Perception and tracking of dynamic objects for optimization of avoidance strategies in autonomous piloting of vehicles

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Abstract. In the autonomous piloting of vehicles, the characterization of nearby dynamic object motion by perception and tracking techniques aids in the optimization of avoidance strategies. Knowledge of the features of object motion in goal-driven navigation allows for accurate deviation strategies to be implemented with appropriate anticipation. This perceptual competence is a fundamental issue in the design of unmanned commercial outdoor vehicles with an often reduced capability for maneuvering. To this aim, a grid map representation of the local panorama is proposed such that laser rangefinder images are converted into grid cells that are segmented and assigned to objects, allowing classification and monitoring. The motion properties of objects are thus used to establish avoidance behavior to smartly control the vehicle steering, such that a safe and optimal detour maneuver is carried out while driving to a target. The developed perceptual ability is demonstrated here in several tests performed in a relatively clutter-free area to detect and track walking pedestrians. Some results are also shown to highlight the modulation of moving object properties on trajectories described by a robot when a fuzzy avoidance strategy is used to control the steering angle.

Keywords: detection and tracking, moving objects, obstacle avoidance, human spatial cognition, dynamic environments, laser rangefinder, fuzzy control, outdoor vehicles.

1 Introduction

The detection of moving objects has been extensively analyzed in Ethology [1], and has inspired the development of artificial perception strategies [2], [3]. Attention and pre-attention visual mechanisms have been studied by psychophysicists, with some authors arguing the existence of motion filters in the brain as a sign of evolutionary utility: a moving target symbolizes either food or danger, so motion detection is a cue for animal survival. An additional, well-known and investigated natural phenomenon involves the maintenance of the moving object in the visual field, i.e., an object tracking strategy [4], [5]. The visual perception of object motion is fundamental to our capacity to understand and interact with our surrounding environment.

In the past, perception algorithms, supported by instantaneous sensor readings, have been implemented in holonomic indoor robots for collision avoidance independently of their motion state, relying both on fast feedback reactive control loops and on a high maneuverability; however these algorithms are unable to generate optimal deviation trajectories [6], [7], [8], [9], [10]. Other approaches on indoor vehicles require that the working area be equipped with a well-distributed set of scanners [11] or team of robots [12], to derive kinematic information to identify moving objects.

Several attempts have been made to develop complex movement strategies based on models of object dynamics [13]; however these models were hampered by restrictions imposed by real systems (sensors, vehicle, environment). In recent years, research has focused on the detection and tracking of moving objects based on the data provided by real sensors. To this aim, a stochastic map building method was proposed to model quasi-static environments, in real time, using a 2D laser [14]. The detection and tracking of walking persons in a cluttered railway station was addressed in [15], but without any reference to their effect on the piloting actions to be performed . In [16] detection, tracking and avoidance of persons in an office-like environment is addressed using a probabilistic model for person locomotion. In a similar manner, the detection and tracking of moving objects, is formulated only as a monitoring system to warn and assist bus and car drivers in advance, from a high temporal resolution laser rangefinder integrated on an urban vehicle [17].

Up to now, research dealing with moving objects and non-holonomic, car-like, vehicles has departed from the formulation of object motion models and has not engaged in the connection between perception and action to locally optimize navigation strategies. However, the optimization of avoidance strategies for car-like vehicles in dynamic environments still remains a challenge in mobile robotics. In this paper, moving objects present in a scene are characterized by a set of features, as a first step to optimize a collision avoidance strategy in goal-driven navigation. Techniques dealing with the visual detection and tracking of moving objects, which have been extensively developed in the field of artificial vision, are out of the scope of the current work, although some visual image processing approaches are used here and adapted to planar laser scanner images [18], [19], [20], [21] .

In the following section, algorithms developed to detect, track and characterize moving objects are depicted. In Section 3, an avoidance strategy, formulated by incorporating knowledge on moving object features into a fuzzy controller in order to derive a more appropriate steering action, is described. Examples of the results obtained with the proposed approach are presented and commented upon in Section 4, while conclusions are presented in Section 5.

2 Detection, tracking and characterization of moving objects

The detection and tracking of moving objects, in a dynamic environment, is a key issue to be addressed in order to achieve the collision-free navigation required for non-holonomic commercial vehicles with limited maneuverability. To this aim, a local grid map representation [22] has been proposed to detect, track and characterize moving objects that could potentially obstruct the vehicle's intended trajectory, accounting for characteristics of both the vehicle and its immediate environment [23]. This grid map (2D cartesian coordinates) is a gross grain representation that acts as a short term memory accumulating the occupancy evidence. Its resolution (cell dimension) can be changed according with the expected objects size. A flow diagram of the processes developed to derive moving object features is displayed in Figure 1.

The dynamic environment is perceived with a laser rangefinder (SICK-LMS 291) that delivers a 2D polar coordinates representation of close objects, at a rate of 5 Hz (RS232 protocol), with 0.5 degrees resolution over a 180 degrees visual field and a maximum measurement range of 30 m. A grid map is then generated by mapping the obtained polar coordinates to a Cartesian coordinates representation of 30×30 meters , composed of cells of 20×20 cm, both selected as a trade-off between the estimated speed of the most likely moving objects and the computational cost. One of three states is then assigned to the grid map cells: occupied, free or unknown. The grid occupancy latency is fixed to 400 ms, corresponding to two complete laser scans at maximum frequency rate. The position of the robot in the grid is updated by means of a Differential Global Position System (DGPS) integrated in the vehicle.

