>    <math>S = 8 &lt; T3</math> <math>DGrass = 3.4 &gt; T2</math></p>	 <p><math>G = 158 &gt; T1</math>    <math>S = 12 &lt; T3</math> <math>DGrass &lt; T2</math></p>
<p><b>Traversability decision</b></p>	<p>Robot continue moving without any modification in trajectory and speed</p>	<p>Robot continue moving without any modification in trajectory and speed, <b>but will have to reduce speed “in a short time”</b></p>	<p>Robot continue moving keeping trajectory <b>at reduced speed</b></p>

Figure 21. Object detection and identification by fusion with LiDAR




<b>B</b>	 <p style="text-align: center;"><math>G = 213 &gt; T1</math>   <math>S = 9 &lt; T3</math> <math>D_{Grass} = 4,2m &gt; T2</math></p>	 <p style="text-align: center;"><math>G = 156 &gt; T1</math>   <math>S = 2 &lt; T3</math> <math>D_{Grass} = 2.6m &lt; T2</math></p>	 <p style="text-align: center;"><math>G = 121 &gt; T1</math>   <math>S = 328 &gt; T3</math> <math>D_{Grass} = 2.9m &lt; T2</math>   <math>D_{Solid} = 3.5m &lt; T4</math></p>
<b>Traversability decision</b>	Robot continue moving without any modification in trajectory and speed, <b>but will have to reduce speed "in a short time"</b>	Robot continue moving keeping trajectory <b>at reduced speed</b>	Robot moves <b>at reduced speed and avoids solid object</b> (tree and branches) (lateral deviation)

Figure 22. Object detection and identification by fusion with TOF

The application of the fusion method developed to detect and identify objects in front of the vehicle, using the geometric data obtained with the LiDAR device and the TOF camera, merged with color camera data, has shown that the mobile robot can improve and optimize its mobility, adapting its speed and trajectory, in real time, taking into account, the sensor data, which bring information about the nature and size of objects in front of it. Both grass and solid objects like tree and branches were considered separately. A supposition was made to consider that both object types were not superposed, but sometimes solid objects were hidden by grass. In these experimentations, LiDAR and TOF camera were embedded on mobile robot with a horizontal position. But depending of the application and of the object type which must be detected, the position and orientation of both sensors can be modified. In various crops, LiDAR devices data were used to detect if grass height was higher than its height from ground (HL). From this information, agricultural vehicles could reduce speed. But this planar information given by this sensor was not sufficient to detect with accuracy solid objects (like tree or branches), whereas TOF camera, which gave geometric information in 3D space, with low resolution (64x16 pixels) permitted, in various lighting conditions, the detection by fusion of both object types (grass and solid objects), in front of vehicle, at different heights from ground. From TOF data, solid objects detected could be avoided by vehicle, and grass detection permitted to reduce vehicle speed. The main problem with this sensor is to choose correctly its position and orientation, in order to be able to detect objects with various heights and various distances from vehicle.

#### 4. Conclusions

A fusion method has been developed, taking into account data from perception sensors such as a color camera, a LiDAR and a TOF camera, and also the ones coming from a IMU device, in order to improve agricultural tasks such as crop row tracking and traversability in the fields. This method consisted in the detection and identification of natural objects such as crops, grass, leaf, soil or other elements in front of vehicle, using the combination of the rich and colored representation provided by the images with the geometric data given by the LiDAR or TOF device. For crop row tracking operation, the results obtained working with a light mobile robot in different navigation conditions, in various crops, showed the robustness of developed fusion method, for realizing stable autonomous navigation for crop row tracking, particularly in the vineyards, with many perturbation and speeds up to 2m/s. Hough method enabled to obtain a better ground truth and less oscillations in navigation than LS technique, because it permitted to detect the exterior points of trees. The mean lateral error between desired and obtained trajectory varied between 0.1 and 0.4m, depending of speed and soil perturbations. Over than 2m/s, the robot could not navigate with stability, particularly in vineyards environment. This developed system, with three aspects (perception/fusion/control) will be carried on heavier vehicles or other mobile robot less sensitive to soil perturbations, to be able to work with high speeds over than 2m/s. For traversability task, both tested sensors LiDAR and TOF camera bring complementary information: LiDAR sensor could detect objects above its height (0.32m in our experimentations) at various distances between vehicle and objects, and TOF camera could detect objects at different heights but this detection depended of the distance. The longer the distance is great plus it can detect objects of low height. Information obtained in real time, by both sensors, was used to detect objects in front of vehicle, at various distances. Despite the low resolution of the TOF camera (64 x 16) objects with different heights from ground and various sizes, such as grass and tree branches, were detected, with accuracy, with this sensor. Image information given by TOF camera permitted to obtain better detection of obstacles (solid or grass) in front of robot than plane information given by LiDAR device. With this TOF camera, 3D maps, in agricultural fields, could be also performed. This should allow having more accurate information on terrain, and on obstacle geometry, allowing considering traversability maps on areas expected to be crossed by the robot. The accuracy of sensor data for autonomous navigation and obstacle detection/avoidance has been investigated under different lighting conditions and various vegetation levels. From the obtained results in the developed fusion method for both operations presented in this paper, traversability and crop row tracking, next works will consist to realize in the same time both operations, with the fourth sensor, working with many perturbations (mud, bumps, a lot of grass) for both operations.

LiDAR data will be used for tracking task, in order to identify crop points with camera, and TOF data will be used for obstacle detection and identification with color camera, in front of vehicle, using a light robot or a bigger vehicle. On main problem, in this work, will be to choose the right height for LiDAR device, in order to be able to detect crop points, every time, without being perturbed by grass height and leaf area. This fusion method which gives geometric and colorimetric information in crops, could be applied, in various fields, in different agricultural tasks, such as environment monitoring tasks, planting, maintenance or harvesting. For safety operations, for detecting people, near agricultural vehicles, or in dangerous areas, in order to avoid accidents, the use of a TOF camera associated with a color camera, could also be used.

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