IEEE Access
Multidisciplinary ⋮ Rapid Review ⋮ Open Access Journal

Received 16 February 2024, accepted 28 March 2024, date of publication 2 April 2024, date of current version 12 April 2024.

Digital Object Identifier 10.1109/ACCESS.2024.3384360

RESEARCH ARTICLE

Retail Robot Navigation: A Shopper Behavior-Centric Approach to Path Planning

ALESSANDRO GALDELLI, (Member, IEEE), ROCCO PIETRINI, ADRIANO MANCINI, (Member, IEEE), AND PRIMO ZINGARETTI, (Senior Member, IEEE)

Vision Robotics Artificial Intelligence (VRAI) Laboratory, Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, 60131 Ancona, Italy

Corresponding author: Alessandro Galdelli (a.galdelli@staff.univpm.it)

This work was supported by 10.13039/100010665 European Union's Horizon 2020 Research and Innovation Programme through the Marie Skłodowska-Curie, Project title "TRUST-digital TuRn in EUrope: strengthening relational reliance through Technology."

ABSTRACT In the ever-evolving landscape of retail, understanding shopper behavior is pivotal for optimizing sales and effectively managing product availability and placement. This study explores the integration of autonomous mobile robots into the shelf inspection process, leveraging advancements in automation, information, and robotics technology. Performing mapping tasks, these robots incorporate insights into customer behavior by exploiting various sources of behavioral data, including trajectories and product interactions. Motivated by the complex and dynamic nature of modern stores, our research seeks to bridge the gap in retail inventory management. Our unique contribution lies in the development of a novel path planning method for robots, specifically tailored for an automated inventory management system. By focusing on customer trajectories and product interactions, we aim to enhance the arrangement and positioning of products within retail spaces. Our research is motivated by the need to address the challenges faced by retailers in optimizing store layouts and product placements. The proposed strategy utilizes a heatmap and a vision-based system to analyze spatial and temporal patterns of shopper behavior. This information is then employed to optimize robot navigation in both highly and less-visited areas. Trajectories and product interactions data from real store installations were utilized in simulation, providing valuable insights into optimal planning for mobile robots to visit Points of Interest (PoI). The active shopping cart tracking system generated heatmaps, while a vision-based system collected shopper-products interactions data. Subsequently, our approach was deployed on a real retail robot for inventory management, and the path planning source code was released. Our findings demonstrate that the path planned by our approach not only avoids collisions with static store sections but also optimizes paths in areas with significant customer-shelf activity.

INDEX TERMS Path planning, planogram, retail, robot, shopper, trajectories, heatmap, UWB, IoT.

I. INTRODUCTION

Oline stores are growing in popularity, but traditional supermarkets still offer customers the opportunity to browse products in person, surrounded by the sights and sounds of a physical store. Companies in the retail and logistics industry are striving to make the shopping experience more enjoyable and convenient, incorporating technology to improve efficiency and lower costs. According to Coherent Market Insights [1] approximately half of all retailers plan to employ in-store robots in some capacity by 2023, broadly speaking, the worldwide retail robot market is expected to grow from 7$ billion in 2020 to over 55$ billion by 2028. This escalating interest in robot workers has been spurred by a variety of drivers, including advances in robotic technology, human labor shortages, and the need for social distancing

The associate editor coordinating the review of this manuscript and approving it for publication was Tao Liu.

in the wake of COVID-19. The H2020 REFILLS Research and Innovation Action [2] was created to improve logistics in a supermarket thanks to mobile robotic systems in close and smart collaboration with humans, addressing the main in-store logistics processes for retail shops: in particular, robots to allow a smarter shelf refilling. Information on the supermarket articles is exploited to create powerful knowledge bases, used by the robots to identify shelves, recognize missing or misplaced articles, handle them and navigate the shop. Retail robots hold the potential to help workers with tedious and repetitive tasks, thereby allowing humans to dedicate more time to engaging with customers. Supermarkets and other retail spaces often offer a wide variety of products, and a planogram[1] is designed to optimize the sales of those products by determining their placement on store shelves. Maintaining planogram compliance is crucial for achieving maximum sales and increase the customer satisfaction. However, ensuring compliance in a large supermarket can be a challenging and resource-intensive task, requiring significant time, cost, and labor. Mobile autonomous robots can be used for this kind of task in retail in a collaborative way with the store staff and the customers, but social aspects need also to be considered in such a potentially crowded environment [3]. Sharing space with mobile robots in close proximity induce in individuals physical responses to some extent, as demonstrated by [4]. Luo et al. [5] in particular, with a biomechanics analysis, showed that shoppers spent more time walking between shelves with a reduced walking speed and have deteriorated walking stability with the mobile robot in the same space. Robots should not interfere in any way with the customer shopping journey, hence knowing and predicting the customer behavior is fundamental. Studying the behavior of shoppers, including their movements and interactions with products in a retail setting, can offer valuable information for improving store design, product placement, and marketing tactics.

In this study, we focus on the possibility for an autonomous mobile robot to exploit customer behavior for the task planning. We refer to task of performing automatic product inventorying and vision-based planogram compliance checking, i.e., verifying the correct position of products on the shelves and counting them. In retail sector, an useful and very common tool used to understand how shoppers move in the space and how they interact with the environment is the heatmap, that can be generated using shopping trajectories data collected by indoor positioning system, i.e., vision-based, IoT. Traffic heatmaps tell us which areas are the most and the less visited, together with their intensity with different granularity and time windows. A higher traffic area will likely have more Shelf Out of Stock (SOOS) and planograms no longer compliant with the original layout than an area with lower traffic and thus requiring more attention. Heatmaps helps to understand the in-store activities of the shoppers and can be used to test new merchandising strategies, and play with layouts of the store in order to increase their effectiveness. Trajectory heatmaps in retail, while visually appealing, have limitations in providing a comprehensive picture of shopper interactions with products. They typically depict only the movement patterns of customers within the store, failing to encompass critical factors such as product engagement and purchasing behavior. This study, however, represents a significant leap forward. It innovatively integrates customer behavioral insights with advanced robotic navigation in retail spaces. Our approach, distinct from previous research, effectively utilizes heatmaps not just to chart shopper movements but also to capture their interactions. By merging these heatmap-derived insights with state-of-the-art robotic navigation, our research fills a critical void in the academic literature, offering a more holistic understanding of customer behavior in retail environments. This innovative integration not only signals a major advancement in the realm of retail analytics but also sets the stage for more sophisticated strategies in inventory management and planogram adherence. By harnessing the power of both shopper trajectory data and interaction patterns, we have developed a unique solution that more accurately captures the dynamic and ever-evolving nature of retail environments and customer behaviors.

The contributions of this work can be briefly summarized as follows:

- the introduction of customers behaviour analysis to adapt the navigation of robots for data collection joining trajectories and interactions;
- an end-to-end strategy to simulate the robot's navigation inside a store given only the heatmap of the store and a list of Shelves of Interest (SOI) based on shopper-products interaction data; heatmaps can be generated by active tracking systems or vision-based systems;
- introducing a novel Traveling Salesman Problem (TSP) for robot navigation, which takes into consideration both its orientation and the heatmaps;
- an open-source implementation of the store path planner, available at https://github.com/vrai-group/heatmap2planner

The paper is organized as it follows. Section II provides an overview of the current state-of-the-art in the field, Section III describes the process of generating waypoints, Section IV outlines the planning method, Section V presents the results of the study. Discussion on results and limitations is presented in Section VI, and finally Section VII concludes the paper by summarizing our overall results.

