

Memory-like Map Decay for Autonomous Vehicles based on Grid Maps

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ABSTRACT : In this work, we present a novel strategy for correcting imperfections in occupancy grid maps called Map Decay. The objective of Map Decay is to correct invalid occupancy probabilities of map cells that are unobservable by sensors. The strategy was inspired by an analogy between the memory architecture believed to exist in the human brain and the maps maintained by an autonomous vehicle. It consists in merging sensory information obtained during runtime (online) with a priori data from a high-precision map constructed offline. In Map Decay, cells observed by sensors are updated using traditional occupancy grid mapping techniques and unobserved cells are adjusted so that their occupancy probabilities tend to the values found in the offline map. This strategy is grounded in the idea that the most precise information available about an unobservable cell is the value found in the high-precision offline map. Map decay was successfully tested and is still in use in the IARA autonomous vehicle from Universidade Federal do Espírito Santo.

KEYWORDS: robotics, self-driving cars, mapping.

Date of Submission: 01-09-2020

Date of acceptance: 16-09-2020

I. INTRODUCTION

The brain allows humans to operate in highly dynamic and complex environments, and to solve general purpose problems. The idea of giving these abilities to artificial entities by reproducing the brain's cognitive processes always fascinated researchers. In several works in the literature, the brain and its processes inspired algorithms and new strategies to solve problems. Milford and Wyeth [1], and posteriorly Ball et al. [2], for example, developed an artificial model of the rat's hippocampus, a region of the brain that is known to represent places. This model was successfully used in Simultaneous Localization and Mapping (SLAM) applications. Rivest et al. [3] analyzed the brain's dopaminergic pathways, i.e. the neural pathways associated with reward-motivated behavior, to propose new reinforcement learning algorithms. Berger et al. presented a novel visual tracking technique inspired by the brain's regions related to saccadic eye movements [4]. The brain's visual cortex also inspired several other robotics applications in cognitive map building and scene understanding [5], self-motion estimation [6], and feature extraction and place recognition [7].

For this work, we also searched for inspiration in the brain to propose improvements in existing algorithms involved in the operation of autonomous vehicles. The brain and its functions were analyzed from the cognitive psychology point of view [8]; in special, the cognitive processes related to memory in its different levels.

The ability of storing information in memory and recalling it when necessary is fundamental to allow the execution of physical procedures, and the pursuit of long-term goals. As important as the capacity of remembering concepts and experiences, is the ability of forgetting what is irrelevant and focusing attention on what momentarily matters.

We analyzed the similarities between the visual-memory architecture believed to exist in the brain and the process of building maps in robotics (and, more specifically, in autonomous cars). Inspired by these similarities, we proposed a novel strategy for removing online noise from occupancy grid maps, called Map Decay. Map Decay consists of merging sensory information obtained in runtime (online) with a priori data from a high-precision map constructed offline. Online or offline data are emphasized according to whether the map cells are observed by the sensors or not. Cells observed by sensors are updated using traditional occupancy grid mapping techniques. However, cells that are not observed are adjusted so that their occupancy probabilities tend to the values found in the offline map. The effect of this adjustment is an apparent fading (decay) of online information in unobservable regions of the map, while high precision offline information is retained.

The main reason for using Map Decay is to correct occupancy probabilities of map cells that were improperly adjusted because of moving objects or incorrect sensor measurements. Although further observations of the cells would correct their occupancy probabilities, due to several factors, the cells may not be observed again. Among these factors, we can mention the sparsity of sensors, the presence of sensorial blind spots, and the natural movement of the autonomous car away from the cell, increasing the flexibility of system [9].

Map Decay addresses these issues by slowly turning the cells probabilities into the values found in the offline map. This strategy was developed under the assumption that the most precise information available about an unobservable cell is the value present in the high-precision offline map. Map Decay was successfully employed and is still in use in the IARA autonomous vehicle (IARA is an acronym for Intelligent and Autonomous Robotic Automobile, figure 1) from Universidade Federal do Espirito Santo (UFES).



Fig. 1: IARA autonomous vehicle from UFES.

II. MEMORIES AND MAPS

In this section, we review the brain's visual-memory architecture as suggested by the cognitive psychology research field. Later, IARA's map architecture is described and, finally, an analogy between the brain's memory architecture and the mapping processes of IARA is discussed.

