Situation Awareness for Intelligent Mobility in Dynamic Environments IRT Nanoelec Perfect Platform

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Abstract: In the field of mobile robotics and intelligent vehicles, a key requirement for basic functionalities, such as collision awareness systems, is the ability to perceive and model a relevant representation of the environment where objects are moving. This crucial task is a challenging step in terms of accuracy, complexity and uncertainty management. The objective of this paper is to describe the multi-sensor Bayesian perception approach which has been developed by Inria[1] in the scope IRT Nanoelec[2], implemented and tested on the IRT experimental platform including an equipped Renault Zoe vehicle. These systems can be adapted to off road environments such as agriculture fields or construction area where workers lives are jeopardized by heavy moving machineries. Embedded multi-sensor Bayesian perception algorithms have been developed on several experimental hardware in cooperation with CEA[3]. For the purpose of computing accurate representation of the dynamic environment, these systems have been implemented on our intelligent vehicle, as well as on portable connected perception units. Shared perception have been implemented using Vehicle to Vehicle (V2V) and Vehicle to Infrastructure (V2I) communication protocols. Experimental results are presented and discussed in the paper.

1 INTRODUCTION

In the field of mobile robotics and intelligent vehicles, a key requirement for basic functionalities, such as collision awareness systems, is the ability to perceive and model a relevant representation of the environment where objects are moving. This crucial task is a challenging step in terms of accuracy, complexity and uncertainty management. Perception systems can provide accurate information of complex environments to drivers as well as fully autonomous vehicles. In off road environments and especially on construction areas and agriculture fields, collision risks between moving vehicles and workers are important. Safety can be greatly improved by using Advanced Driver Assistance Systems (ADAS) and/or Vehicle to Vehicle (V2V) or Vehicle to Infrastructure (V2I) communications.

Inria and CEA are working together on situation awareness systems using the knowledge of Inria on perception algorithms for Advanced Driver Assistance Systems solutions (Negre, 2014, Rummelhard, 2014, 2015, Lussereau, 2015) and the expertise of CEA on software / hardware integration (Rakotovao, 2015, 2016). IRT Nanoelec provides funding for technology transfer of research activities conducted by Inria as well as a secured platform that replicates realistic roads and intersections that are used to safely conduct experiments involving vehicles, pedestrians and other lightweight transportation systems.

[1] French National Institute for Research on Computer Science and Control
[2] Technological Research Institutes Nanoelec, http://www.irtnanoelec.fr/
[3] French Alternative Energies and Atomic Energy Commission

In this paper we present a framework for the perception of the environment capable of merging data from different types of sensors and different sources of information. This data redundancy increases the reliability and robustness of the perception system compared to mono sensor solutions. In this framework, data are shared amongst distributed systems through the ITS-G5 geonetworking protocol and fused using Bayesian filtering algorithms. First, in section 2, we assess risks involving moving vehicles and workers in farming exploitation and construction areas. Then, in section 3, we present existing approaches and the principles of our perception framework, followed by its implementation on an experimental set up and the associated results.

2 WORKERS SAFETY

2.1 Farming Exploitations

Risks in agriculture fields have been studied and well summarized in Groupama "Attitude Prevention" booklet[4]. The report mentions three main categories of collision risks:

- Collision risks with private cars when farm tractors are backing off from the exploitation into regular traffic. In this case, risks come from the poor visibility of the tractor driver and the speed difference between the two vehicles.

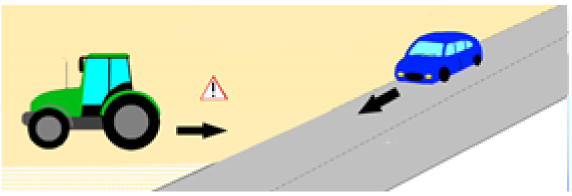

Figure 1: Collision risk when tractors are backing off into traffic

- Collision with a pedestrian on exploitations caused by low visibility from field dirt, machinery large blind spots and lack of attention of the driver due to task repetitiveness.

- Collision with another private vehicle of the exploitation caused by the same reasons mentioned in the second case.

The various level of customization and control over vehicles and worker safety equipment suggests different approaches. Cost and power requirements must also be adapted, whether it targets a human or a machine.

2.2 Construction Site

Risks in construction site are even more critical and very well detailed in INRS (French research and security Institute) report "risk prevention involving vehicles and machines driven on construction site"[5]. Risks are similar to the ones in farming exploitations but have a much higher probability to occur due to vehicle density, the large number of workers, and how often they cross vehicle paths.

