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SURVEY PAPER

Enhancing Robot Task Completion Through Environment and Task Inference: A Survey from the Mobile Robot Perspective

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Abstract
In real-world environments, ranging from urban disastrous scenes to underground mining tunnels, autonomous mobile robots are being deployed in harsh and cluttered environments, having to deal with perception and communication issues that limit their facilitation for data sharing and coordination with other robots. In these scenarios, mobile robot inference can be used to increase spatial awareness and aid decision-making in order to complete tasks such as navigation, exploration, and mapping. This is advantageous as inference enables robots to plan with predicted information that is otherwise unobservable, thus, reducing the replanning efforts of robots by anticipating future states of both the environment and teammates during execution. While detailed reviews have explored the use of inference during human–robot interactions, to-date none have explored mobile robot inference in unknown environments and with cooperative teams. In this survey paper, we present the first extensive investigation of mobile robot inference problems in unknown environments with limited sensor and communication range and propose a new taxonomy to classify the different environment and task inference methods for single- and multi-robot systems. Furthermore, we identify the open research challenges within this emerging field and discuss future research directions to address them.

Keywords Mobile Robot · Environment Inference · Task Inference · Communication Limited Environments · Multi-robot Cooperation

Classification Code 93C85 · 68T40

1 Introduction

Mobile robots are needed to explore and navigate various environments for applications such as warehouse and retail automation [1, 2], planetary exploration [3], espionage [4], mining and excavation [5], patrolling [6], material handling and transportation [7], and search and rescue [8]. However, these real-world scenarios can often be unknown prior to robot deployment as well as partially observable to the robots during execution due to limited perception and communication between multiple robots. For example, when navigating an initially unknown environment, robot path planners mainly use iteratively obtained sensor readings to generate feasible collision-free paths. However, these approaches only consider the spatial layout of what is directly observed by the robot [9], which can result in slower navigation speeds and less efficient paths due to the lack of *occupancy anticipation* for the spatial layout in unobserved parts of the environment (e.g., upcoming corners and turns). Furthermore, when multiple robots are cooperatively exploring an environment together, they require explicit sharing of information such as goal locations and navigation costs to jointly agree on an overall allocation plan [10]. Thus, during communication dropout as a result of connectivity or communication range issues, robot teams can become uncoordinated and execute redundant tasks that can degrade overall team performance [11]. In such scenarios where robot perception and communication are limited, mobile robot inference can be used to enhance robot reasoning and awareness by predicting the unknown layout of the environment and the intentions of teammates to successfully achieve task completion [12].

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Existing survey papers on the topic of inference [13–21] have mainly focused on: 1) computational agents in human–machine interaction (HMI) applications [13–16] such as smart homes [22, 23], surveillance [24], decision support systems [25], and dialogue interpretation [26]; or 2) physical human–robot interactions (HRI) in social settings [17–21] such as domestic assistance [27, 28], medical rehabilitation [29, 30], and social compliant navigation [31, 32]. In the first set of applications, a computational agent observes a human and makes predictions about the activity, plan, or goal of the human [14]. In particular, activity prediction involves predicting human actions [22], while plan prediction is focused on inferring the actions that a human intends to execute next (i.e., the plan) to achieve their goals [24, 25]. Lastly, goal prediction infers the overall objective of a human to understand his/her intention in achieving a specific goal [23, 26]. However, these methods typically assume a static observer that is not acting on the observed environment and situations where the observed human is not aware that he/she is being observed [14].