A. The Brain's Memory Architecture

Cognitive psychologists organize the human memory systems in three levels: sensory memory, short-term memory (or working memory), and long-term memory [8], [10]. Although all of these memories have the

common role of retaining information, they vary in several aspects such as how long memories last in them, how memories are encoded, and how much associations they have with other memories previously acquired.

The sensory memory is the first level of memory (the nearest to the sensing organ) and stores information coming from our sense organs for very short time. This information is constantly updated and quickly decay as new stimuli arrive [11]. Visual sensory memory manifests itself as the image that we still see for a moment after closing our eyes.

The short-term memory receives information from several sources (both external information from sensors, and internal information from different brain processes) and is able to store integrated information for a time long enough to enable the accomplishment of simple day-to-day tasks, such as rotating the image of an object [8]. It also has control processes that allow the exchange of information with the long term memory [8; 11].

The long-term memory can store large amounts of information for long periods time. The information stored in this memory, such as names of old friends, places where we lived, and what we have learned, can be brought to the short-term memory if necessary and used in day-to-day tasks [11]. The long-term memory is the ground over which our life experience is build. It stores the network of concepts that allows us to make sense of the world and holds the brain's most consolidated information.

B. IARA's Mapping Architecture

IARA represents the world using occupancy grid maps [12]. In these maps, the environment is represented as a two-dimensional grid. Each cell of the grid stores the probability that the region it covers is occupied by obstacles [13]. IARA employs three occupancy grid maps: an instantaneous map, an offline map, and an online map.

The instantaneous map is constructed projecting sensorial data into a momentary occupancy grid map. This map only lasts while novel sensory information does not arrive. As soon as new sensor data are received, the last instantaneous map is discarded and a new one is constructed. This map reflects the area of the world observed by the most recent sensor reading. The instantaneous map is not directly used and it is only employed as an intermediary resource for the construction of the other maps.

The offline map is constructed prior to runtime by (i) driving IARA over a path of interest while storing its sensorial data, (ii) estimating the poses visited by IARA using as much resources and data as possible, and (iii) by integrating consecutive instantaneous maps in a single map of the whole environment [12]. A human expert performs a post processing in this map to remove eventual imperfections still present in the map (basically, moving objects registered as static objects). The offline map is used during runtime for estimating the IARA's position in the world (global localization and position tracking [7], [14]) and also as source of information for the production of the online map.

The online map represents the state of the world at runtime. It is constructed by merging the offline map and the instantaneous map. The motivation for merging these maps is the benefit of using the high quality information present in the offline map and the most recent information present in the instantaneous map. The online map is used by the IARA's software modules related to planning and navigation.

Fig. 2 (a), (b), and (c) show examples of instantaneous, offline, and online maps, respectively. In these maps, grayscale pixels represent the cell's occupancy probabilities with black being maximal occupancy probability and white being minimal occupancy probability. Blue pixels represent cells that were not observed by sensors yet.

C. Analogy between Memories and Maps

Like the long-term memory, that is responsible for keeping our life long experience, the offline map stores the most consolidated and reliable information the car has about the world. Such information serves as working material to other processes when the instantaneous information they need cannot be observed by sensors.

Like the short-term memory, that integrates information coming from the long-term memory and from other external sensors, the online map integrates consolidated data (offline map, long-term memory) with new data perceived by the sensors, and keeps such information as long as necessary for allowing the execution of relevant tasks. These tasks take in consideration what IARA has learned during the offline phase and also the current appearance of the world, as observed by sensors.

To complete our analogy, the instantaneous map, like the sensory memory, keeps the information captured by sensors, while a new reading is not performed. However, in this work, differently from the human sensorial memory in which information fades away with time, we consider that the instantaneous map decays immediately with the arrival of new information.

The analogy between maps and memories has the potential of inspiring new insights and new algorithms. This potential is leveraged by our Map Decay strategy. Map Decay was inspired by the brain's

ability of forgetting short-term memory information that is no longer necessary and the ability of using information from the long-term memory to make sense of incomplete sensorial information.

III. IARA SYSTEM

In this section, we start by presenting the hardware and software of IARA, with emphasis to the set of modules that support its mapping system. Next, the algorithm employed to construct the offline and instantaneous maps from sensorial data is discussed. Finally, the algorithm for creating the online map and the Map Decay strategy are described.