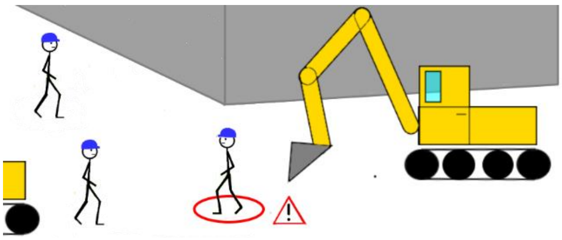

Figure 2: Collision risk in a busy construction areas.

INRS and similar institutes are recommanding to use driving assistance systems on construction machines, which is why solutions already exist on the market. Existing solutions use ultrasonic sensors, cameras, lidars or radio detection. These solutions are based on a single sensor, each kind having its own drawbacks:

- Ultrasonic solutions have a very short range (a few meters).
- Camera images can often be hard to understand due to heavy dust and dirt on site.
- Radio solutions imply that workers always wear badges, which might not be possible.
- Lidar-based solutions generate too many false alarms due to dust and heavy rain.

These mono sensor solutions have very limited sensor fusion and filtering capabilities compared to multi-sensor systems that we describe in this paper.

[4] https://www.groupama.fr/assurance-agricole/exploitation/prevention-agricole.html

[5] http://www.inrs.fr/media.html?refINRS=R%20434

3 SENSOR FUSION AND FILTERING

3.1 Introduction

In the field of perception of dynamic environments, the most classical approach has been to Detect and Track Moving Objects (DATMO), which leads to complex multiple targets object tracking literature (Petrovskaya, 2012), (Formtmann, 1980), (Khan 2004). Another common approach is the field of occupancy grids (Elfes, 1989), (Movarec, 1988), which works on spatial occupancy without higher level segmentation. This approach presents significant advantages. The model is by design spatially dense, and properly represents information about free space, which is an important data in mobile robotics and intelligent vehicles. Furthermore the delicate data segmentation and recognition step required in object-based representation can be avoided.

The field of occupancy grid based interpretation of the environment is a developed study domain, overlapping various applications, such as intelligent environment management, automatic autonomous navigation or extended vehicle perception. The aim is to produce a compact, regularly subdivided, probabilistic estimation of the spatial occupancy, without requiring the concept of objects. These approaches have been rarely used in dynamic enrironemnt because it requires to enrich each cells with the estimation of velocities which has been computationnaly too heavy for real time applications (Coué 2006, Thrun 2005, Gindele 2009, Danescu 2011).

The Inria CHROMA[6] and eMotion[7] research teams have been working on vehicle perception for more than 15 years. One of the main application domain is embedded perception and decision-making for driver assistance systems or autonomous cars. These research studies have led to the development of a perception framework based on Bayesian approaches, which is briefly described in the sequel.

3.2 Occupancy Grids

Our perception algorithms are based on a generic occupancy grid framework, initially developed within the Hybrid Sampling Occupancy Filter approach (HSBOF) (Negre, 2014) and further extended in the Conditional Monte Carlo Dense Occupancy Tracker (CMCDOT) (Rummelhard, 2015). This approach infers dynamics of the scene through a hybrid representation of the environment consisting of static and dynamic occupancy, empty spaces and unknown areas. This differentiation enables the use of state specific models (classic occupancy grids for motion-less components and sets of moving particles for dynamic occupancy) as well as proper confidence estimation and management of data-less areas. The approach leads to a compact model that dramatically improves the accuracy of the results and the global efficiency in comparison to previous models.

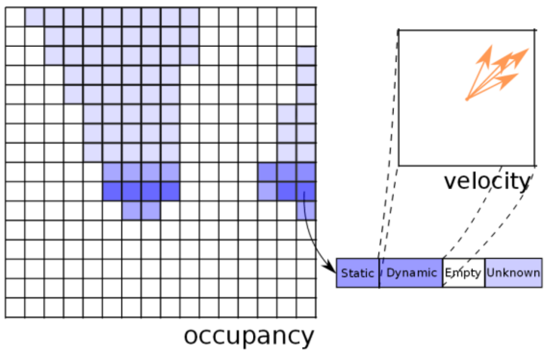

Figure 3: Data representation in CMCDOT formulation. The environment is divided into cells, with which static, dynamic, empty and unknown variables are associated. The dynamic part of each cell is represented by a set of particles.

This methodology is particularly suitable for heterogeneous sensor data fusion (camera, lidars, radars etc…) both spatially and temporally. The occupancy of each cell over time can be estimated from various sensors data whose specific uncertainty (noise, measurement errors) are taken into consideration. Filtered data of each cell are thus much more robust leading to a very reliable global occupancy of the environment reducing by far the number of false detection.