With respect to survey papers on robots in HRI applications, inference has been used to predict human intentions (i.e., object to pick up, walking direction) in order for robots to effectively collaborate or coexist with their human counterparts [33], utilizing inputs such as human action habits [34], gaze direction [35], haptics [36, 37] and natural language processing [38]. In particular, human–robot collaboration surveys have explored human intention prediction for robot manipulators [17–19] engaged in object hand-over [39], manipulation [40], and/or carrying [41] tasks. Whereas human–robot coexistence surveys have investigated socially compliant mobile robot navigation in human-centered environments based on constraints imposed by human comfort levels (i.e., interpersonal distances) and social norms (i.e., right of way) [20, 21]. As a result, existing HRI surveys have been limited to robots inferring only short-term human intentions such as body part motion and walking direction with the aim of: 1) providing robot manipulator assistance on a joint task [17–19], or 2) safely navigating in crowds of people in known environments [20, 21], respectively. However, mobile robots, whether a single robot or a robot in a robot team, that need to operate in unknown and partially observable environments with communication-limitations address a different problem, where they infer the spatial configurations of unobserved regions (environment inference) in order to plan beyond the sensor horizon to improve spatial awareness of unknown environments [42]. Furthermore, mobile robot teams can infer long-term teammate intentions that describe high-level tasks such as exploration goals (task inference) in order to coordinate their efforts and increase robot team awareness in communication-limited environments. Thus, the objective of teammate intention inference in a cooperative multi-robot scenario is to predict long-term mobile robot goals (contrary to short-term human actions in existing HRI surveys) in order to prevent redundant task allocation among team members.

Currently, there has not yet been an encompassing survey paper that investigates the use of inference for mobile robotics, where robots use predicted information about the unknown environment and team member intentions for tasks such as navigation, search, and exploration in unknown structured and unstructured environments using single and/or multi-robot teams. Both environment and task inference are important challenges to address in the mobile robotics community for robots working in unconstrained and unstructured environments, where robot perception can be occluded and uncertain (due to harsh illumination challenges and natural weather elements), and/or communication is unreliable and limited [43]. Common mobile robot environment and task inference methods include: 1) heuristics that exploit characteristics of known environments (i.e., rectilinear walls) and tasks (i.e., location), 2) statistical methods that utilize previously acquired maps or Bayesian estimation to predict occupancy distribution over the unexplored environment and possible tasks, and 3) learning methods that extract non-linear combinations of environmental and task features during offline training to complete partially occluded maps, and allocate tasks amongst the team, during mobile robot environment and task inference. Motivated by this gap in the literature, we present the first comprehensive survey of environment and task inference from the perspective of mobile robots to enhance robot task completion. Our novel contributions include: 1) the development of the first classification taxonomy for mobile robot inference to address the deployment of autonomous robots in unknown and partially observable environments with communication limitations; and 2) the identification and discussion of open challenges in mobile robot inference to inform future research directions in this emerging area. The objective of this survey paper is to provide a new perspective on the use of inference strategies for mobile robots. To the best of our knowledge, we are the first to present an extensive investigation of inference methods for single robot and multi-robot teams and to introduce a novel taxonomy to classify existing inference methods using a systematic approach that allows for distinct classifications and comparisons to be made within this emerging field.

The manuscript is organized as follows: Sect. 2 defines the mobile robot inference problem and presents our proposed classification taxonomy. Section 3 presents and discusses the inference methodologies for single robot environment inference, focusing on both map and topology prediction. Section 4 presents and discusses the methods used for multi-robot task inference. Section 5 provides a detailed discussion on the current open challenges and future research directions for inference in the context of mobile robotics. Lastly, Sect. 6 provides a summary of the important topics discussed in this paper.

2 Mobile Robot Inference

Mobile robot inference can be defined as the prediction of unknown information, given partial observations of a robot's environment layout and/or teammates' actions [14]. In particular, mobile robot applications typically involve tasks that are spatially distributed; thus, requiring robots to navigate and explore the environment in order to successfully complete these tasks, whether it be in teams or on their own. Thus, there are two main types of unknown information, which are: 1) the environment configuration and 2) teammates' intentions during robot execution. These problems are addressed, by considering the use of environment inference or task inference when considering the actions of the robots. In environment inference, the goal is to predict the unknown geometry and topology configuration of the unobserved environment during robot deployment to enhance spatial awareness and reasoning [44, 45]. Task inference considers the intentions of robot teammates (with respect to the execution of their goals) to achieve effective cooperation with limited communication [46, 47]. Both these types of inference can be further categorized based on the specific approaches used.