A. The IARA Platform

IARA's hardware is based on a Ford Escape Hybrid, which was adapted by Torc Robotics to enable: (i) electronic actuation of the steering wheel, throttle and brake; (ii) reading internal information (e.g., car odometry); and (iii) powering several high-performance sensors and computers. IARA is equipped with the following set of sensors: one Light Detection and Ranging (LIDAR) Velodyne HDL 32-E; a high precision GPS RTK Trimble; four stereo cameras Point Grey Bumblebee; an Inertial Measurement Unit (IMU) XSSENS MTi; and up to four computers Dell Precision R5500 (currently only two are used).

IARA's software modules were structured using the LCAD's version of the CARMEN robotics framework [14]. This local version is open to the scientific community (it can be accessed in https://github.com/LCAD-UFES/carmen_lcad). The software modules are factored into four main functions: mapping, localization, navigation, and control. Mapping addresses the problem of continuously creating a map of the environment, which contains information describing the places the car may or may not be able to navigate through. Localization addresses the problem of estimating the car's pose (position and orientation) relative to the origin of the map. Navigation addresses the problem of continuously planning a trajectory (list of control commands composed of velocity and steering wheel angle, along with the respective execution durations) from a car's state to a goal state using the map. Finally, the control module is responsible for calculating the set of steering wheel, throttle and brake efforts that allows the car to follow the trajectory planned by the navigation module. Other auxiliary modules were developed to provide additional features such as obstacle avoidance, health monitoring, behavior selection, logging, and simulation.

B. The IARA Mapping System

We refer to the set of modules related to mapping as the mapping system. The sensors used by the mapping system are GPS, IMU, car odometry (linear velocity, and steering wheel angle), and the Velodyne (3D point clouds). The mapping system presents two different operation modes depending on whether it is running offline or online.

In the offline mode, a human drives IARA over a path and the data captured by the sensors are stored in a log file. The poses visited by IARA are calculated using the pose-based GraphSLAM presented in [12]. GraphSLAM is a Full-SLAM algorithm that uses all the data collected by sensors to estimate the robot poses. The set of estimated poses along with the Velodyne data are sent to the mapping system in order to construct the offline map.

In the online mode, IARA drives itself autonomously from a starting point to a destination goal. In this operation mode, only the most recent data are used to compute IARA's pose and to update the map. The process of computing the pose in online mode consists of two steps. In the first step, odometry, IMU and GPS data are fused together using a particle filter [15]. This data fusion process is performed by a fused odometry module that outputs a 6D pose (x , y , z , roll, pitch, yaw). In the second step, the x , y , and yaw components of the pose estimated by the fused odometry module are refined by a Monte Carlo localization algorithm [13] (the values of the other components remain the same). This algorithm refines the values of the components using a second particle filter. Firstly, particles are spread using odometry data and the IARA's motion model. After that, the obstacles detected by Velodyne are projected to 2D using the technique presented in [12] and compared with the offline map to weight the particles. Finally, particles are resampled and the average pose is returned. As in the offline mode, the pose estimated by the localization algorithm and the Velodyne point cloud are sent to the mapping system in order to construct the online map.

The mapping system, as the whole mapping architecture, has two modes operation modes: one online and the other offline. In both modes, the occupancy probabilities of the cells are updated considering whether Velodyne rays hit obstacles related to them or not. This update follows the traditional occupancy grid map algorithm [13]. However, both online and offline modes have unique features that differentiates them.

The online mode has two particularities not present in the offline mode. The first difference is that the cells of the online map are initialized with the values found in the offline map. By doing so, the initial values of the online map are the most consolidated information available about the environment. As soon as new information arrives, the cells are updated to reflect the actual state of the world. The second difference of the

online map is that the map is subject to map decay (see below) before the update performed by the occupancy grid mapping algorithm. Given enough time, map decay will correct imperfections left in cells unobservable by sensors.

The offline mode also has a peculiarity that is not present in the online mode. In order to improve the quality of the offline map, a post-processing step is performed by a human expert. In this post-processing step, the expert cleans-up potential imperfections present in the map, e.g., traces left by moving objects or inexistent obstacles caused by sensorial noise.