This grid-based approach can be computationally very heavy but highly parallelizable, resulting in real time performances on GPUs as shown in paragraph 4.5.2.

3.3 Collision Risk Assessment

Most methods for risk estimation detect and track dynamics objects in the scene. The risk is estimated through a Time to Collision (TTC) approach by projecting objects trajectories into the future. Our

[6] https://team.inria.fr/chroma/en/

[7] https://team.inria.fr/e-motion/en/

approach is based on the grid-based CMCDOT framework (Rummelhard, 2015). The idea is to compute estimations of the position in the near future of every static and dynamic part of the grid, instead of reasoning on objects themselves, as well as the trajectory of the vehicle. These estimations are iteratively computed over short time periods, until a potential collision is detected, to which is then associated a TTC. In each cell, the associated TTC are cumulated over different time periods (1, 2, 3 seconds) to estimate a cell-specific risk of collision. This way we generate risk grids, and global risk aggregates, on which we base our reasoning.

This strategy avoids solving the difficult problem of multi-objects detection and tracking while integrating the totality of the information available. It provides a probabilistic estimation of the risk associated to each part of the scene (Rummelhard, 2014).

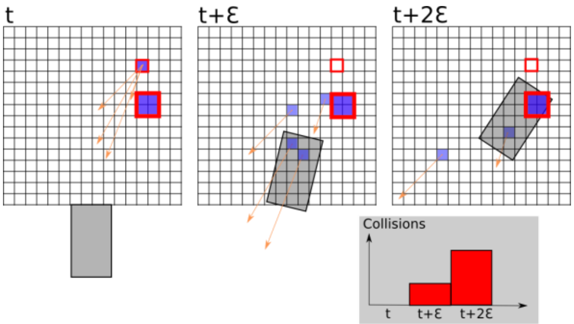

Figure 4: Collision risk estimation over time for a specific cell. The cell position is predicted according to its velocity, along with the moving vehicle. This risk profile is computed for every cell and then used to integrate over time the global risk.

3.4 Dynamic Object Clustering

So far has been described a method how to track spatial occupancy in the scene without object segmentation, but detection and tracking of moving objects (DATMO) is often required for higher level processing, like pedestrian detection. The CMCDOT introduces an object clustering method with limited additional computation. It is based on a particle filter resampling mechanism that associates a unique ID to all of the dynamic particles of an object.

These objects provide a higher level of representation, with much more condensed information that can be easily communicated between various connected systems: vehicles, embedded perception units or lightweight connected devices. This is a first step towards distributed perception.

4 EXPERIMENTAL SET UP

The described perception framework has been tested and improved throughout the years on several experimental platforms. In this contribution we present the most recent ones that were designed and tested within the scope of IRT Nanoelec.

For our experiments, we chose to use a single type of sensor : lidars, even though our perception framework can fuse heterogeneous kinds of sensors. Lidars are currently very expensive and fragile because of their internal moving mirrors but these issues will certainly be solved in the near future by the release of solid state lidars from companies like Quanergy[8] or Leddartech[9]. This new generation of lidars will not have any moving parts, reducing drastically their cost and making them more suitable in vibrating environment like farming or construction machines.

4.1 Intelligent Vehicle

The first platform that was designed for our experimentations is a Renault Zoe equipped with sensors and processing power. Such a small city car was chosen because of its low cost and ease of driving compared to heavy machines. The purpose of that intelligent vehicle is to run experimentations on the perception of the environment as well as V2V[10] and V2I[11] experiments. The controls of the vehicle will be automated in the near future for active driving assistance system experiments. It has been equipped with a set of sensors: lidars, IMU, GPS and cameras. Our perception algorithms are based on lidars only, cameras have been integrated as well for object recognition and image-based processing algorithms. We chose IBEO Lux lidars which have 4 planar laser beams. Three are placed at the front and one at the rear of the car. They are synchronized using the IBEO fusion box. Fused lidar data are then filtered on a Nvidia Titan X GPU in a PC, in the trunk of the car. An IMU is used to get the displacement of the car.