II. RELATED WORKS

The use of service robots are increasingly involved in our everyday life, with different embodiment and hardware design tailored to the services they provide [6], [7], as for example in the retail domain, where has garnered significant interest due to the challenging nature of such complex

[1] A planogram is a visual representation or diagram that shows how products should be displayed on shelves or fixtures in a retail store.

environments. Using mobile robots for retail monitoring has been pioneered by Priya Narasimhan's group at Carnegie Mellon University with their AndyVision project [8]. Kumar et al. [9] proposed a Virtual Reality (VR) based system for automating data collection and surveying in a retail store using tele-operated mobile robots and, later a novel method for obtaining product count directly from images recorded using a monocular camera mounted on a mobile robot [10]. Song et al. [11] recently studied the impact of a recommender service robot in both customer behavior and store performance, demonstrating a positive impact. In 2018 Alves et. al. [12] introduced an autonomous shopping cart that by means of a Route Scheduling System, is able to find the shortest tour that passes only through required shelves with a Genetic Algorithm using the TSP model. In 2021, Sonawani et al. [13] presented a setup where using a monocular camera and Bluetooth Low-Energy (BLE) obtained a robot system which can immediately be used after placing sensors in the environment. The camera information is used to synthesize 3D point clouds, in which the BLE data is adopted to integrate into a map of the examined environment.

Commercial robotic solutions for full store inventory are already available on the market, equipped with Radio Frequency Identification (RFID) technology, as for example AdvantRobot [14] or Tory robot [15] from *MetraLabs* or available also with cameras on-board as Tally [16] developed by *Simbe Robotics* and StockBot [17] from *Pal Robotics*. Valori et al. [18] validated with a cross-domain approach collaborative robotic applications from the perspective of safety testing and assessment, including Stockbot. Indeed, the primary function of these robots is inventory management taking into account the safety of humans in the robot's working area. However, their built-in navigation system can be considerably augmented by integrating customer behavioral data. This enables the robots to perform more complex tasks, like inspecting planograms [19]. The application of deep learning algorithms further enhances their ability to efficiently conduct these intricate tasks, thereby maximizing their utility and efficiency within the retail environment. Currently, at the best of our knowledge, only few studies tried to exploit shoppers behaviours for robot task planning. Human behavior understanding in retail has been an important area of research for many years, specially for trajectory collection and action recognition. Among the various tracking systems based on Internet of Things (IoT) technologies, those that utilize Ultra Wide Band (UWB) technology have been widely adopted due to their effectiveness in collecting customers' trajectories [20], [21]. In order to collect data on customers' trajectories within a predetermined area, the UWB tracking system relies on a network of accurately positioned UWB antennas and battery-powered active tags mounted on shopping carts and baskets, as shown in Figure 1. Shopper behavior understanding solutions currently employed is not however limited to active tracking systems, in fact by using cameras and advanced algorithms, vision-based systems can also

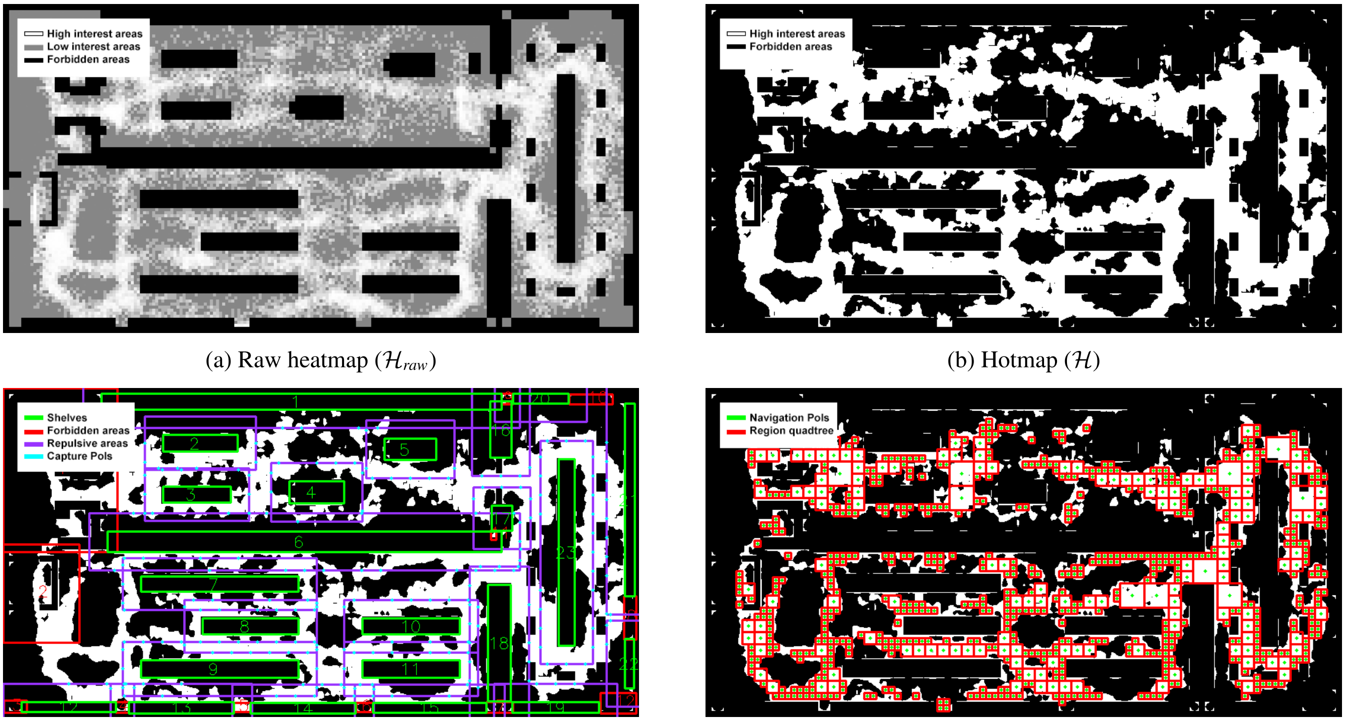
FIGURE 1. UWB tag mounted on a shopping cart and basket.

track the trajectories of shoppers, and in addition recognize shopper interactions with the products (such as picking up an item, putting the item back, touching the item) [22] which can give even more valuable insights about shoppers behavioral patterns. Maiolini et al. [23] proposed a strategy to predict the trajectory of shoppers inside a store that could be used by the navigation planner of a robot to map highly visited areas. The approach could be also used to avoid the customers during their shopping in order to minimize the bother caused by the presence of a mobile platform. ROCKy [20] is a mobile robot for data collection and surveying in a retail store that autonomously navigates and monitors store shelves based on purely trajectory-based store heatmaps. The system has been designed to automatically detect SOOS and Promotional Activities (PA) based on Deep Convolutional Neural Networks (DCNNs). An artificial potential field algorithm has been used for path planning without considering any vision related aspects to take optimal shelves pictures. Based on the above ideas and inspired by these works we propose a data-driven approach to retail path planning using heatmaps of shopper traffic, enhanced with interaction data.