An image segmentation algorithm then groups occupied cells in ensembles using an adjacency criterion. Thus, the grid map is scanned by searching for adjacent occupied cells, recording simultaneously all visited cells, and exploring only those cells marked as occupied. From the segmentation process a collection of clusters is obtained, namely objects, which are ascribed to the $Object\_List(t) = \{O_1(t), O_2(t), ..., O_n(t)\}$, with n being the number of detected objects at time t. Each object of the Object_List is described by the set of adjacent occupied cells and its motion is represented by its centroid motion (1).

$$O_i(t) = \{ID_i(t), cells_i(j,k)(t), \boldsymbol{r}_{cent_i}(t), \boldsymbol{v}_{cent_i}(t)\} \tag{1}$$

$ID_i(t)$ is the identification of object $O_i(t)$, and $cells_i(j,k)(t)$, the locations of the cells that represent object i. The two last descriptors, position and speed of the object centroid (2), are defined by the following expressions.

$$\begin{aligned} \boldsymbol{r}_{cent_i}(t) &= \sum \boldsymbol{r}_{cell_i}(j,k)(t)/M \\ \boldsymbol{v}_{cent_i} &= (\boldsymbol{r}_{cent_i}(t) - \boldsymbol{r}_{cent_i}(t-1))/\Delta t \end{aligned} \tag{2}$$

Correspondence between objects in Object_List (t) and in Object_List (t-1) is completed according to a Nearest-Neighbor criterion, widely used for its sim-

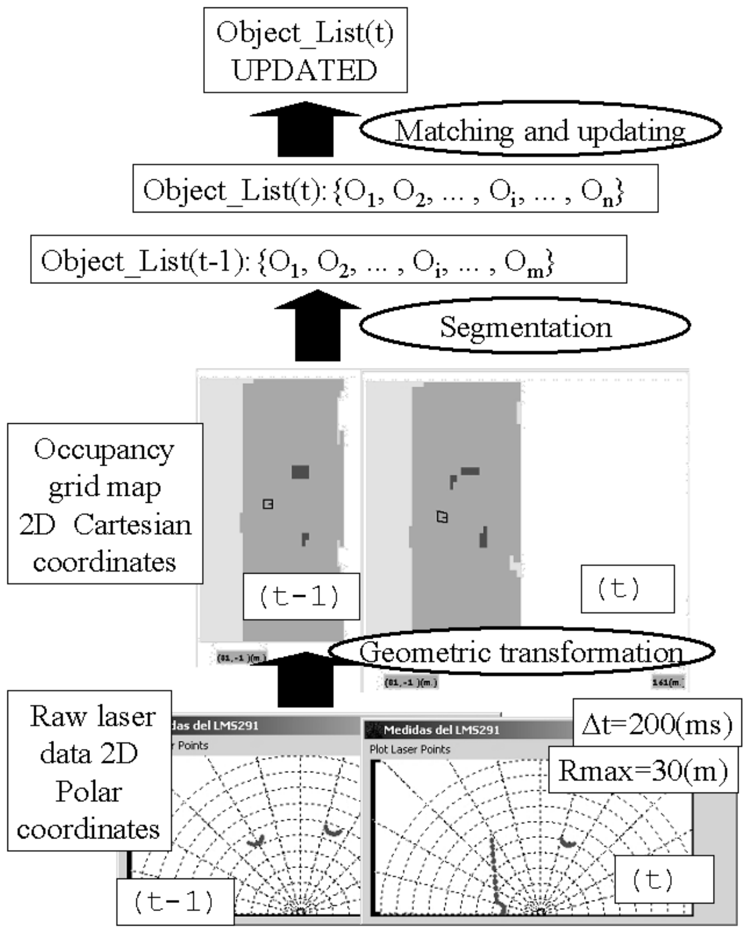

Fig. 1. Flow diagram of representations and processes developed for object detection, tracking and characterization

plicity and good performance in real-time applications, in contrast to more complex approaches such as the Hungarian algorithm [24]. The matching similarity function is the Cartesian metric between object centroid current and predicted position. The Object_List (t-1) is scanned by searching for a correct correspondence among objects at (t-1) and objects at (t), extracting only those that are within a circle of radius R centred at the predicted position at (t) of objects at (t-1). The distance threshold R has been set to one meter according to the maximum speed that could be detected. The predicted position at (t) of objects belonging to the Object_List (t-1), is calculated as follows (3):

$$\boldsymbol{r}_{PREDICTED_{cent_i}}(t) = \boldsymbol{r}_{cent_i}(t-1) + \boldsymbol{v}_{cent_i} \cdot \Delta t \tag{3}$$

An object having a maximum number of overlapping cells, among all possible candidates, is selected, and object features are updated. The first selection of candidates greatly reduces the search space, as only the closest obstacles are investigated in the matching process. The proposed overlapping criterion for candidate selection helps to prevent incorrect obstacle associations being made. The updating of the object features in the Object_List is performed at a rate of $\Delta t = 200$ ms, although the algorithm computational cost is around 5 ms.

All described processes are embedded in a perceptual agent, namely MOVING_OBSTACLES, which entails the moving objects characterization competence.

3 Avoidance strategy optimization

The avoidance strategy designed is devoted to perform smart deviations when objects, either static or dynamic, unexpectedly appear within a bounded ring region in the laser scanner viewing angle while the vehicle is en route to a defined target. The avoidance strategy proposed here, AVOID, has been encapsulated as an agent of the multiagent architecture already implemented in an unmanned lawnmower for use in outdoor environments [25]. Three concurrent basic motion agents, ADVANCE, AVOID and STOP, in conjunction with a perceptual agent MOVING_OBSTACLES, determine the piloting competence. The processes contained in the ADVANCE strategy are directed to drive the robot to a specific location through free-space areas, with the STOP agent acting only in emergency situations, that is, when an object is detected at a distance less than 2m. The AVOID agent detours the vehicle in order to maintain collision-free piloting when an object enters the ringed region of radius 2-10m from the laser-centred reference system. At the piloting level, motor agents are designed so that they are activated by mutually exclusive perceptions. In addition, a redundant coordination mechanism prioritises the agents, thereby ensuring that only one agent is active within each control cycle. The highest priority is assigned to the STOP agent.