In the following subsections, we present the general occupancy grid mapping rule used for updating the map probabilities in both modes of operation and, then, we describe the Map Decay algorithm used only in the online mode.

C. Occupancy Grid Mapping

The maps maintained by IARA are updated for every new point cloud captured by the Velodyne. The point cloud is firstly moved from the sensor reference system to the world reference system using a pose-dependent transform. After that, an instantaneous map is constructed using the point cloud. Finally, the cells of the map (either online or offline) are updated according to the occupancy probabilities of the instantaneous map.

The instantaneous map construction is directly related to the principle of data acquisition of the Velodyne. The sensor revolves a set of 32 lasers horizontally. The 32 lasers are positioned in an array with increasing vertical angles (the first laser points downwards, the second points a bit higher than the first, and so on). We will refer to this set of 32 rays as a vertical scan. A Velodyne point cloud is composed of several vertical scans captured with different horizontal angles.

The instantaneous map is constructed: (i) by calculating the probability that each ray of a vertical scan hit an obstacle,

(ii) by projecting the 3D points hit by the rays to the floor (i.e. to 2D), and (iii) by adjusting the occupancy probabilities of the cells corresponding to the projected points accordingly. The strategy for calculating the probability that a ray hit an obstacle is described in [12] and an alternative strategy can be found in [16]. The occupancy probabilities of all IARA's maps are represented using log-odds [13]. To update the long-term and short-term maps, the cells of the instantaneous map are projected to the respective cells of the long-term or short-term map and the log-odds (that represent the occupancy probability) are summed.

Besides adjusting the cells hit by the Velodyne rays, we also perform a raycast and set to free (i.e. close to zero probability) all cells between the position of the first ray of a vertical scan and the position of the first ray that hit an obstacle in the same vertical scan. These cells are set to free because we assume that, if there was an obstacle between these two positions, some ray would have hit it.

D. Map Decay

Map Decay is a method for removing imperfections from occupancy grid maps. We use it here inspired by the brain's ability of releasing from short-term memory information that is no longer necessary, and of making sense of incomplete sensorial data by filling it with long-term knowledge.

These imperfections have several causes. When a dynamic object crosses the cells of a map, for example, their occupancy probabilities are raised. Due to IARA's motion, these cells may no longer be observed leading to a trace in the map. The same happens when a false obstacle is detected due to natural sensor error. As before, the later observation of the region should correct the occupancy probability. However, if the cells are not observed again either because the robot is moving, or because the cells are into a sensorial blind spot, the occupancy probability will not be corrected.

Imperfections left by moving objects could potentially be handled by one of the several techniques proposed in the literature for mapping in dynamic environments [12], [17]. The conventional technique to handle dynamic objects is to detect and track these objects, and then either treat them as outliers (in landmark maps) or filter them out from the map (in occupancy grid maps) [18], [19], [20]. An alternative technique is storing in the map an history of how the cells change over time, and try to identify moving obstacles analyzing the patterns of changes in the spatiotemporal data [21], [22]. Map Decay is a simpler and more efficient (in terms of use of computational resources) solution than the previously listed methods.

The Map Decay strategy consists of making the probabilities of the cells of the online map tend to the values of the offline map with time. All cells of the online map are updated according to the following rule:

$$M_{on}(x, y) = \frac{M_{on}(x, y)W_{on} + M_{off}(x, y)W_{off}}{W_{on} + W_{off}} \quad (1)$$

where $M_{on}(x, y)$ refers to the cell with coordinates (x, y) from the online map, $M_{off}(x, y)$ refers to the cell with the same coordinates from the offline map, W_{on} and W_{off} are importance weights defined by an expert and used

to adjust how fast the decay will happen. Preliminary experiments have shown that $W_{on} = 10$ and $W_{off} = 1$ present a good tradeoff between the maintenance of obstacles recently observed and the removal of long-term imperfections of the map for a car mapping system with update rate of 20Hz.

The Map Decay equation (Equation 1) can be seen as a weighted average between the values of the offline map and the values of the online map. The effect of Map Decay is that imperfections left in the map fade away when they are not observed by sensors for some time. The values of the unobservable cells of the online map are slowly replaced by the values found in the offline map – this highlights the importance of having a good offline map. On the other hand, regions observed by sensors, either free or occupied, retain their values and are not significantly affected by Map Decay.