III. WAYPOINTS GENERATION

A. HEATMAP PROCESSING

A heatmap is a store map divided into cells (in our case they result squares of 20 cm $\times$ 20 cm). Each cell has associated



(a) Raw heatmap ($\mathcal{H}_{raw}$)

(b) Hotmap ($\mathcal{H}$)

(c) Shelves, forbidden and repulsive areas

(d) Quadtree decomposition

FIGURE 2. An overview of the maps used in this paper. From top-left: in a) the store raw heatmap coming from the recorded customers trajectories, and in b) the hotmap resulting after the processing detailed in algorithm 1 obtained by applying a majority filter with kernel size of 13. In c) all the heatmap details and properties are shown: Shelves in green, forbidden areas in red, repulsive areas in purple and the capture PoIs highlighted in light-blue. Finally, in d) the disposition of the navigation PoIs highlighted in green are shown after the Quadtree decomposition.

a class, which, in our case, can be "Wall", "Free", "Shelf" and an intensity. The intensity of a single cell of the class "Free" represents the number of times a shopping basket or cart has been recorded within that cell by the UWB tracking system, or by a vision-based tracking system. Regarding the tracking system, it is important to note that vision-based systems can track every single customer, whereas active systems (e.g., those utilizing UWB technology) are limited to tracking only customers who choose to use shopping carts or baskets. Consequently, using UWB technology for tracking results in the exclusion of customers who do not use these items. Nevertheless, this loss of tracking is negligible since customers who use shopping carts or baskets are statistically more likely to interact with a greater number of products, making their behavior potentially more intriguing for analysis compared to individual customers without a shopping cart or basket. From the resulting map, hereafter referred as store raw heatmap ($\mathcal{H}_{raw}$), we extract three different maps: the static map ($\mathcal{M}$), the hotmap and coldmap ($\mathcal{H}$).

$\mathcal{M}$ encodes all the static elements of the store: shelves, fridges, cash desks and walls. This map represents the planimetry of the stores which normally is, in retail settings, known. Normally, this map is relatively static although some areas are dynamic, such as promotional islands and modular shelf reconfiguration. Equivalently, it can represent a deterministic occupancy grid (with binary occupancy probability: an occupancy probability of 100% with a black pixel and of 0% with a white pixel) that can be used for the simulation, which will be discussed in Section V.

Hotmap is also a binary map which implicitly encodes internally the information of the static map. It represents the areas that are considered of interest for robot navigation (white) and the areas that should be avoided (black). Using a duality approach, the latter regions represent the store zones where the customers with shopping carts or baskets stopped more often (white areas) or less often (black areas). A hotmap is shown in Figure 2b. Finally, the coldmap is simply the dual of the hotmap. The Algorithm 1 shows the steps performed to obtain these three maps.

Algorithm 1 A Pseudo-Code Showing the Store Raw Heatmap Processing

Input : `csv` file containing cells coordinates, cells class (Wall, Shelf, Free) and cells intensity
Output: Static Map ($\mathcal{M}$), hotmap / coldmap ($\mathcal{H}$)

$\mathcal{H}_{raw}$, $\boldsymbol{\mathcal{M}} \leftarrow$ `parseCsvFile`(`csv` file)
$\mathcal{H}_{equalized} \leftarrow$ `equalizeHeatmap`($\mathcal{H}_{raw}$)
$\mathcal{H}_{smoothed} \leftarrow$ `smoothHeatmap`($\mathcal{H}_{equalized}$, filter_type, kernel_size)
$\boldsymbol{\mathcal{H}} \leftarrow$ `binarizeHeatmap`($\mathcal{H}_{smoothed}$, threshold)

Heatmap is provided as `csv` file, after this file has been parsed, the $\mathcal{H}_{raw}$ and $\mathcal{M}$ maps are loaded. The $\mathcal{H}_{raw}$ map has been equalized ($\mathcal{H}_{equalized}$) to obtain a better global contrast and a better heat level distribution. The filtering or smoothing step instead, has been performed using Majority filtering from $\mathcal{H}_{equalized}$ to reduce the localization noise due to the UWB sensors used and to obtain more homogeneous regions, thus creating heat levels that better reflect customers' behaviour ($\mathcal{H}_{smoothed}$ map). Finally, starting from this latter map, image binarization is performed (using a desired threshold) to create a mask and thus divide the heatmap only in hot zones and cold zones where the robot, according to the selected mode, should or should not navigate.

B. SHELVES OF INTEREST

Shelves of Interest define those shelves that should be visited by the robot, based on interaction data during a fixed time-frame. We used the system proposed by [22] to detect shopper-products interactions using RGB-D cameras in top-view configuration. The original classification for positive and negative interactions has been used: a positive interaction is detected when a customer picks a product from the shelf, while a negative is defined when the product is put back. Both these actions can affect the planogram compliance and generate SOOS. Based on the quantity of interactions, SOIs are selected among all the shelves.

C. PROBLEM FORMULATION

Given a binarized map $\mathcal{H}$ that encodes customer behavioral data about trajectories and a list of SOIs, the objective is to find an optimal path, that is a sequence of points of interest, to be visited by the robot for inventory management and planogram control.

Assuming to have a $\mathcal{H}_{raw}$ map as the one showed in Figure 2a, it is possible to infer different properties or objects from it, as for example the static shelves positions and areas where the robot is not allowed to go. Therefore, we define the set of shelves as $\mathcal{S} = \{s_1, \ldots, s_m\}$ with m the known number of the shelves in the store. A single shelf object is composed by 6 elements: $s_i = \{id_i, x_i, y_i, w_i, h_i, z_i\} \in \mathcal{S}$ which encode respectively the unique `ID` of the shelf inside the $\mathcal{H}_{raw}$ map, the four coordinates (position of the x_i and y_i central point, the width w_i and height h_i) defining its Region Of Interest (ROI) and the height (z_i) of the shelf. In addition, we also define those regions that are forbidden from a robot navigation point of view, considering as forbidden also the store entrance and the cash desks, as $\mathcal{F} = \{f_1, \ldots, f_k\}$ where k is the total number of forbidden areas. The former are highlighted in green in Figure 2c while the latter are colored in red. Both are associated with their corresponding `ID`s. Moreover, assuming to have fixed-mounted cameras on the robotic platform, which is often the case, it is necessary to calculate, for each shelf in the $\mathcal{H}_{raw}$ map, the minimum distance d_{min} from where the robot cameras can successfully enclose vertically the whole shelf.

Given the height of the shelf s_i and the camera properties (mounting point on the robot and vertical Field Of View (FOV)) the minimum capturing distance can be calculate as follows [23]:

$$d_{min_i} = \frac{(z_i - z_{top\_camera})}{\tan(\text{vfov}/2)} \tag{1}$$

This minimum distance is implicitly encoded into the definition of repulsive areas, hereafter referred as the set $\mathcal{R}$, depicted in Figure 2c with the purple color. A repulsive area has the same properties of a shelf object defined above. They share the same unique `ID` and the ROI center.