[8] http://www.quanergy.com/
[9] http://leddartech.com/
[10] Vehicle to Vehicle
[11] Vehicle to Infrastructure

Table 1: Sensors types integrated in the Zoe

Hardware	Renault Zoe
GPS	Garmin 18x LVC
Lidar	4 IBEO + Velodyne HDL 64
IMU	XSens MTXG
Stereo Camera	Point grey Bumblebee
Camera	IDS uEye

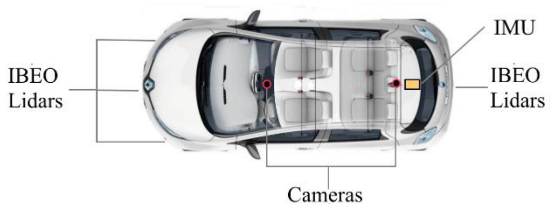

Figure 5: Sensor location in the Zoe.

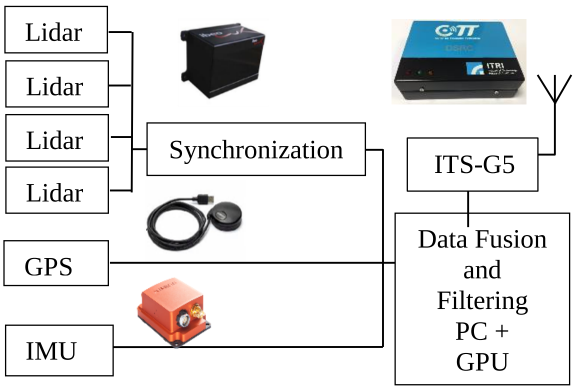

Figure 6: System architecture of our intelligent vehicle.

Such a solution is applicable when machines can either be industralized or customized with sensors and processing capabilities. It could be suitable for construction machines or tractors that could be equipped with perception capabilities like the Zoe.

We are also working on connected technologies, for vehicle to vehicle and vehicle to infrastructure use cases. All of our experimental platforms are equipped with communication capabilities. The communication protocol that was chosen is the ITS-G5 protocol, the current European standard for V2X communications (V2V and V2I communications). It is a geonetworking peer-to-peer solution that does not require any infrastructure. We chose the implementation made by ITRI (Industrial Technology Research Institute)[12] because of its SDK, Linux toolchain and it was the most open and customizable solution.

Object detected by the Zoe from our perception algorithms can be sent through the ITRI unit to other connected devices including other vehicles or infrastructures as explained in distributed perception use cases described in paragraph 4.4.

4.2 Connected Devices

Using this ITS-G5 geonetworking communication protocol, other lightweight connected devices has been implemented, like a connected traffic cone. It reads its position from a GPS and broadcasts it to neighboring connected vehicles. It can be placed next to dangerous areas, warning vehicles of a risk ahead of time, when danger may be hidden by other vehicles in front of the car or by a curve.

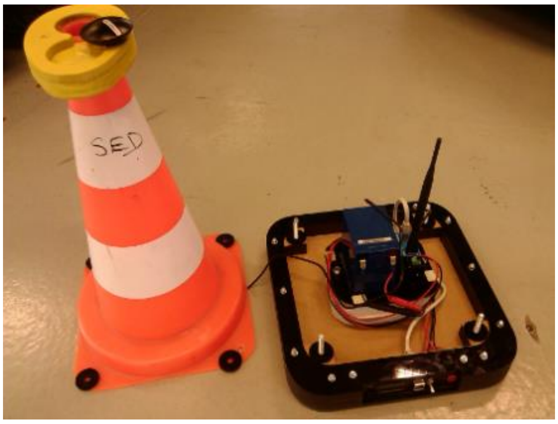

Figure 7: Connected traffic cone.

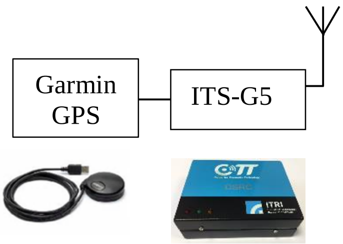

Figure 8: Connected Traffic cone architecture.

This architecture can be used for any other connected devices like worker hats and small V2X boxes that could be mounted in any vehicles. These solutions would be especially useful when it is impossible to integrate sensors or processing units into existing vehicles.

[12] https://www.itri.org.tw

In order for such distributed systems to work, all of the connected vehicles and devices must be synchronized. In our case, this is done through the Network time protocol (NTP), the current time and PPS (1 pulse per second) signal are read from Garmin 18x LVC GPSs.

4.3 Perception Units

The third type of equipment that are developed are perception units. The idea is to design portable units, capable of perceiving the environment the same way our intelligent vehicle can, through a set of sensors and a processing unit running our Bayesian filters. Like all of our other connected platforms, they are able to communicate information through ITRI units. These units could be placed in the field or on infrastructures, and communicate detected objects to neighboring vehicles and connected devices. Intelligent vehicles capable of perceiving the environment could receive information from perception units and increase their field of perception, as described in paragraph 4.4.3.