IV. EXPERIMENTS AND RESULTS

To validate our mapping system, we used two real-world datasets collected in a large-scale and complex environment – the 3.7 km beltway of the main campus of Universidade Federal do Espírito Santo. The first dataset was used to build the offline map, and the second to build the online map and to evaluate the map decay strategy.

The online mapping system with Map Decay was evaluated qualitatively. Figure 2 presents a comparison between the maps constructed by the online mapping system with and without Map Decay. The images in figure 3 (a) and figure 3

(b) show the Velodyne point cloud (blue dots) and the occupied cells of the short-term map (red boxes) when a car is overtaking IARA. It can be seen that traces are left in the map due to the moving car. It is important to note that the cells affected by the car's motion fall into a sensor blind spot and that its traces are not cleared up later.

Figure 4 highlights the difference in the contents of the short-term map computed with and without Map Decay. Figure 4 (a), (c) and (e) show that, without Map Decay, the cells of the map remain occupied even when the car already passed IARA. As noted previously, the explanation for this comes from the fact that the Velodyne rays do not observe the affected cells again once they fall into a blind spot of the sensor. The inability to clear the cells hinders and can even forbid the execution of IARA's navigation plan.

Figure 4 (b), (d) and (f) show the effect of using Map Decay in the same situation. As time progresses, the cells set as occupied fade away, the information captured by sensors online decay, and their occupancy probabilities become the values found in the offline map. It is important to note that cells occupied by obstacles and observed by the sensor maintain high occupancy probability. Such situation is exemplified by the car behind IARA. Even when Map Decay is used, the car is still well represented in the map. A video that demonstrates the Map Decay strategy in action can be accessed online at <https://youtu.be/cyIfGupar-8>. In the video, the reader can appreciate the behavior of the algorithm with different decay rates.

V. CONCLUSIONS AND FUTURE WORK

In this work, an analogy between the memory architecture believed to exist in the human brain and the mapping algorithms of an autonomous car is presented. The offline map, a high precision representation of the world constructed in an offline phase using GraphSLAM is associated with the human long-term memory. The snapshot map, a map constructed using a single sensor reading is associated with the human sensory memory. Finally, the online map given by the integration of the offline and the snapshot maps and used by the navigation module to plan the actions of the autonomous vehicle is associated to the short-term memory.

This analogy inspired the development of a strategy for removing noise from occupancy grid maps called Map Decay. Map Decay consists of making the occupancy probabilities of the online map tend to the values of the offline map as time progresses. It allows the correction of the values of map cells modified incorrectly and not observed again by the sensors. If not properly handled, such situations could forbid the correct operation of the autonomous vehicle.

An important assumption of Map Decay is the high quality of the offline map. Although the structural quality of the map is guaranteed by the GraphSLAM algorithm, the occupancy probability of their cells is still subject to noise left by moving objects and incorrect measurements. In this work, these imperfections in the map were corrected by a human expert. In future works, the possibility of performing these corrections automatically will be studied. In special, we will investigate the removal of noise left by moving objects within a cognitive science perspective.

ACKNOWLEDGMENTS

The authors would like to thank Conselho Nacional de Desenvolvimento Científico e Tecnológico – CNPq, Brazil (grants 552630/2011-0 and 12786/2013-1), Coordenação de Aperfeiçoamento de Pessoal de Nível Superior - CAPES, Brazil, and Fundação de Amparo à Pesquisa do Espírito Santo – FAPES, Brazil (grant 48511579/2009), for their financial support to this research work.