To disallow the activation of the AVOID behaviour in those situations where there is no risk of collision, in spite of the moving object is within the emergency bounded ring area, the *collision_angle* α, Figure 2, is calculated in two consecutive instants elapsed 500 miliseconds. Consequently, only when the *collision_angle* remains constant, the AVOID behaviour is activated, Figure 3.

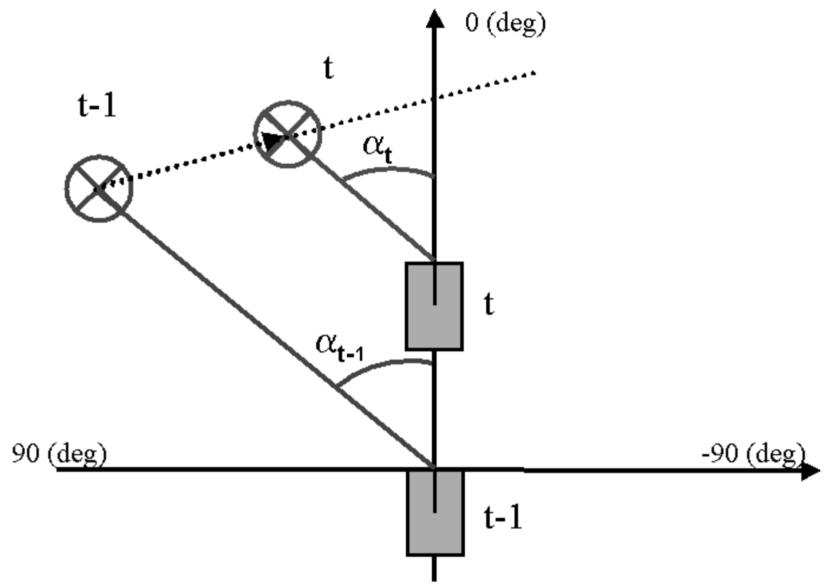

Fig. 2. Collision_angle α, in t and $t-1$, measured with respect to the vehicle heading. Constant values of the *collision_angle* variable in a time period indicates collision risk

The perceptual information required by the three motor agents is available in the data structure, Object_List(t), which is updated by the perceptual agent MOVING_OBJECTS, and is recorded in a shared memory among agents. The AVOID agent is modeled as a fuzzy controller that mimics human avoidance strategies in response to detected moving obstacles. Basic driving control strategies proposed in the fuzzy heuristic approach is a deviation to the left when an object is on the right and vice-versa. This strategy varies when object motion is detected, such that the robot must turn in the opposite direction to that of the moving object, independently of its angular location.

Only two input variables are required: the angular object position γ, *obstacle_position*, and the object motion direction calculated as $[\gamma(t) - \gamma(t-1)]$, namely *movement_direction*, displayed in Figure 4. The output of the fuzzy controller is the robot wheel angle β, *wheel_angle*. The linguistic labels associated to the former variables and their definitions by trapezoidal membership functions are displayed in Figure 5. A "decision" on the *wheel_angle* is made each 500 ms. The unique output control variable of the detour strategy is the *wheel_angle*, which is related to the steering system, as the lawnmower mechanical design inhibits speed changes.