Perception units are equipped with a GPS to localize the unit, a lidar to detect objects, an embedded GPU and a V2X communication device. We chose a Quanergy M8 lidar that generates point clouds of the whole environment for a reasonable price.

Table 2: Sensors integrated on a perception unit.

Hardware	Perception Unit
GPS	Garmin 18x LVC
V2X	ITRI
Lidar	Quanergy M8
GPU	Nvidia Jetson TX1

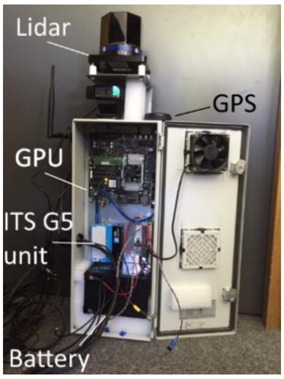

Figure 9: Perception unit hardware components.

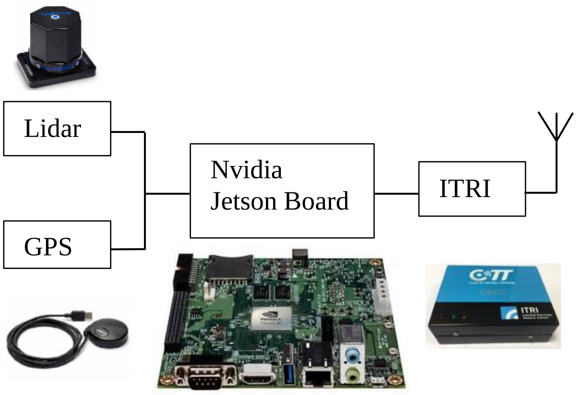

Figure 10: Perception Unit System Architecture.

4.4 Improving Off Road Safety

4.4.1 Intelligent Machines

From these experimental platforms, modular solutions can be designed to solve the use cases described in paragraph 2. Off road machines could be equipped with sensors and processing power the same way our intelligent Zoe was. For example, on construction sites, as it is shown in Figure 11, moving machines could detect workers and other vehicles through their own sensors and embedded processing power.

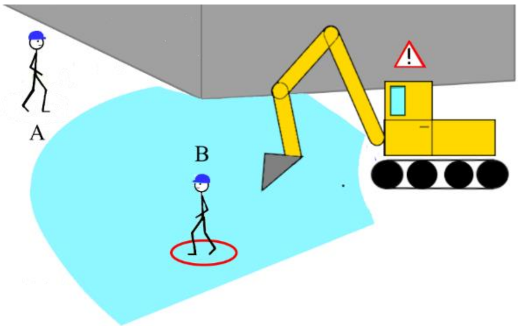

Figure 11: Workers detection from intelligent construction machines. The sensor field of perception is represented in blue. Worker B would be detected as a collision risk.

Likewise, tractors could be able to detect incoming cars when backing off in traffic as shown in Figure 12.

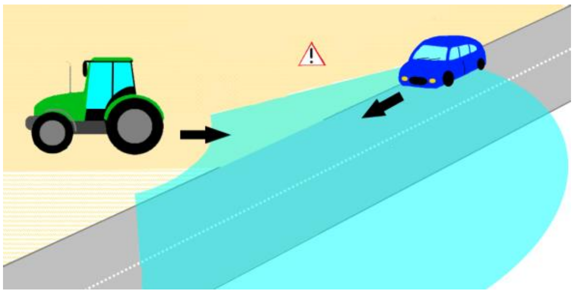

Figure 12: Vehicle detection from an intelligent tractor. The sensor field of perception is represented in blue. The car would be detected as a collision risk by the processing unit of the tractor.

4.4.2 V2X Solutions

Another way of estimating collision risk on construction site would be to use connected devices that would signal one another locations as shown in Figure 13. Small low energy connected devices would be placed in worker hats and in vehicles, connected traffic cones would be used to signal dangerous areas and machines.

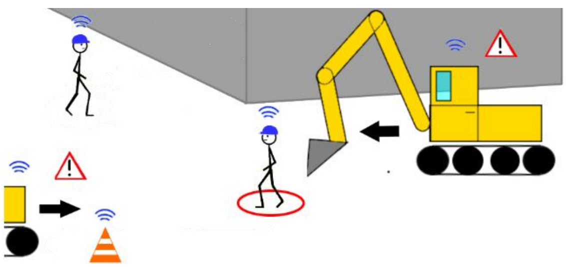

Figure 13: Example of a construction site equipped with connected devices in worker hats, vehicles and traffic cones. The digger on the right is warned by the presence of a worker. The digger on the left is informed of the location of a hazardous area by the traffic cone behind it.