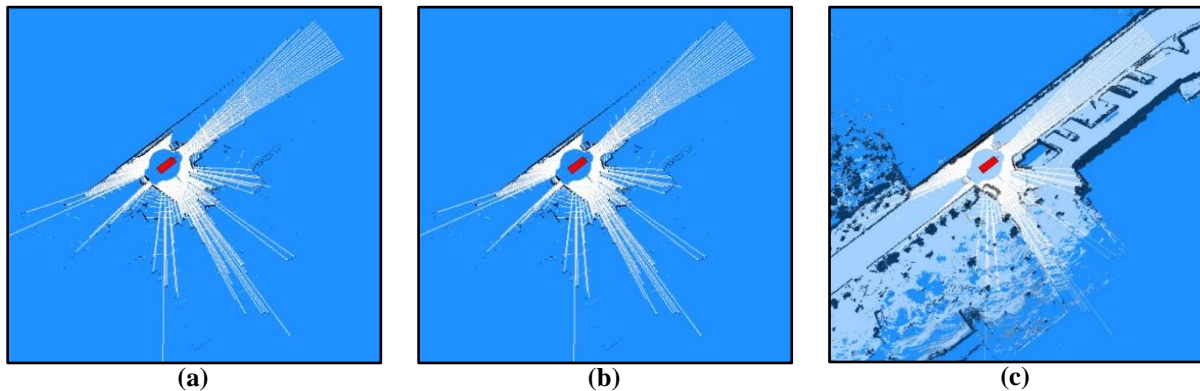


Fig.2. Maps used by IARA. Blue pixels represent maps' cells that were not observed by sensors yet, and pixels in shades of gray represent the occupancy probability of the maps' cells. Black pixels represent maximal occupancy probability, while white pixels represent minimal occupancy probability (a) The instantaneous map that is constructed using a single Velodyne point cloud and represents the sensory memory. (b) The offline map that stores the most consolidated information that IARA has about the world. It represents the long-term memory. (c) The online map that is used by the navigation algorithms and represents the short-term memory

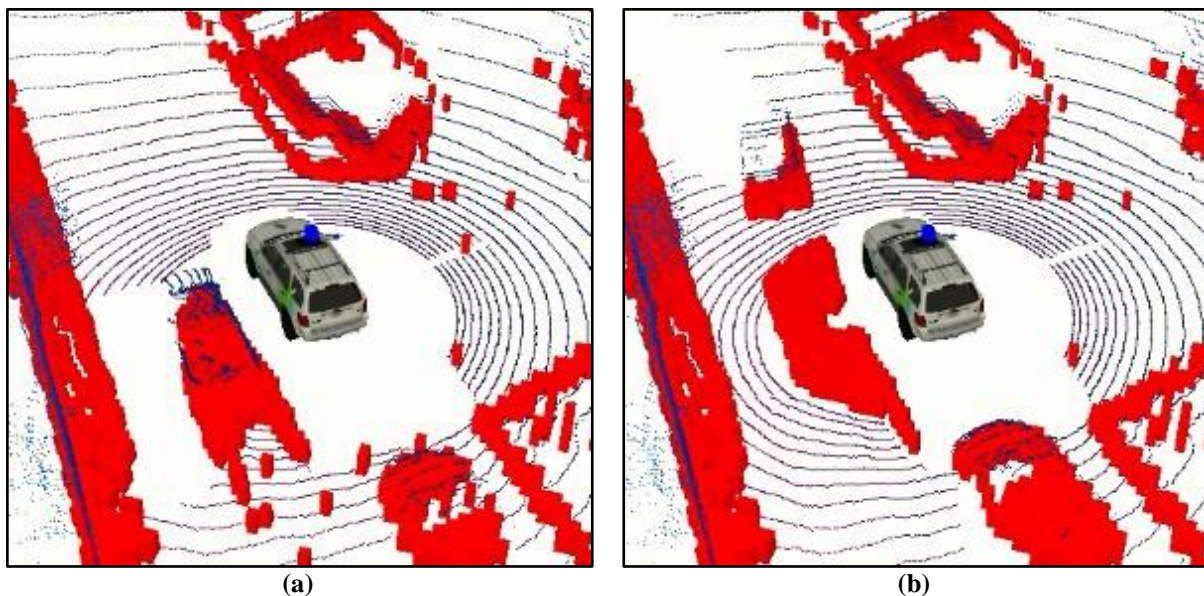


Fig. 3. Comparison of the online mapping system output with and without map decay in an overtaking situation. The images in figures (a) and (b) show a 3D visualization of the overtaking. In these images, blue dots represent the points of the Velodyne readings and red boxes represent the cells with high occupancy probability.