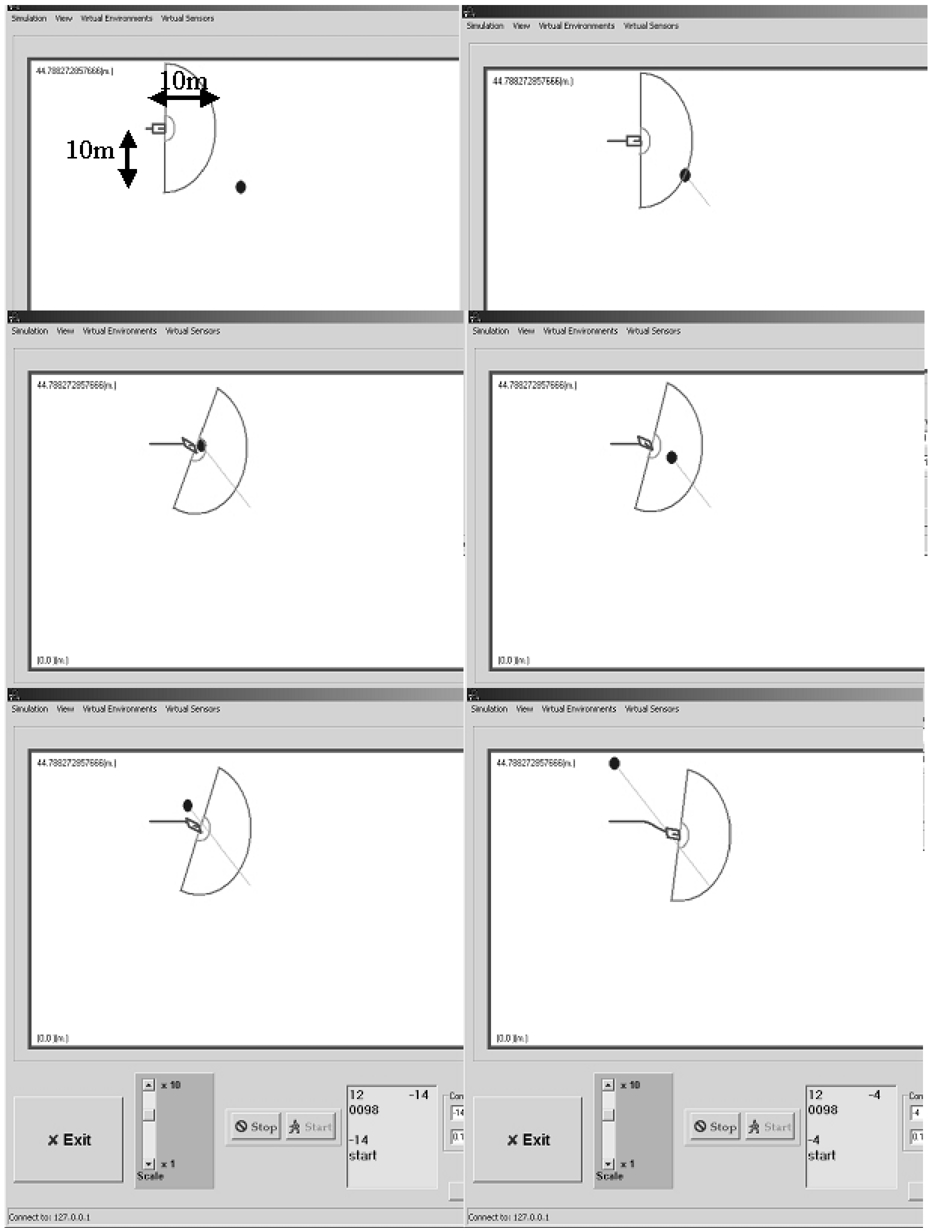

Fig. 3. Robot (black) and object (grey straight line) trajectories. The goal-driven robot trajectory is slightly deviated from its target through the activation of the AVOID strategy as collision risk is detected. ($v_{robot} = 0.3$ m/s, $v_{object} = 0.5$ m/s).

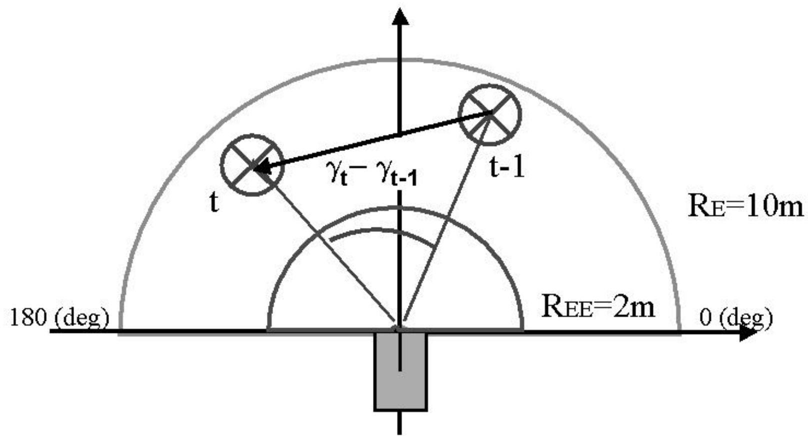

Fig. 4. Inputs to the AVOID strategy :$\gamma(t)$ moving object angular distance in t, relative to a laser-centred reference system, and $[\gamma(t-1)-\gamma(t)]$ angular distance variation of the moving object location in two successive steps. R_{EE} is the radius of the extreme emergency zone, while R_E corresponds to the emergency area

The knowledge base of the AVOID fuzzy control system is composed of the following nine rules:

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R1:  IF obstacle_position  IS left AND movement_direction IS right
     THEN wheel_angle IS left
R2:  IF obstacle_position  IS left AND movement_direction IS zero
     THEN wheel_angle IS right
R3:  IF obstacle_position  IS left AND movement_direction IS left
     THEN wheel_angle IS right
R4:  IF obstacle_position  IS center AND movement_direction IS right
     THEN wheel_angle IS left
R5:  IF obstacle_position  IS center AND movement_direction IS zero
     THEN wheel_angle IS right
R6:  IF obstacle_position  IS center AND movement_direction IS left
     THEN wheel_angle IS right
R7:  IF obstacle_position  IS right AND movement_direction IS right
     THEN wheel_angle IS left
R8:  IF obstacle_position  IS right AND movement_direction IS zero
     THEN wheel_angle IS left
R9:  IF obstacle_position  IS right AND movement_direction IS left
     THEN wheel_angle IS right
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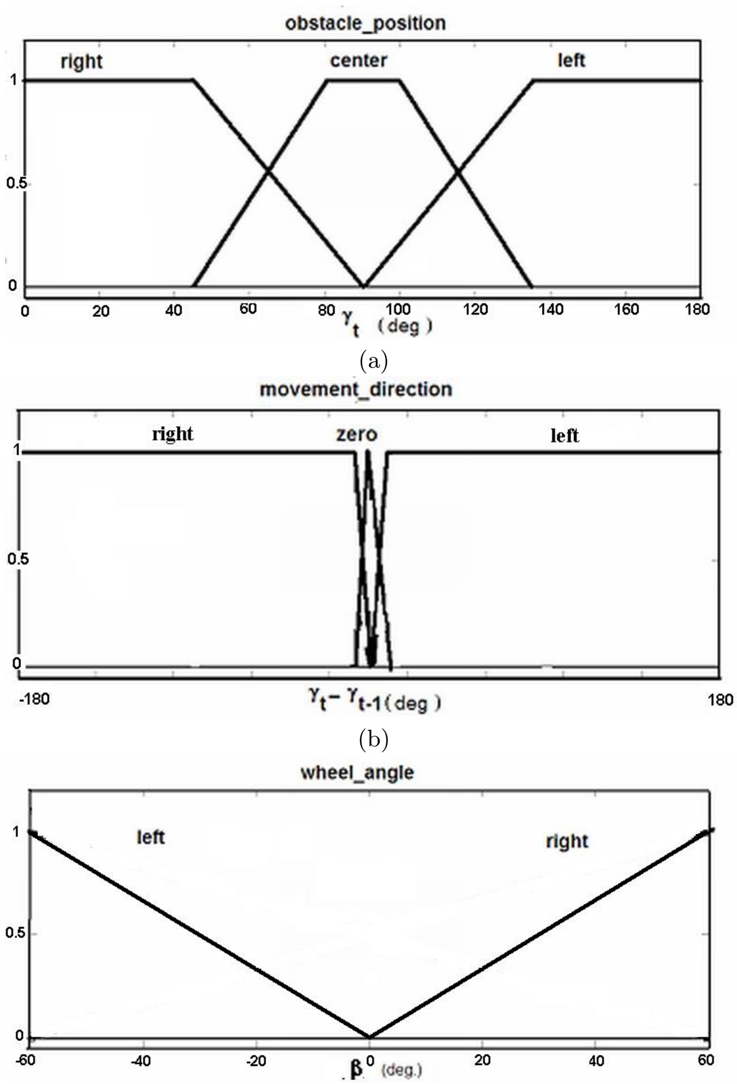
In those scenarios where unexpected obstacles are static only three rules of the proposed knowledge base are fired, R2, R5 and R8, corresponding to a zero value for the variable *movement_direction*. The *movement_direction* variable takes into account the moving object motion direction, so as to overcome unde-