4.4.3 Distributed Perception

Sharing or distributing the perception of the environment is possible using the experimental platforms described in paragraph 4. It is possible for an intelligent vehicle to share detected objects with other vehicles and for perception units to warn connected vehicles of hidden risks.

For example, two connected vehicles on a construction site could communicate the location of workers to each other reducing the size of their respective blind spots. Figure 14 shows an example of a V2V communication where the vehicle on the right sends the location of worker B to the vehicle on the left, preventing it from backing into the worker.

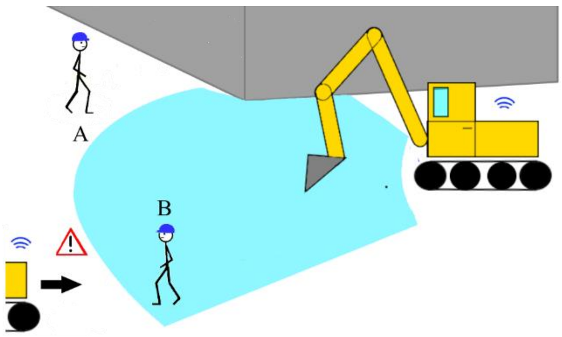

Figure 14: Distributed perception between two vehicles able to perceive the environment in front of them. The digger on the right perceives worker B though its sensors and sends the location of this worker to the digger on the left to prevent him from backing into worker B.

Perception units could be useful in many use cases, for example when tractors are backing off their exploitations. Farmers would place the perception unit on dangerous crossing, the unit would perceive incoming cars from its sensors and warn the driver of the tractor of incoming cars.

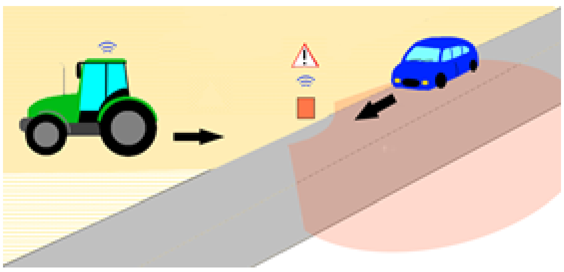

Figure 15: Detection of a private vehicle from a perception unit in orange. The driver of the tractor receives a warning from the unit.

Another use case is the distribution of the perception between an intelligent vehicle and a perception unit. In dangerous crossing, some of the environement might be hidden by signes or bushes, the perception units could be placed at stategic locations to perceive hidden areas are send object locations to drivers. For example, in Figure 16, worker A is hidden behind the building and is walking towards the digger. The perception unit in orange sees the worker through its sensors and sends its location to the connected digger. Even though the digger is equipped with perception capabilities, the worker is not in its field of perception, preventing the digger from seeing him.

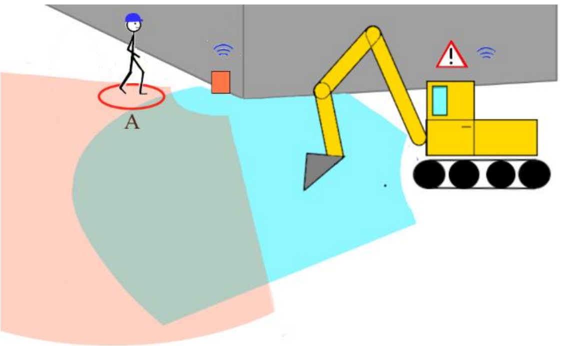

Figure 16: Shared perception between a perception unit and a digger. The field of perception of the unit is in orange, the one of the digger in blue. The worker is seen by the perception units that sends its location to the connected digger.

Our solutions can solve many more use cases, these are some examples of how the environment can be perceived depending on the specificities of each situation and the ability to equip vehicles with sensors.

4.5 CMCDOT Software Implementation

4.5.1 ROS

We use the Robot Operating System (ROS) framework[13] that lets us prototype solutions quickly, write reusable code and take advantage of the large community of academic users. A variety of ROS drivers for many kind of sensors are available, it provides many useful tools for code troubleshooting and for graphical visualization of data. We use ROS to encapsulate CMCDOT algorithms, manage and synchronize incoming data from various set of sensors (lidars, cameras, IMU, GPS).