Finally, we define a Point of Interest (PoI) as an object composed by a pose and a shelf `ID` associated with it: $PoI = \{x, y, \theta, s\_id\}$. Within the resulting maps, two distinctive types of PoI can be found: capture PoIs and navigation PoIs.

The **Capture PoIs** define those store locations related to SOIs where the robot has to stop and capture the shelves with the on-board cameras. The PoIs will be positioned on the boundaries of the repulsive areas $\mathcal{R}$ to assure the minimum capturing distance from the shelves sides. The orientation θ of a PoI reflects the robot's yaw when performing a capture to the query shelf (encoded into s_id). These PoIs are depicted in Figure 2c with the light-blue color.

The **Navigation PoIs**, instead, are stops where the robot should pass to avoid store areas which are bare or crowded, dependently on the selected mode. For this reason, all the navigation PoIs are defined to have a null shelf id. They are calculated by performing a quadtree decomposition on the binary map $\mathcal{H}$ resulting from the planner mode. A quadtree is a tree-like data structure where each node has or zero or four children. Quadtree decomposition is normally employed to partition recursively an image into four parts (children). If a specific condition is met, the recursive search or division stops, otherwise the current block size is divided into the four children and the condition is run on all of them. Figure 2d shows the navigation PoIs resulting from the quadtree decomposition of the $\mathcal{H}$ map (Figure 2b). In this work, the condition that has been used for the quadtree decomposition is the intensity average of the pixels composing the block itself. If the average of the current block exceeds a certain threshold T (a threshold of 230 has been selected in this work) the recursive division stops. It is essential to underscore that this threshold value was chosen carefully considering the trade-off between time efficiency and trajectory feasibility with respect to forbidden/repulsive areas. This threshold value operates within a range from 0 (many points and high TSP algorithm processing times) to 255 (few points and possibility of not meeting certain imposed constraints). Our decision to set the threshold at 230 was made to strike an ideal balance. This choice enables the robot to navigate the supermarket with an optimal combination of speed and efficiency while simultaneously upholding the integrity of our constraint requirements, including avoiding forbidden areas.

Both PoIs have to be refined to be used for robotic navigation. As previously mentioned, the capture PoIs will lie on the boundaries of the repulsive areas to enclose the shelf vertically. However, it is necessary to define another distance in order to horizontally include all products present on the shelf, which is the distance between two consecutive capture PoIs that refer to the same shelf. Given the horizontal FOV of the cameras, and the capturing minimum distance as in (1), it results:

$$h\_d_{min_i} = 2d_{min_i}\tan(\text{hfov}/2) - \epsilon \tag{2}$$

where ϵ determines the desired overlap between two images of the same shelf. Only points distant at least $h\_d_{min_i}$ that are moreover located on white zones are considered as capture PoIs of interest for the selected navigation mode. This distance was also used as the minimum distance between navigation PoIs. Both types of points that fall within prohibited areas are not considered in the final PoIs sequence and thus removed. The docking position inside the store is then added and it will be used as depot (namely the first and the last PoI which the robot has to be visit). All the above steps are summarized in the Algorithm 2. Once all the desired PoIs are calculated, the last step concerns the optimization of the sequence the robot will have to follow. This step is detailed in the Section IV.

IV. POIS SEQUENCE PLANNER

In this section, we propose a custom optimization TSP approach, called Heatmap-TSP, to find the optimal PoIs sequence that the robot should follow. The formulation is set up as an Integer Linear Programming (ILP). The optimization problem is solved through the python wrapper for the Or-Tools solver [24].

A. PRELIMINARIES

We denote with $\mathcal{G} = \{V, E\}$ an undirected graph where the set of vertices $V = \{v_1, \ldots, v_n\}$ encodes the set of all possible store locations on which the robot should navigate (PoIs) and the set of edges $E = \{(v_i, v_j)\}$ encodes the shortest path between the pair of locations v_i and v_j. As previously mentioned, there is a substantial difference between the capture PoIs, where the robot has to stop to perform a shelf capture, and the navigation PoIs. To distinguish among them we split the vertices set defined above such: $V = V_{cap} \cup V_{nav}$. In addition, with $n = |V|$ we indicate the total number of vertices. The binary decision variables $x_{ij}, i, j \in V$ that can be expressed equivalently as $x_{e_k}, e_k \in E$ result active ($x_{ij} = 1$), if the robot passes throughout the edge $e_k \in E$ in the solution, $x_{kj} = 0$, otherwise. The cost d_{ij} represents the travelling distance, in Euclidean sense, from the vertex v_i to the vertex v_j inside the map, or equivalently the length of edge e_k. More details about the optimization costs will be given in the subsection IV-C.

B. HEATMAP-TSP

The proposed optimization problem differs from the classical TSP by modifying the distance d_{ij} and by encoding two additional costs which are the robot orientation (o_{ij}) and the brightness index (b_{ij}). The new terms introduced in this context, o_{ij} and b_{ij}, refer to the cost incurred by the inventory

Algorithm 2 Pseudo-Code Showing the Strategy Adopted for the PoIs Generation

Input : $\mathcal{H}$ (Hotmap / coldmap), docking_position, interaction_data
Output: PoIs sequence

$\mathcal{S}, d_{min}, h\_d_{min} \leftarrow$ `calculateShelves` $(\mathcal{H})$
$\mathcal{SOI} \leftarrow$ `calculateSOIs` $(\mathcal{S}, interaction\_data)$
$\mathcal{F} \leftarrow$ `calculateForbiddenAreas` $(\mathcal{H})$
$\mathcal{R} \leftarrow$ `calculateRepulsiveAreas` $(\mathcal{S}, d_{min})$
$capture\_pois \leftarrow$ `calculateCapturePoIs` $(\mathcal{H}, \mathcal{SOI}, \mathcal{R}, h\_d_{min})$
$quadtree\_pois \leftarrow$ `quadTreeDecomposition` $(\mathcal{H}, T)$
$nav\_pois \leftarrow$ `calculateNavigationPoIs` $(quadtree\_pois, h\_d_{min})$
$final\_pois \leftarrow$ `filterPoIs` $(capture\_pois, nav\_pois, \mathcal{F})$
$final\_pois$.append $(docking\_position)$
$pois\_sequence \leftarrow$ `heatmapTSP` $(final\_pois)$

Function `calculateCapturePoIs` $(\mathcal{H}, \mathcal{SOI}, \mathcal{R}, h\_d_{min})$ **:**
  forall $s \in \mathcal{SOI}$ **do**
    $points \leftarrow$ `pointsAroundShelf` $(s, \mathcal{R}, h\_d_{min})$ **forall** $poi \in points$ **do**
      if min (`euclideanDists` $(points \setminus poi)) \leq h\_d_{min}$ **then**
        if `liesOnWhitePatch` $(poi, \mathcal{H})$ **then**
          $capture\_pois$.append (poi)
        end
      end
    end
  end
  return $capture\_pois$
Function `calculateNavigationPoIs` $(quadtree\_pois, h\_d_{min})$ **:**
  forall $poi \in quadtree\_pois$ **do**
    if min (`euclideanDists` $(quadtree\_pois \setminus poi)) \leq h\_d_{min}$ **then**
      nav_pois.append (poi)
    end
  end
  return nav_pois
Function `filterPoIs` $(capture\_pois, nav\_pois, \mathcal{F})$ **:**
  forall $poi \in capture\_pois \cup nav\_pois$ **do**
    if poi `isOutsideForbidden` $(\mathcal{F})$ **then**
      $final\_pois$.append (poi)
    end
  end
  return $final\_pois$

robot when repositioning itself between two consecutive PoIs, as well as the additional cost that arises when the robot has to traverse a low-interest area while transitioning between two adjacent PoIs, respectively.