(a) (b) (c)

Fig. 5. Membership function definitions for the linguistic labels assigned to the AVOID fuzzy controller inputs (*obstacle_position*, *movement_direction*) and output variables (*wheel_angle*)

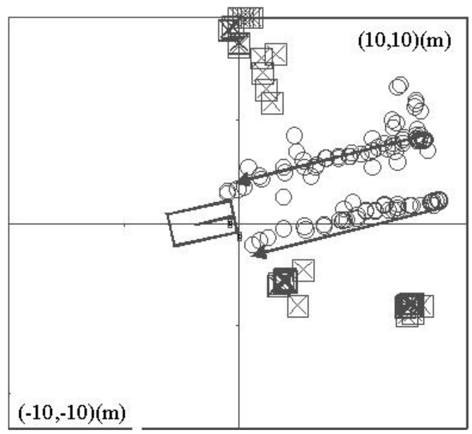
sirable avoidance trajectories, based on the dynamic objects features previously calculated.

4 Results

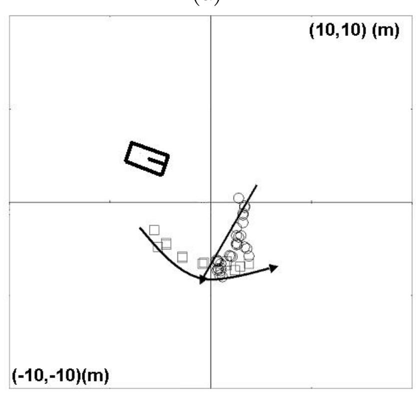
Some results of different trials are presented here to show the performance of the perceptual agent MOVING_OBJECTS in the detection and tracking of dynamic objects in an outdoor scenario. Experiments were performed with a commercial lawnmower in a garden-like area of the IAI-CSIC Institution Campus, located between office buildings and warehouses, where pedestrians cross at speeds ranging from 0.25 to 1.50 m/s. Experiments were aimed at demonstrating the performance and limitations of the proposed approach under different conditions. The laser rangefinder was mounted on the front of the lawnmower in a fixed position at a height of 50 cm above the ground. Two representative examples have been selected and are presented here, highlighting situations where two moving objects are approaching the vehicle and where the intended trajectory of the objects is occluded in front of the vehicle.

In the first experiment, two pedestrians describe parallel trajectories towards the vehicle, Figure 6a. In the second one, a straight and curved trajectories, intersecting in front of the vehicle Figure 6b, are displayed. In both trials the moving objects were accurately detected and tracked during the complete run, even during the occlusion phase. The results of first experiment reflect the extended time that the pedestrians remained in their initial position before beginning to move. That is, a higher density of circles are evident at each pedestrian's departure location than in the remainder of their trajectory, Figure 6a. In second experiment, both pedestrians are correctly detected and tracked by the proposed algorithms, with higher density of circles at the end of the trajectory, and correct classification of each object just after the obstruction, relies on knowledge of previous motion properties, that is, it is expected that the object describing the curved trajectory will continue going on.

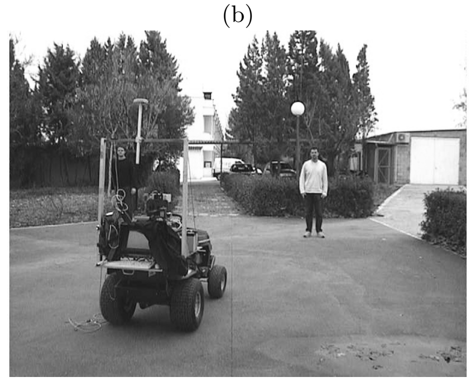
The limit to low speed detection is related to the grid map cell size, meaning that objects moving at a speed below 10 cm/s are considered to be static. High speed object detection was limited in current work by the maximum sampling rate of the sensing system (laser RS-232 serial connection), 5 Hz, which corresponds to an object speed of 5 m/s. The correspondence between moving objects in two consecutive laser images for objects moving faster than 5 m/s would obviously fail due to the maximum laser sampling rate. Nevertheless, this is not a major drawback as in most outdoor applications, with the exception perhaps of sporting competitions, objects could be expected to move at speeds far below 5 m/s (18 km/h). A high speed harvester, for example, moves at 6 km/h. The robot-centred grid map representation employed, moves jointly with the vehicle and allows for ease of use of global positioning (DGPS) in outdoor scenarios for both the vehicle and objects. A further challenge concerns the relatively improbable situations wherein objects move at speeds less than 5 m/s but change suddenly of direction in a time period of less than 200ms.