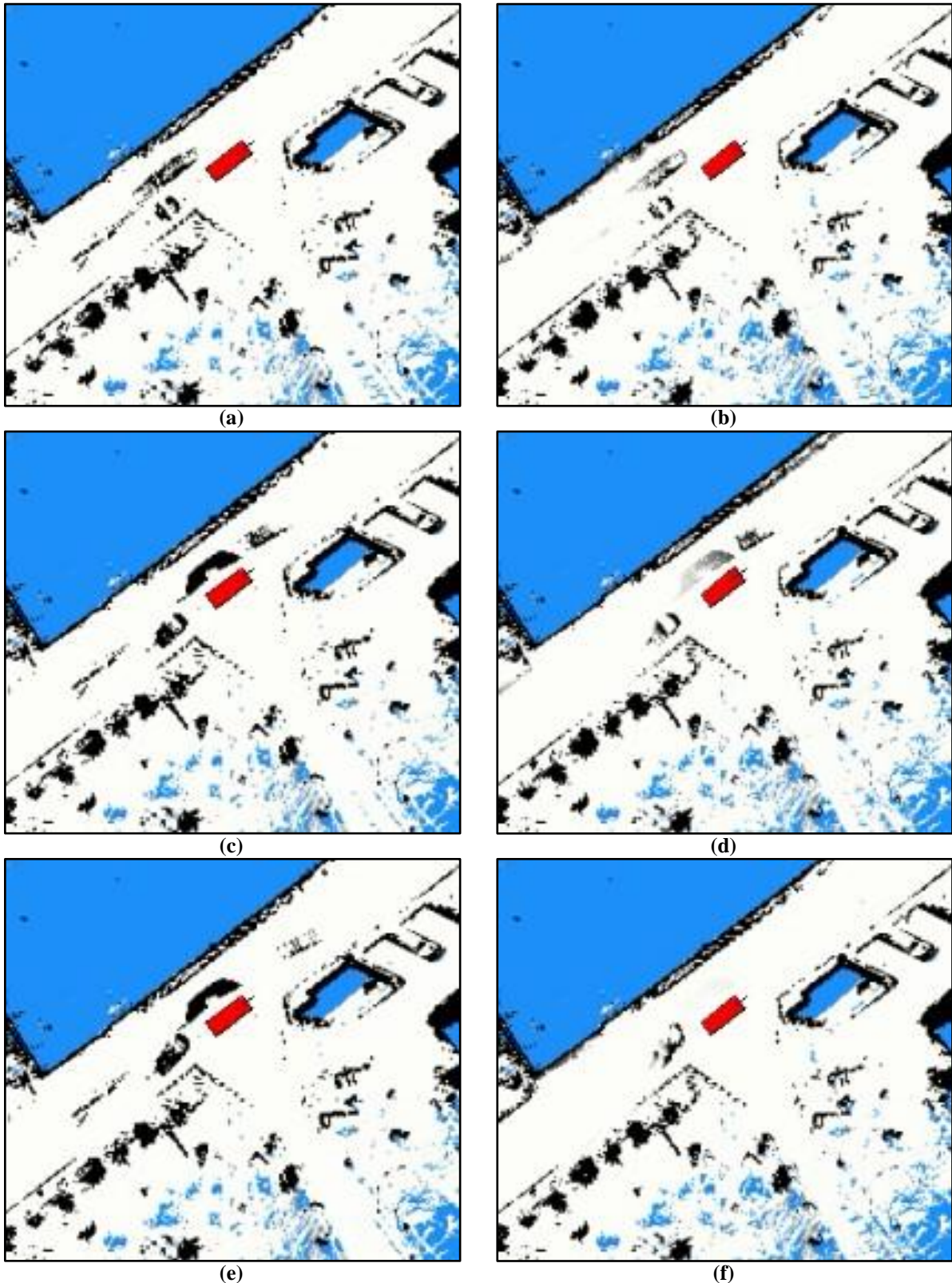


Fig. 4. Comparison of the online mapping system output with and without map decay in an overtaking situation. The images (figures (c) to (h)) show IARA's online map in the same situation of figure 3. If map decay is not employed, cells to the left of the car are marked as obstacles and are not set as free again because they fall into a sensor blind spot (see figures (c), (e) and (g)). If map decay is employed, the cells marked as obstacles slowly fade away as they decay to the offline map values (see figures (d), (f), and (h)).

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Thomas Teixeira, et. al. "Memory-like Map Decay for Autonomous Vehicles based on Grid Maps." *American Journal of Engineering Research (AJER)*, vol. 9(9), 2020, pp. 63-71.