Formulation 1 : Heatmap-TSP

$$\text{minimize} \quad \sum_{i=1}^{n} \sum_{j \neq i, j=1}^{n} (d_{ij}^{norm} + o_{ij}^{norm} + b_{ij}^{norm})\, x_{ij} \tag{3a}$$

$$\text{subject to} \quad x_{ij} \in \{0, 1\} \quad i, j = 1 \ldots n \tag{3b}$$

$$u_i \in \mathbf{Z} \quad i = 2 \ldots n \tag{3c}$$

$$\sum_{i=1, i \neq j}^{n} x_{ij} = 1 \quad j = 1 \ldots n \tag{3d}$$

$$\sum_{j=1, j \neq i}^{n} x_{ij} = 1 \quad i = 1 \ldots n \tag{3e}$$

$$u_i - u_j + n x_{ij} \leq n - 1 \quad 2 \leq i \neq j \leq n \tag{3f}$$

$$1 \leq u_i \leq n - 1 \quad 2 \leq i \leq n \tag{3g}$$

The proposed solution is bound to be binary (3b) while constraints (3d) and (3e) ensure that the robot will arrive and will depart from each vertex, or stop, exactly one time. Constraints (3f) and (3g) are the so-called ''Subtour Constraints'', disabling the possibility of having two or more disjoint tours as solution of the optimization problem.

C. HEATMAP-TSP COSTS

The distance matrix that encodes the Euclidean distances between the stops takes into account also the shelves disposition inside the map.

$$d_{ij} = \begin{cases} \|v_i - v_j\| & \text{if } e_k \text{ do not cross shelves set } \mathcal{S} \\ \infty & \text{otherwise} \end{cases} \tag{4}$$

In this way a solution that considers as sequential two PoIs whose path crosses any of the store shelves is discouraged. This avoids the necessity for the robot to bypass the shelves. The term o_{ij} adds an additional cost if the orientation of the robot between two capture PoIs changes. It is defined as follows:

$$o_{ij} = \begin{cases} |\theta_{v_i} - \theta_{v_j}| & \text{if } v_i \text{ and } v_j \in V_{cap} \\ 0 & \text{otherwise} \end{cases} \tag{5}$$

If both vertices are capture PoIs, the weight equals the absolute difference between their two orientations; otherwise, its contribution is set to 0. In this respect, the orientation cost is composed of four possible values: $o_{ij} = \{0, 90, 180, 270\}$. With the addition of this contribution, the solution will try to maintain the robot orientation between successive capture PoIs while it won't bring any contribution in the navigation PoIs case. The last term in the objective function (3a) is a path brightness index, normalized on the path length, that aims to discourages the activation of edges that pass through dark paths (i.e., regions which are of no interest for the selected planner mode).

$$b_{ij} = \frac{\mathcal{H}[e_k] == 0}{length(e_k)} \tag{6}$$

All the above costs have been normalized into the same interval, thus they equally contribute to the final solution.

V. RESULTS

This section describes the results obtained from the tests conducted in order to prove the effectiveness of the proposed approach. Since testing with robots and cameras in public environments such as supermarkets requires compliance with security and privacy constraint, the GAZEBO [25] robotic simulation toolbox was initially used. The dataset used to validate the proposed approach consists of four different stores located in Germany and Indonesia [23]. The map and the world that are necessary for the simulation of each individual store are inferred from the static map $\mathcal{M}$ as if it would be produced by `gmapping` [26] with binary occupancy probability: an occupancy probability of 100% with a black pixel and of 0% with a white pixel. To obtain

FIGURE 3. The inventory robot StockBot used for optimizing retail path planning in real environment.

the map $\mathcal{M}$, the kernel size was set to 13 and the Majority filter was used. For the robot instead, a model was built to interface with the Robot Operating System (ROS) [27].

The purpose of the robotic system is to check for planogram compliance, SOOS situations, and PA by capturing a whole shelf both horizontally and vertically, as explained in [20]. Once one of these events has been identified, these are instantaneously and securely recorded on a Hyperledger Fabric blockchain network hosted on Amazon Managed Blockchain [28], leveraging IoT and Cloud technology [29], [30]. This decentralized ledger offers an immutable, time-stamped record of all such events, thereby providing an efficient system of accountability and enabling streamlined operations through real-time response to stock management needs.

To achieve this, we selected the Tiago-Base [31], which is an indoor mobile robot that is fully open-source and has been fitted with three RGB cameras positioned vertically on its right side. The decision to use three cameras was based on certain parameters which are: (i) the maximum/minimum height of the shelves in real stores, (ii) the space available in the corridors and (iii) the overlap region necessary to stitching different images to reconstruct the shelf. Each camera has a 3840×2160 resolution and a 60° horizontal FOV and is fixed-mounted vertically on the support base with the image plane perpendicular to the ground. The Tiago-Base's configuration for in-store navigation remains unchanged, except for the installation of the cameras. The robot base model comes equipped with a 2D laser scanner, the TiM571 from Sick [32], which is used for this purpose. Additionally, two RGB cameras on the front of the robot can be activated for navigation.

The Algorithms 1, 2 and the Formulation (1) run all offline while the final PoIs are sent to the `move_base` [33], which is a well-established navigation stack in ROS. Since the terms in the Heatmap-TSP formulation have different units and contribute equally to the final solution, normalization is performed; the range chosen for the test