(a)



(b)



(c)

Fig. 6. Real time detection and tracking of two pedestrians: (a) walking in parallel toward the lawnmower, and (b) walking in trajectories that intersect in front of the lawnmower. Pedestrians are represented by circles, and static objects, such as bushes or walls, by a cross within a square, in a 2D Cartesian representation of the detected objects in a time period. A visual snapshot of test (a) departure positions is displayed in image (c).

Experimental work with outdoor robots to correctly tune each navigation behaviour is hard and bothersome, due to mechanical and energy failures in addition to adverse weather conditions. To speed up the tunning process a simulator of sensors and worlds, namely AGRO-SIM, has been developed to test and debug the different navigation strategies. One of the relevant features of current simulator is the use in the robot of the same code generated in simulation, by defining a client/server communication architecture. Both, robot and simulator are server applications allowing the connection of client programs to each one indistinctly.

Some preliminary results of the modulation of moving object descriptors on the AVOID agent deviation behaviour are displayed. The simulation environment [26], AGRO-SIM, has been used to test the different models that linguistically describe the avoidance strategies learned from human experience. The AVOID knowledge base rules are defined from the object motion descriptors calculated in real-time by the MOVING_OBJECTS agent. The *movement_direction* variable takes into account the moving object motion direction, so as to overcome undesirable "persecution" trajectories such as the one displayed in Figure 7, when knowledge on object motion features lacks and therefore unexpected objects appearing in the scene are treated as static. The integration of the fuzzy *movement_direction* variable permits to reason on object motion features to make a correct decision on next *wheel-angle* turn direction, to optimise the resulting trajectory avoiding unnecessary deviations, Figure 8.

The AVOID behaviour activation pre-conditions greatly reduce the changes in the steering angle to perform a safe an optimum navigation goal-driven in dynamic environments, under the general model embedded in the AVOID fuzzy knowledge base. Spatio-temporal evolution of the vehicle and object for configurations of either high or low speed object, relative to the vehicle motion, are successfully solved. Two cases, of unnecessary activation of the AVOID agent, uncorrectly activated in the experiments displayed in Figures 7 and 8, despite of the object being within the emergency areas 2m. $\leq d <$ 10 m., are displayed in Figure 9 for a speedy object and in Figure 10 for a very slow object relative to the robot speed. In these situations the *collision_angle* shows a temporal variation and thus prevents the activation of the AVOID agent.

In those cases where objects move parallel to the robot within the emergency area and at the same speed of the vehicle, risk of collision is detected as the collision angle remains constant and consequently the AVOID behaviour is activated to slightly deviate the lawnmower. However if the obstacle is not within the emergency area the detour strategy is not fired.

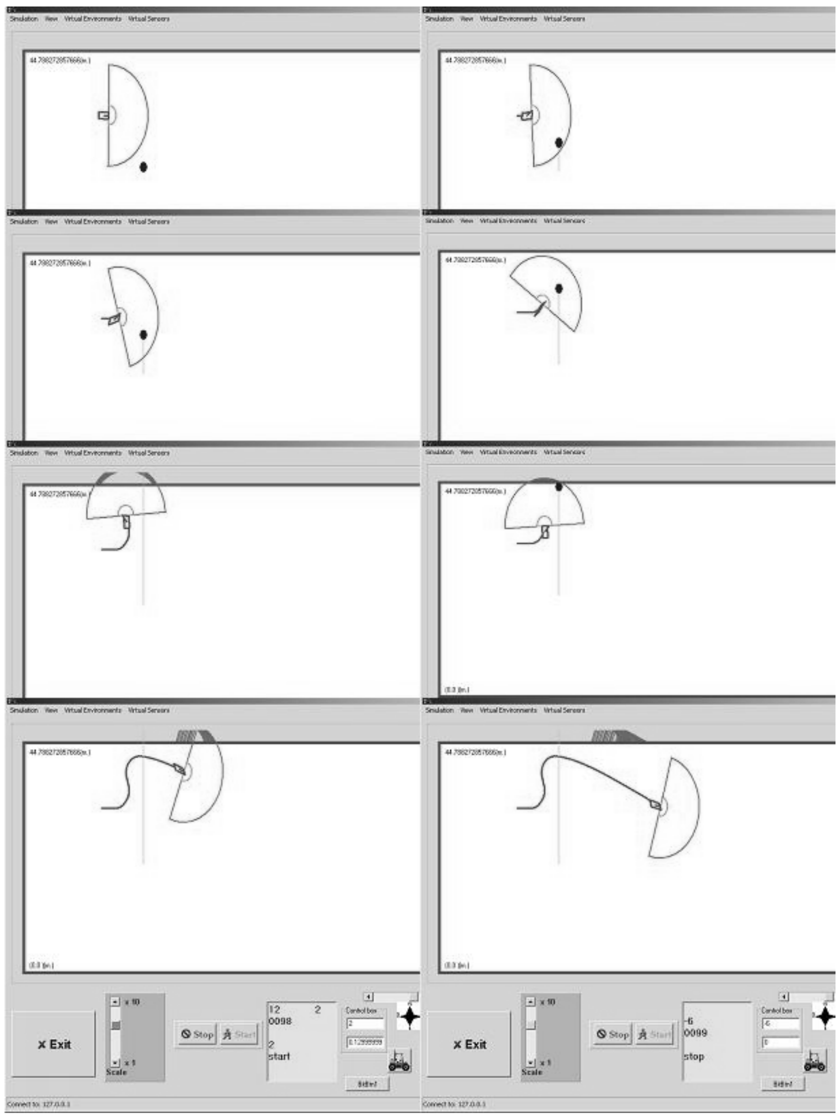


Fig. 7. Robot trajectory (black) described by the activation of only three rules from the AVOID strategy, due to the lack of knowledge on the moving object. Vehicle and obstacle speed are 0.3 and 0.5 m/s, respectively. Object trajectory is represented by a grey straight line, and semicircles limit the emergency areas.