Existing robot inference classification taxonomies focus on the prediction of low-level, short-term *human intentions* in known environments in human–robot collaboration tasks [17–19], and in human–robot coexistence scenarios [20, 21]. In particular, for human–robot collaboration, robot inference approaches have been categorized based on: 1) the type of communication between humans and robots (explicit vs. implicit) [17], 2) shared human–robot control and autonomy [18], 3) types of sensors used to measure human intent [19], and 4) robot planning methods [17, 19]. As human–robot coexistence addresses the social compliant navigation problem; robot inference approaches have been mainly categorized based on: 1) coupled or decoupled human intent prediction and robot path planning methods [21], 2) robot performance metrics (i.e., human comfort levels) [20], and 3) human intent prediction methods based on human trajectories [20]. Both human–robot collaboration and coexistence scenarios focus on known environments without communication dropout between humans and robots. To the best of our knowledge, there currently does not exist a classification taxonomy for both mobile robot environment and task inference for high-level robot intentions during mobile robot/muti-robot task completion (i.e., exploration) in unknown, partially observable environments with communication limitations.

Our methodology for this survey consisted of conducting a two stage search on environment and task inference for wheeled mobile robots. For the first stage, a systematic search was conducted using a meta-search engine which included such databases as Compendex, IEEE Explore, and Inspec. The keywords used in our search consisted of mobile robots, exploration, navigation, multi-robot systems, environment inference, map inference/prediction, topology inference/prediction, multi-robot task allocation, intention inference/prediction, and global goal recognition. For the second stage, the following inclusion criteria were considered for article selection: 1) inference methods for mobile robots with wheel actuation (i.e., differential drive), and 2) inference methods to address mobile robotic tasks such as exploration, mapping, and navigation. Over 150 scholarly articles were identified, for which an in-depth study was completed to design an inference classification taxonomy on the current state of inference for mobile robot tasks. The findings were also combined to identify research challenges and future directions for this field.

Figure 1 presents the inference classification taxonomy for mobile robots that we have developed to encompass the various classes of methods. Namely, environment inference can be classified using map and topology-based inference approaches, where the former predicts the geometric configuration of unexplored regions and the latter predicts the semantic label and spatial relationships in unknown regions of a partially explored environment. Within map inference, global and local inference strategies can be used to predict