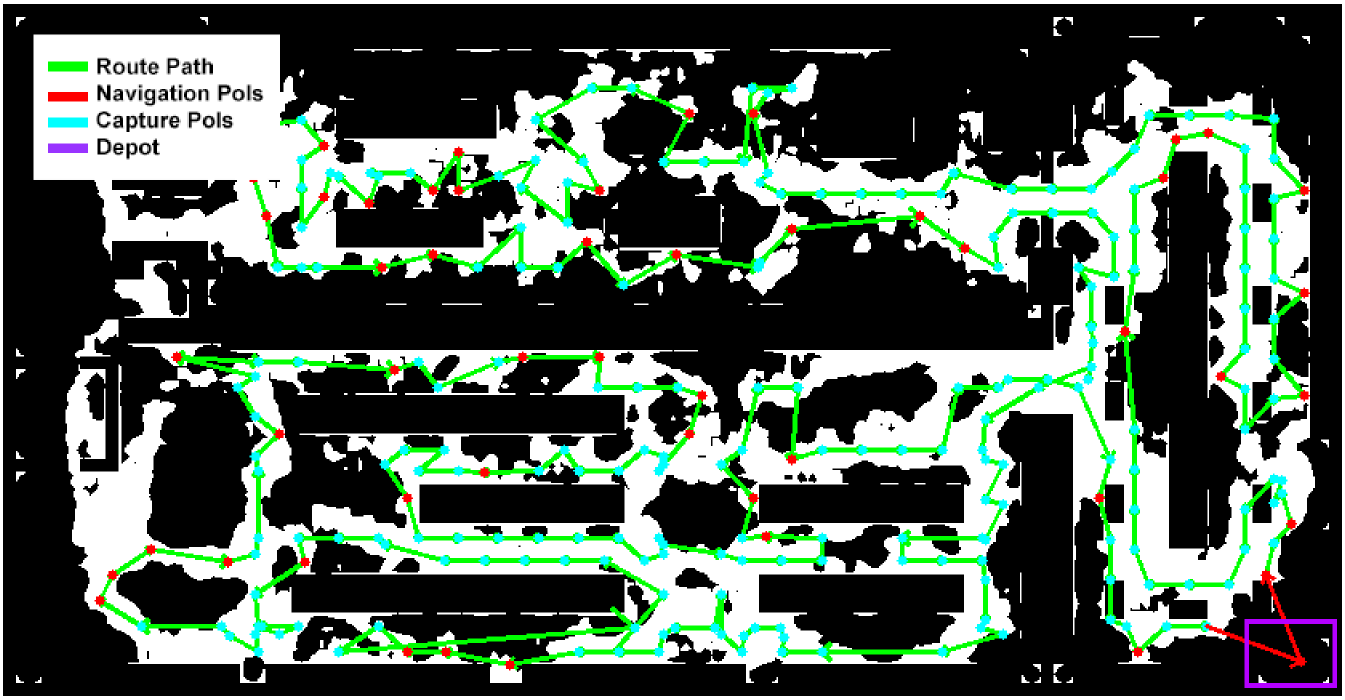


FIGURE 4. Final solution heatmap-TSP (1) considering distance matrix as in (4) in the problem formulation and with the addition of (5) and (6) costs. The bottom-right red arrows show the arcs from and to the PoI which is defined to be the docking station for the inventory robot. Notice how the capture orientations are respected in consecutive capture PoIs.

setup is 10 − 1000. A remark should be made on the global planner inside `move_base`. The robot can always find a suitable path between two consecutive PoIs, given the feasibility of the two stops inside the selected store. Indeed, since all the store corridors in the dataset are large enough, the robot's passage is always possible. Another enabling factor to always find a path given two consecutive PoIs has been to let the orientation of the desired PoI for the robot not constrained, i.e., any configuration of arrival is accepted by the planner, while for the position the default threshold of 20 cm from Tiago-Base has been left for both axis. At this point, to validate the proposed approach in a real case study, the model validated in simulation has been deployed on a real robot. For this purpose, the selected inventory robot that most closely approximates the characteristics of Tiago-Base is the StockBot [17] (shown in Figure 3), which is a professional service robot for retail environments relying on the `move_base` global planning algorithm and safety protocols to share environment with customers. Stockbot is provided with cameras in the same configuration used in our simulation and with RFID sensors for inventory management. In our experiments, PoIs generated by our algorithm has been fed to Stockbot navigation system for shelves picture collection.

In our real-world experiment conducted in an 800 m^2 store, we applied a modified version of the TSP infused with human behavioral insights. The testing was carried out during two distinct time periods over two consecutive weeks each month throughout 2021: a low-traffic slot and a peak hour slot with higher crowding. In low-traffic scenarios, both algorithms (classical TSP and our proposed variant) demonstrated similar performance, as our additional modules do not significantly alter the classical TSP model under these conditions. Conversely, in peak hour conditions, our method exhibited a performance improvement of approximately 30% in surveying time compared to the conventional TSP method, showcasing its enhanced efficacy in crowded environments. Our focus was on the practical impact of the commercial robot on surveying time, specifically targeting shelves with significant human-product interactions (more than 10 in the last hour). The comparative study included both our behavior-aware TSP and the traditional version. We noted that in similar shelf-visit scenarios, the classic TSP struggled in busy areas, often halting progress and leading to longer completion times and increased battery usage. Our modified approach significantly enhanced surveying efficiency in a live store setting, demonstrating its potential to improve the functionality of autonomous mobile robots in retail spaces. The result obtained from the proposed Heatmap-TSP algorithm is shown in Figure 4. We want to emphasize that, the final path cost loses its metric meaning having introduced the new terms (5)-(6). In fact, the goal of the planner in our settings is to optimize the sequence of point visits (capture and navigation PoIs) while maintaining the robot's orientation for successive image capture to ensure image overlapping and minimizing crossings in forbidden areas. Therefore, the proposed Heatmap-TSP algorithm only returns the sequence of visiting points and thus the robot's navigation direction. The actual path planning, i.e., the path to be followed in an environment with the presence of people, is left to the standard `move_base` global planning algorithm. The arrows in Figure 4 show the connection between successive PoIs, not the robot's actual path.

VI. DISCUSSION

The implementation of our system significantly streamlines the inventory process and ensures precise compliance and positioning of products on shelves, outperforming traditional methods managed by human operators. This efficiency is not merely about speed; it heralds a transformative shift in workplace dynamics. Employees, who were previously engaged in the time-consuming and monotonous task of inventory management, are now liberated to focus on more engaging and varied responsibilities. This shift fundamentally enhances employee well-being, fostering a more dynamic and satisfying work environment. Furthermore, our system operates in near real-time, seamlessly adapting to the ever-changing dynamics of the retail environment as the robot navigates. Heatmaps provide a historical snapshot, yet the real value lies in our system's ability to adjust to changes as they occur. This agility depends on several factors: the robot's speed, the distance it traverses, and the obstacles it encounters. Crucial to this process is a deep understanding of the store's layout and shelf dimensions, bolstered by a robust infrastructure for tracking customer movements. Importantly, our system recognizes and responds to the varying patterns of customer behavior, which shift depending on the time of day, whether it's a weekday or weekend. This sensitivity to temporal changes ensures our solution remains relevant and effective, accurately reflecting the dynamic nature of customer interactions and store traffic in different time frames. In our methodology for generating heatmaps using technologies like UWB RTLS, we intentionally concentrate on shoppers utilizing a cart or basket. This focus is necessitated by the inherent limitations of the UWB RTLS system, which is equipped to track only those customers using baskets and carts. As a result, customers navigating the supermarket without a cart or basket remain outside the purview of our heatmap generation.It's essential to recognize that shoppers with baskets or carts not only constitute the majority of customers but also significantly impact the overall crowd dynamics due to their increased spatial occupancy. By focusing on shoppers with carts or baskets, our analysis zeroes in on a more influential segment of consumer behavior, offering critical insights for the optimization of store layout and product placement. This methodology underscores the vital role that shoppers with carts or baskets play in dictating the flow and interaction patterns within a retail environment.