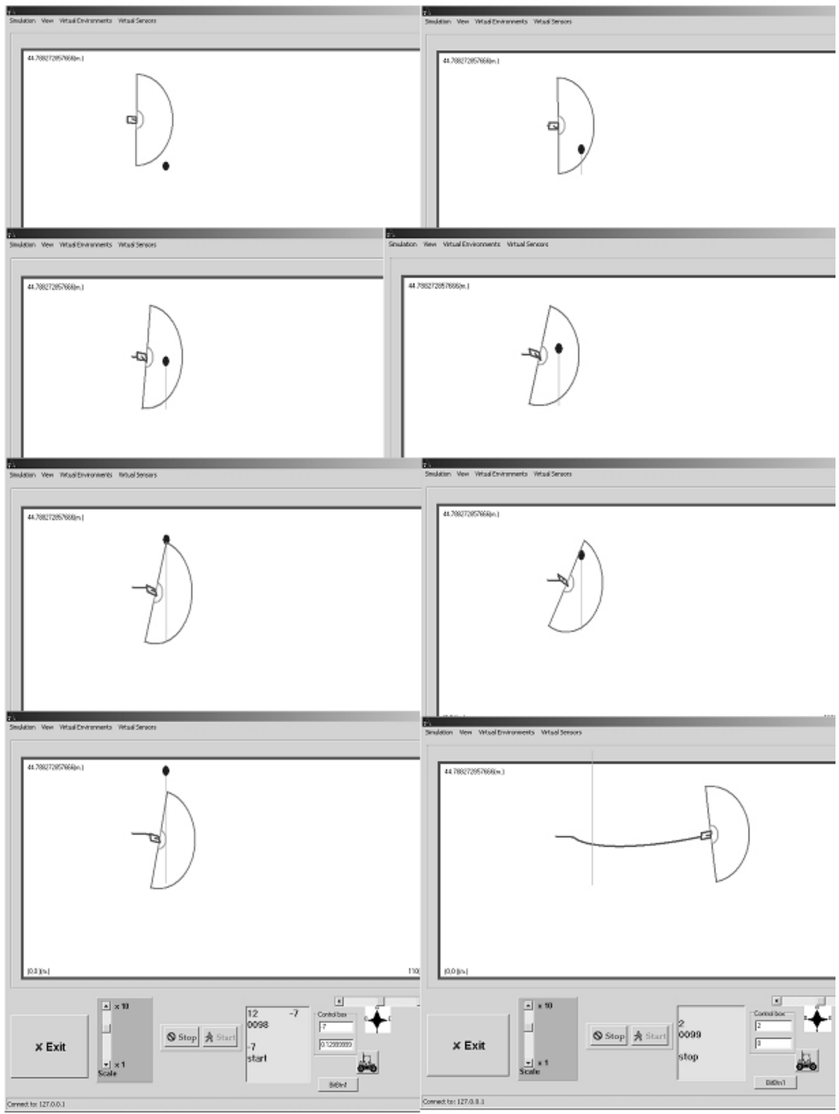


Fig. 8. Robot (black)and object (grey) trajectories. Deviations from the robot goal-driven tentative trajectory are optimised due to the existing knowledge on moving object descriptors. Vehicle and obstacle speed are 0.3 and 0.5 m/s, respectively.

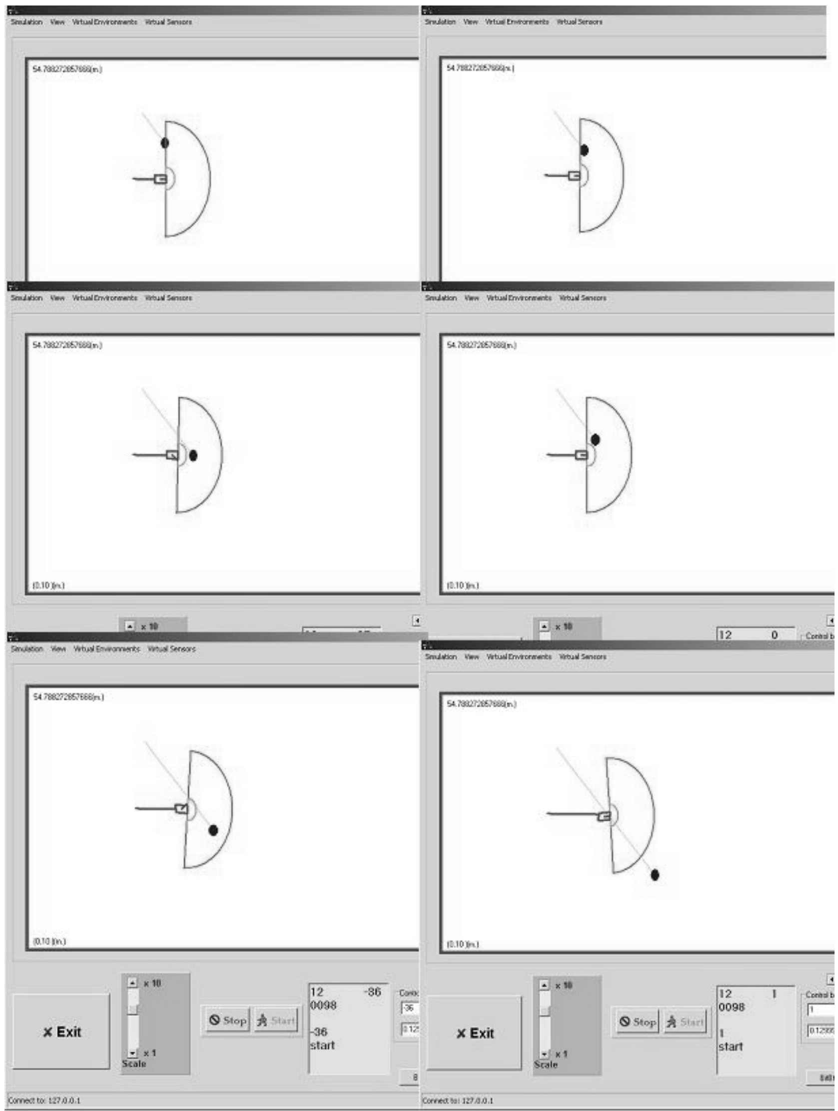


Fig. 9. Robot (black)and object (grey) straight line trajectories. The AVOID agent is not activated as collision risk is not detected, in spite of a speedy object is within the emergency area. ($v_{robot} = 0.3$ m/s, $v_{object} = 0.5$ m/s).