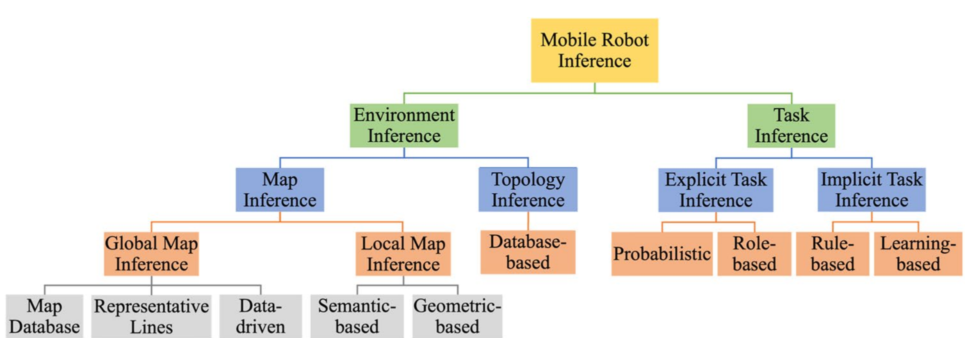


Fig. 1 Proposed taxonomy for mobile robot(s) inference

the spatial configuration of an environment (Global Map Inference) and missing observations within each robot's immediate vicinity (Local Map Inference), respectively. Global map inference methods can be further categorized by map database, representative lines, and data-driven approaches, while local map inference techniques are categorized by semantic-based and geometric-based approaches. For task inference, either explicit or implicit strategies can be used. For explicit task inference strategies, robot task inference and allocation are decoupled where mobile robots use probabilistic or role-based approaches to first predict teammates' intended tasks to execute. Then, the predicted teammate intentions are subsequently utilized for task allocation. Whereas in implicit task inference strategies, robot task inference and allocation are coupled, where teammate intentions are predicted and incorporated as a property of the resultant task allocation. This is achieved through either rule-based or learning-based approaches. The following sections will discuss the details of each of the classes represented within our proposed taxonomy.

3 Environment Inference for Mobile Robots

The environment inference problem for mobile robots is defined as the prediction of unexplored regions based on observations of explored regions in the same environment [44, 45]. Namely, environment inference provides both 1) geometric and 2) topological information to improve spatial reasoning in mobile robot tasks such as exploration and navigation [12, 48, 49].

Geometric information is represented by the spatial boundaries and shape of the environment [50]. Thus, the inferred geometric information regarding unexplored regions can be used to improve: 1) the selection of exploration goals to reduce the overall exploration time and 2) the coverage of inaccessible regions [44, 51–53]. Mobile robots can utilize the predicted geometric information to select exploration goals that lead to higher information gain as well as map regions that are not physically accessible. Furthermore, it can also be used to predict potential loop closures during simultaneous localization and mapping (SLAM) to minimize uncertainty in robot states. This creates more accurate maps compared to traditional non-predictive SLAM approaches [54] such as GMapping [55], Hector [56], and Cartographer [57]. In mobile robot navigation tasks, geometric information helps to anticipate obstacles in unknown regions in the environment during path planning [12, 58]. This is advantageous for robot tasks with perception occlusions such as search and rescue [43], and planetary exploration [59], where such environments are cluttered, obstructive, and unknown prior to robot deployment [9].

Topological information is represented by spatial semantic labels such as room types (office, reception area) in a building and the relationships between these labels such as proximity and travel distances [50]. This information is important for mobile robot spatial awareness and reasoning in human-centric environments as human-defined concepts such as rooms are essential for: 1) high-level search policies (i.e., mugs are in the cupboard in the kitchen), and 2) human–robot interactions (i.e., the person to provide a reminder to is asleep on a bed in the bedroom) [60].

In general, environment inference is a challenging problem to solve as unknown environments can be: 1) stochastic due to variability in their configurations and layouts, such as in human structural designs, natural habitats, and disastrous scenes; and 2) dynamic due to mobile humans and objects. Furthermore, as environment inference is dependent on the observed information from the explored regions, noisy sensory readings can further amplify uncertainties regarding the unexplored regions; making environment inference an even more challenging problem [61, 62]. As a result, existing environment inference methods have focused on single robot systems deployed in structured and repetitive environments, where geometric and topological information of the unobserved regions are predicted using structural cues from the observed regions. These methods can be categorized into either: 1) map inference [9, 12, 44, 45, 49, 51–54, 58, 63–70], or 2) topology inference [48, 60, 71].

3.1 Map Inference

Map inference is used by mobile robots to predict geometric information such as the occupancy and shape of unexplored regions within a partially explored map [9, 52]. The problem is similar to the scene completion problem in computer vision applications, where the objective is to construct partially occluded scenes with high-resolution surfaces based on dense volumetric and semantically annotated data [72, 73]. However, scene completion methods cannot be directly transferred to the robotic map inference problem, as they do not consider: 1) real-time execution, 2) the dynamics of the mobile robots as they complete navigation and exploration tasks, and 3) require careful selection of object views for training [12, 49, 58]. Alternatively, robotic map inference methods predict the geometry and occupancy of unknown regions in real-time at either a global [44, 45, 51–54, 63–65], or local [9, 12, 49, 58, 66–70] level, as shown in Fig. 2. At the global level, existing inference methods primarily utilized 2D maps for prediction [34, 44, 51–54, 63–65], whereas local inference methods have utilized either 2D maps [9, 58, 66, 68–70] or 3D RGB-D sensory information from robot ego-centric perspectives [12, 49, 67] for prediction.