Our UWB RTLS approach represents a middle ground when juxtaposed with traditional traffic estimation methods, like standard people counting solutions, and full-coverage camera systems employed in cashierless stores such as Amazon Go. Traditional methods, known for their simplicity and low implementation costs, primarily focus on quantifying foot traffic but fall short in capturing detailed shopper behavior or their interactions with store layouts. On the other hand, Amazon Go's full-coverage cameras and sophisticated sensor arrays offer a comprehensive checkout-free shopping experience by tracking detailed shopper behavior and interactions, not limited to those with carts or baskets. While this technology provides deep insights into shopper behavior and operational efficiency, its deployment demands a considerable revamp of the retail environment and a hefty investment in technology, rendering it less feasible for many retailers. Moreover, Amazon Go predominantly aims to enhance the checkout process, with less emphasis on optimizing store layout and product placement strategies.

In this landscape, our UWB RTLS system finds its niche by offering in-depth behavioral insights akin to Amazon Go's technology but with a focus on a specific yet significant segment of the retail market: shoppers using carts and baskets. These shoppers are crucial for understanding store dynamics due to their spatial occupancy and purchasing patterns. Although our approach also entails initial setup costs and the need for customization to accommodate various retail environments, it does so without necessitating the extensive infrastructure modifications required by Amazon Go. This positions the UWB RTLS system as a versatile and valuable asset for retailers aiming to improve store efficiency and customer satisfaction. By providing actionable insights for store layout and product placement optimization, our method addresses the critical need for a balanced approach between capturing detailed shopper behavior and maintaining implementation feasibility.

VII. CONCLUSION

This paper introduces an approach to optimize the planning and navigation of autonomous robots within stores. The approach involves the use of a heatmap and interaction data to encode shopper behavior over space and time, which can be used to exploit shopper behavioral data during a particular time-frame. This can aid store managers in optimizing the robot's path to achieve specific objectives, such as visiting high-attendance areas. The proposed approach also enables an end-to-end scenario and can seamlessly transition from simulation to a real-world scenario without requiring additional effort, thanks to the benefits of the ROS ecosystem. This work allows a dual application with regard to robot navigation. In fact, coldmaps can be used instead of hotmaps to check less visited areas of the store for issues that perhaps prevent shopper visits and to reduce interations with human. Moreover, considering the rising incidents of retail theft and shoplifting, this system serves as an additional layer of security by cross-verifying the quantity of items selected by the customer and computed by our system, ensuring alignment with the total products tallied at the conclusion of the purchase, as indicated on the receipts generated by the cash registers. The source code for this approach is available online at https://github.com/vrai-group/heatmap2planner.

Future works will focus to integrate computer vision pipeline for product recognition to solve task such as product category-based topological mapping of the store and real-time human behavior analysis letting the robot freely browsing the store. Such a change will incorporate new dynamic aspects of the store environment. In addition, to comprehensively evaluate the robustness and reliability of our proposed algorithm, a Monte Carlo study will be conducted in the future in order to thoroughly evaluate the performance of our algorithm under a wide range of conditions and to provide more robust insights into of its behaviour. Furthermore, we are actively considering additional experiments in both simulated and real environments to comprehensively evaluate and enhance the algorithm's performance. Large store in addition will require multiple robots to efficiently map the environment, a collaborative framework for multi-robots interaction and task planning will be explored.

ACKNOWLEDGMENT

The authors would like to thank Jacopo Maiolini for his support in implementing the proposed approach and for sharing his experience in the field of robotic navigation. Many thanks to Grottini Lab (https://www.grottinilab.com/) for providing their datasets of the stores used to validate the proposed approach. We acknowledge support from the European Union's Horizon 2020 research and innovation programme under the Marie Skłodowska-Curie grant agreement No. 101007820. This publication reflects only the author's view and the REA is not responsible for any use that may be made of the information it contains.

REFERENCES

[1] Coherent Market Insights. *Retail Robots Market Analysis*. Accessed: Jul. 20, 2023. [Online]. Available: https://www.coherentmarketinsights.com/market-insight/retail-robots-market-4535

[2] European Commission. *Refills Project, ICT-25-2016-2017—Advanced Robot Capabilities Research and Take-Up*. Accessed: Jul. 20, 2023. [Online]. Available: http://www.refills-project.eu/

[3] E. Frontoni, M. Paolanti, and R. Pietrini, *People Counting in Crowded Environment and Re-identification*. Cham, Switzerland: Springer, 2019, pp. 397–425.

[4] Y. Chen, Y. Luo, C. Yang, M. O. Yerebakan, S. Hao, N. Grimaldi, S. Li, R. Hayes, and B. Hu, "Human mobile robot interaction in the retail environment," *Sci. Data*, vol. 9, no. 1, p. 673, Nov. 2022.

[5] Y. Luo, Y. Chen, M. O. Yerebakan, S. Hao, N. Grimaldi, C. Yang, R. Hayes, and B. Hu, "How do humans adjust their motion patterns in mobile robots populated retail environments?" in *Proc. IEEE 3rd Int. Conf. Human-Machine Syst. (ICHMS)*, Nov. 2022, pp. 1–6.

[6] S. García, D. Strüber, D. Brugali, A. Di Fava, P. Pelliccione, and T. Berger, "Software variability in service robotics," *Empirical Softw. Eng.*, vol. 28, no. 2, pp. 1–67, Mar. 2023.

[7] A. Galdelli, D. P. Pagnotta, A. Mancini, A. Freddi, A. Monteriu, and E. Frontoni, "Empowered optical inspection by using robotic manipulator in industrial applications," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Nov. 2019, pp. 2006–2013.

[8] K. Mankodiya, R. Gandhi, and P. Narasimhan, "Challenges and opportunities for embedded computing in retail environments," in *Sensor Systems and Software*, F. Martins, L. Lopes, and H. Paulino, Eds. Berlin, Germany: Springer, 2012, pp. 121–126.

[9] S. Kumar, G. Sharma, N. Kejriwal, S. Jain, M. Kamra, B. Singh, and V. K. Chauhan, "Remote retail monitoring and stock assessment using mobile robots," in *Proc. IEEE Int. Conf. Technol. Practical Robot Appl. (TePRA)*, Apr. 2014, pp. 1–6.

[10] N. Kejriwal, S. Garg, and S. Kumar, "Product counting using images with application to robot-based retail stock assessment," in *Proc. IEEE Int. Conf. Technol. Practical Robot Appl. (TePRA)*, May 2015, pp. 1–6.

[11] S. Song, B. Jun, J. Nakanishi, Y. Yoshikawa, and H. Ishiguro, "Service robots in a bakery shop: A field study," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst. (IROS)*, Oct. 2022, pp. 134–140.

[12] R. Alves, B. A. Linhares, and J. R. Souza, "Autonomous shopping cart: A new concept of service robot for assisting customers," in *Proc. Latin Amer. Robotic Symp., Brazilian Symp. Robot. (SBR), Workshop Robot. Educ. (WRE)*, 2018, pp. 451–456.

[13] S. Sonawani, K. Maneparambil, and H. Ben Amor, "Multimodal data fusion for power-on-and-go robotic systems in retail," 2021, *arXiv:2103.12241*.