[13] www.ros.org

4.5.2 CUDA

CMCDOT algorithms have been highly parallelized in Cuda kernels and optimized to run on multiple Nvidia GPUs: Titan X and embedded Jetson TX1. Our algorithms run in real time, in our experiments they are more than able to fuse and merge lidar data outputs, which are at 20Hz (50 ms per frame) as shown in Table 3.

Table 3: Computational time of sensor data fusion in the grid and CMCDOT algorithms.

Nvidia Boards	Grid fusion in ms	CMCDOT processing time in ms
Titan X	0.3	7
Jetson TX1	0.7	17

4.6 Close-to-Market Solutions

Within the IRT Nanoelec we are working closely with our partners at CEA in order to bring our solutions closer to the actual market requirements. CEA conducts efforts to implement our perception framework on low cost, low power architectures like embedded many core. They work on optimized integer implementations of the data fusion that better fits these hardware architectures (Rakotovao, 2015), (Rakotovao, 2106).

5 EXPERIMENTATIONS

IRT Nanoelec provides a platform, the PTL[14] where experiments are conducted in a secured and dedicated environment that replicates actual roads and infrastructure. Experiments are conducted on two use cases:

- Risk assessment from a Renault Zoe
- Distributed perception between the Renault Zoe and a perception unit

5.1 Risk Assessment a Renault Zoe

A crash test dummy was designed by Laurence Boissieux from the Inria Grenoble SED team, the dummy simulates a pedestrian crossing a street. Figure 17 shows our collision risk avoidance

[14] Technology Liaison Platform

experiments on the PTL site with the Renault Zoe and the dummy.

Figure 17: Risk collision experiments with our dummy crossing a street. © Inria / Photo H. Raguet.

We are able to merge and filter data from four IBEO lidars into a single occupancy grid as shown in Figure 18. White dots are lidar impacts merged into a single occupancy grid. Black areas correspond to empty spaces and the gray one to hidden areas, where it is impossible to know if there are objects or not. The red box represents an object with a high risk of collision. This risk was computed based on the Zoe trajectory, cell occupancy and velocity.

The collision risks are shown on the upped image of Figure 19 as red circles. As expected, the dummy was detected as a collision risk for the car. Red arrows indicates the direction of the target. The lower graph corresponds to the probability risks at 3 time horizons, 1 (red), 2 (yellow) and 3 (green) seconds.

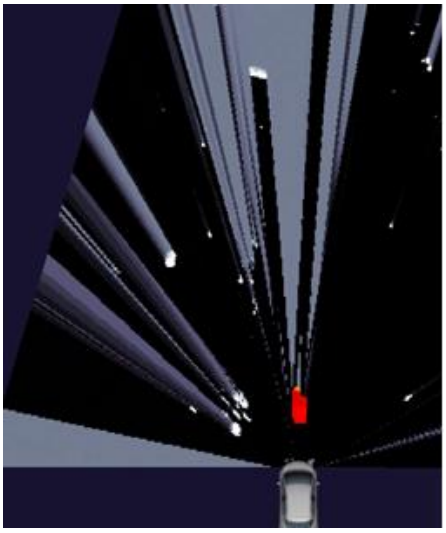

Figure 18: Filtered occupancy grid constructed from lidar data.

Figure 19: On the upper camera image, red circles correspond to collision risks and arrows the direction of moving targets. On the lower image, graphs correspond to collision risk probabilities for 3 time horizons: 1s (red), 2s (yellow) and 3s (green).

5.2 Distributed perception between a Renault Zoe and a Perception Unit

In these experiments, we want to demonstrate how the field of perception of a vehicle can be enlarged with perception units. The map at the lower right of Figure 20 shows a top down view of the PTL, our experimental site. The Renault Zoe has been parked next to the green building so that most of the environment on the left of the car was hidden. The field of perception of the Zoe is the area shown in blue, we placed a perception unit (red dot) at the lower left angle of the green building. Its field of perception is represented in red. A, B and C yellow crosses represent pedestrians moving in front of the vehicle. Pedestrian A is invisible to the driver because of the green building.