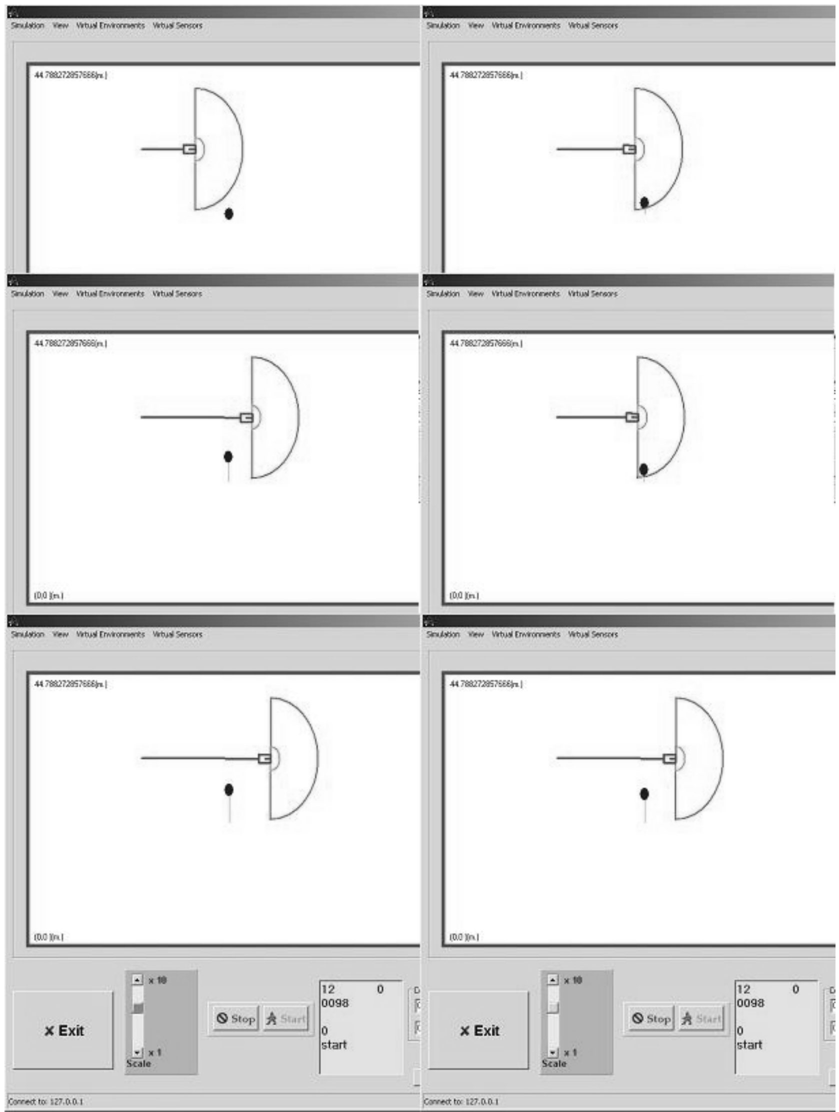


Fig. 10. Robot (black) and object (grey bottom-up) straight line trajectories. Optimized robot trajectory in the presence of an object in the emergency area. No detour is performed as there is no collision risk ($v_{robot} = 0.3$ m/s, $v_{object} = 0.05$ m/s).

5 Conclusions

Identification of the dynamic state of moving objects has a crucial influence on the implementation of safe and optimized avoidance strategies in robot navigation. This point is a major issue for non-holonomic vehicles operating in outdoor scenarios, such as in agriculture, horticulture or gardening.

Likely outdoor obstacles could be people, animals or commercial vehicles. Pedestrian and animal motion is difficult to characterize as its characteristics may abruptly change in a short time period. In such scenarios, neither static nor quasi-static probabilistic techniques are able to cope with dynamic and unpredictable situations, meaning that the matching of objects in successive grid maps on a spatio-temporal representation would better serve as an appropriate and flexible model. To this aim, a detection, tracking and characterization algorithm for moving objects, based on laser rangefinder readings and grid maps, has been proposed and demonstrated here in relatively uncluttered outdoor scenarios.

Current approach relies on the calculated moving-object features to search for the best match among objects in different time steps. The moving objects matching algorithm proposed here has been selected to deal with real-time applications, being a simple and efficient process with low computational cost. The updating of object features in the Object_List is performed at a rate of 200 ms, but detection and tracking algorithm computing cost is about 5 ms, which is well below the maximum scan frequency of the laser rangefinder.

Preliminary tests show the adequateness of the calculated moving object features to optimise avoidance maneuvers in goal-driven navigation, heuristically defined by means of a set of fuzzy rules. Strategies are tested and tuned with the aid of the AGRO-SIM application that simulates real systems and behaviours. The piloting tests clearly show the improvement of the vehicle detour trajectory, when the AVOID strategy integrates moving objects descriptors. More simulated and real experiments are now being performed to derive a general framework to optimise detour trajectories, particularly in those cases where more than one object is present in the working scenario.

Other fuzzy control agents such as FOLLOW_WALL or APPROACH_OBJECT can be easily implemented, using the same sensor systems and multi-agent proposed approach.

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