[14] M. Morenza-Cinos, V. Casamayor-Pujol, J. Soler Busquets, J. Sanz, R. Guzman, and R. Pous, "Development of an RFID inventory robot (AdvanRobot)," in *Robot Operating System (ROS): The Complete Reference (Volume 2)*, A. Koubaa, Ed. Cham, Switzerland: Springer, 2017, pp. 387–417, doi: 10.1007/978-3-319-54927-9_12.

[15] MetraLabs GmbH. *Metralabs*. Accessed: Jul. 20, 2023. [Online]. Available: https://www.metralabs.com/en/rfid-robot-tory/

[16] R. Bogue, "Strong prospects for robots in retail," *Ind. Robot, Int. J. Robot. Res. Appl.*, vol. 46, no. 3, pp. 326–331, May 2019.

[17] Pal Robotics. *Pal Robotics Stockbot*. Accessed: Jul. 20, 2023. [Online]. Available: https://pal-robotics.com/robots/stockbot/

[18] M. Valori, A. Scibilia, I. Fassi, J. Saenz, R. Behrens, S. Herbster, C. Bidard, E. Lucet, A. Magisson, L. Schaake, J. Bessler, G. B. Prange-Lasonder, M. Kühnrich, A. B. Lassen, and K. Nielsen, "Validating safety in human–robot collaboration: Standards and new perspectives," *Robotics*, vol. 10, no. 2, p. 65, Apr. 2021.

[19] R. Pietrini, A. Galdelli, A. Mancini, and P. Zingaretti, "Embedded vision system for real-time shelves rows detection for planogram compliance check," in *Proc. 19th IEEE/ASME Int. Conf. Mech. Embedded Syst. Appl. (MESA)*, Aug. 2023, Art. no. V007T07A003.

[20] M. Paolanti, L. Romeo, M. Martini, A. Mancini, E. Frontoni, and P. Zingaretti, "Robotic retail surveying by deep learning visual and textual data," *Robot. Auto. Syst.*, vol. 118, pp. 179–188, Aug. 2019.

[21] M. Contigiani, R. Pietrini, A. Mancini, and P. Zingaretti, "Implementation of a tracking system based on UWB technology in a retail environment," in *Proc. 12th IEEE/ASME Int. Conf. Mech. Embedded Syst. Appl. (MESA)*, Aug. 2016, pp. 1–6.

[22] M. Paolanti, R. Pietrini, A. Mancini, E. Frontoni, and P. Zingaretti, "Deep understanding of shopper behaviours and interactions using RGB-D vision," *Mach. Vis. Appl.*, vol. 31, nos. 7–8, pp. 1–21, Nov. 2020.

[23] J. Maiolini, L. Rossi, R. Pietrini, A. Mancini, E. Frontoni, and P. Zingaretti, "Prediction of users trajectories to mimic/avoid the customer behaviour during mapping tasks of an autonomous robot in retail environment," in *Proc. 18th IEEE/ASME Int. Conf. Mechatronic Embedded Syst. Appl. (MESA)*, Nov. 2022, pp. 1–6.

[24] Google LLC. *Or-Tools*. Accessed: Jul. 20, 2023. [Online]. Available: https://developers.google.com/optimization

[25] Open Robotics. *Gazebo Simulator*. Accessed: Jul. 20, 2023. [Online]. Available: https://gazebosim.org/

[26] G. Grisetti, C. Stachniss, and W. Burgard, "Improved techniques for grid mapping with rao-blackwellized particle filters," *IEEE Trans. Robot.*, vol. 23, no. 1, pp. 34–46, Feb. 2007.

[27] Open Robotics. *ROS*. Accessed: Jul. 20, 2023. [Online]. Available: https://www.ros.org

[28] Amazon Web Services. *Amazon Managed Blockchain*. Accessed: Jul. 20, 2023. [Online]. Available: https://aws.amazon.com/managed-blockchain/

[29] A. Galdelli, A. Mancini, E. Frontoni, and A. N. Tassetti, "A feature encoding approach and a cloud computing architecture to map fishing activities," in *Proc. 17th IEEE/ASME Int. Conf. Mech. Embedded Syst. Appl. (MESA)* (International Design Engineering Technical Conferences and Computers and Information in Engineering Conference), vol. 7, Aug. 2021, Paper V007T07A003. [Online]. Available: https://asmedigitalcollection.asme.org/IDETC-CIE/proceedings-pdf/IDETCCIE2021/85437/V007T07A003/6800406/v007t07a003-detc2021-69799.pdf

[30] A. N. Tassetti, A. Galdelli, J. Pulcinella, A. Mancini, and L. Bolognini, "Addressing gaps in small-scale fisheries: A low-cost tracking system," *Sensors*, vol. 22, no. 3, p. 839, Jan. 2022.

[31] Open Robotics. *ROS TiAGo-Base*. Accessed: Jul. 20, 2023. [Online]. Available: http://wiki.ros.org/Robots/TIAGo-base

[32] Sick. *2D LiDAR Sensors TiM*. Accessed: Jul. 20, 2023. [Online]. Available: https://www.sick.com/it/en/lidar-sensors/2d-lidar-sensors/tim/tim571-2050101/p/p412444

[33] Open Robotics. *ROS Planning*. Accessed: Jul. 20, 2023. [Online]. Available: https://github.com/ros-planning/navigation

ALESSANDRO GALDELLI (Member, IEEE) received the master's degree (cum laude) in computer and automation engineering and the Ph.D. degree in artificial intelligence systems, in 2021. He is currently an Assistant Professor with Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Italy. His research interests include computer vision and artificial intelligence, with practical applications spanning various domains, including robotics, video analysis, precision/smart agriculture and fishing, remote sensing, and cloud-based technologies and big data. He is a member of the Computer Vision, Pattern Recognition and Machine Learning (CVPL) and International Association for Pattern Recognition (IAPR).

ROCCO PIETRINI is currently an Assistant Professor in object oriented programming and data structures with Università Politecnica delle Marche, Italy. His main research interests include human behavior understanding (HBU) in intelligent spaces. The use of computer vision and deep learning for HBU in retail context have been the main application area. He is a member of the Computer Vision Foundation (CVF).

ADRIANO MANCINI (Member, IEEE) received the master's degree (cum laude) in industrial automation and the Ph.D. degree in artificial intelligence systems, in 2010. He is currently an Associate Professor with Dipartimento di Ingegneria dell'Informazione, Università Politecnica delle Marche, Ancona, Italy. His research interests include computer vision and artificial intelligence, with applications in robotics, video analysis, human behavior analysis, and the automatic classification of images. He is also involved in several national and international projects (EU and Industry funded projects) in the field of precision/smart agriculture, remote sensing, robotics, cloud-based technologies, and big data.

PRIMO ZINGARETTI (Senior Member, IEEE) is currently a Full Professor in computer engineering with Università Politecnica delle Marche, Italy. His main research interests include artificial intelligence, robotics, intelligent mechatronic systems, computer vision, pattern recognition, image understanding, and retrieval and information systems. Robotics vision and geographic information system have been the main application areas, with great attention directed to the technological transfer of research results. He has authored over 200 scientific research articles. He is a member of ASME, a Co-Founder of AI*IA, and the Vice-President of CVPL.

Open Access funding provided by 'Università Politecnica delle Marche' within the CRUI CARE Agreement