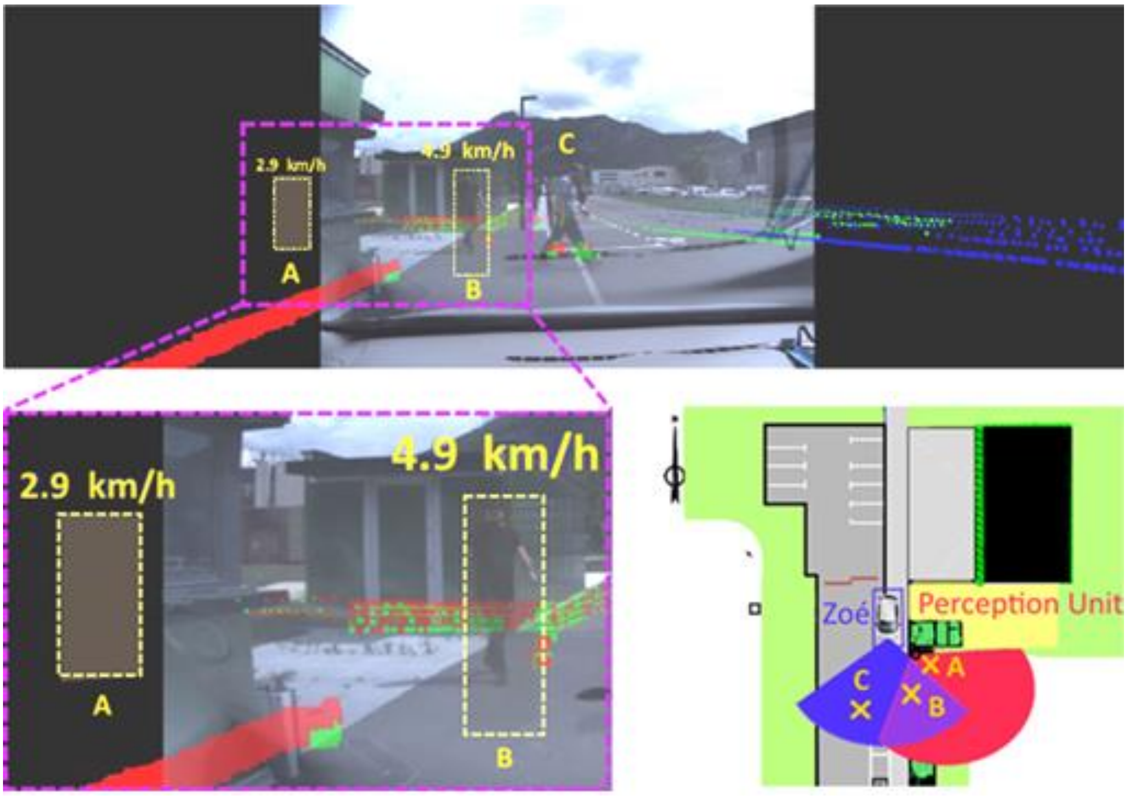

Figure 20: Pedestrian detection in a distributed perception environment. Pedestrian A and B are detected by the perception unit, their locations are sent to the car.

Figure 20 shows the front camera of the vehicle along with lidar impacts on the environment. The field of perception of combined lidars is greater than in the camera, which explains the lack of camera images on each side (black rectangles instead). Red dots correspond to impacts from the lidar on the left of the car, the green ones from the lidar centered at the front of the car and the blue ones from the lidar on the right. Pedestrian B and C have lidar impacts (on their feet) since they are in the field of perception of the vehicle. The perception unit is able to send the location of pedestrians A and B through V2X communication protocol. These objects are represented by the yellow dashed boxes. Pedestrians A and B and their associated speed have been detected and sent to the car. This shows that we are able to enlarge the field of perception of drivers using stationary perception units located in the field.

6 CONCLUSIONS

In this paper we presented a detection and tracking framework for the perception of dynamic environments, based on Bayesian occupancy grids. We briefly introduced the HSBOF and CMCDOT frameworks that can filter data temporally and spatially from heterogenous kinds of sensors. From the grid representation of the environment where cells states can be static, dynamic, free or unknow, we were able to estimate spatial occupancy, velocity and then cluster objects.

The experimental platforms, including an intelligent vehicle along with connected devices and perception units has been described. The experimental results on pedestrian detection with the Renault Zoe, show that we are able to robustly detect collision risks in real time using highly parallelized algorithms on GPUs. It has also been shown that collision detection algorithms can be run on embedded GPUs in connected perception units, and that perception between intelligent vehicles and perception units can be distributed using V2X communications.

A couple of frequent collision risks that occure on farming exploitations and construction sites has been described. Multiple solution for each of these off-road use cases has been explained using our perception algorithms and/or V2X communications depending on the type of equipment that can be integrated into existing vehicles and safety devices.

Future work includes the enhancement of object classification. Some work has already been completed using lidar data to compute the location of objects and camera to run deep learning techniques (neural network algorithm) to differentiate pedestrians from vehicles, bikes, trucks, etc. We also started implementing higher level object tracking algorithms to track multiple objects over longer period of time and anticipate their behavior and social interactions.

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