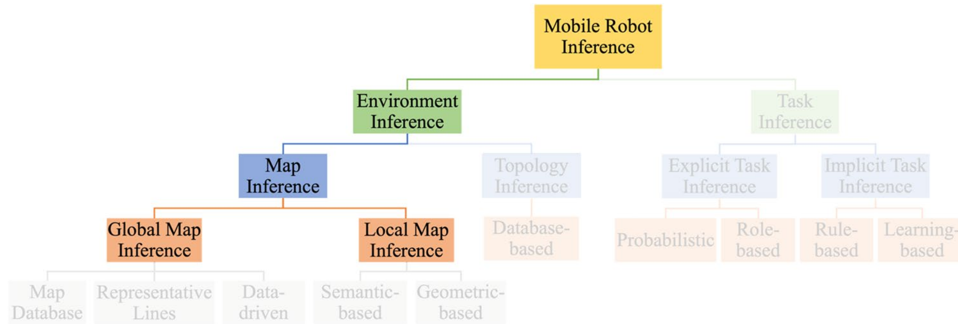


Fig. 2 Mobile robot(s) environment inference methods

3.1.1 Global Map Inference Strategies

Global inference methods represent strategies that predict the 2D geometric information of all unexplored regions within the entire environment [65]. Global inference strategies are mainly used in mobile robot exploration tasks, where mobile robots make decisions regarding goal locations to visit to maximize coverage. Thus, using the inferred 2D map for the unknown regions of an environment can aid in the selection of goal locations based on metrics such as inferred information gain [53], and the potential for loop closures [54]. As a result, global map inference can improve exploration performance by 1) reducing the total exploration time required by maximizing coverage, and 2) improving map accuracy by minimizing robot state uncertainty during localization, using the predicted geometric information when compared to traditional non-predictive exploration approaches such as frontier and utility-based methods [44, 51, 52, 63]. Existing global inference approaches for mobile robots, Fig. 3, can be categorized as: 1) map database [54, 63, 64], 2) representative lines [53], and/or 3) data-driven [44, 45, 51, 52, 65] techniques.

Map Database Approaches Map Database inference is contingent on the assumption that the target unknown regions share strong similarities in terms of geometric features with the observed regions of the environment [54]. Therefore, they are advantageous in environments with repetitive structural features such as room/region shapes and passages. In map database approaches, each mobile robot is equipped with a database of previously acquired 2D maps that are similar to the environment of interest, and inference is achieved using this database through a two-stage approach [54, 63, 64]. In the first stage, a target unknown region is compared with the stored maps to find a reference map. Specifically, 1) visual features such as walls and corners [54, 63] or 2) 2D laser scan features such as range data [64] are utilized to query the database for a similar map. To quantify similarity, the metrics considered are: 1) discrete feature vectors obtained from the visual bag-of-words approach using Fast Appearance Based Mapping (FabMAP2) [54], 2) the number of overlapping occupied cells [63] and 3) the map with the highest probability of generating the same features as the target region [64]. The highest similarity map in the database is selected as the reference map. In the second stage, a candidate for the target unknown region is generated based on this reference map. This is achieved by merging the reference map with the target region using either: 1) RANSAC-based alignment of the underlying Voronoi graphs [54], 2) spatial alignment via homogenous transform matrices [63], and 3) Gaussian filtering to improve cohesiveness [64] when merging the reference map with the target region. Since a target unknown region can be anywhere within the entire environment, database methods are therefore global inference techniques.

The aforementioned map inference methods have been utilized in robot exploration of structured environments and compared against more traditional approaches to highlight

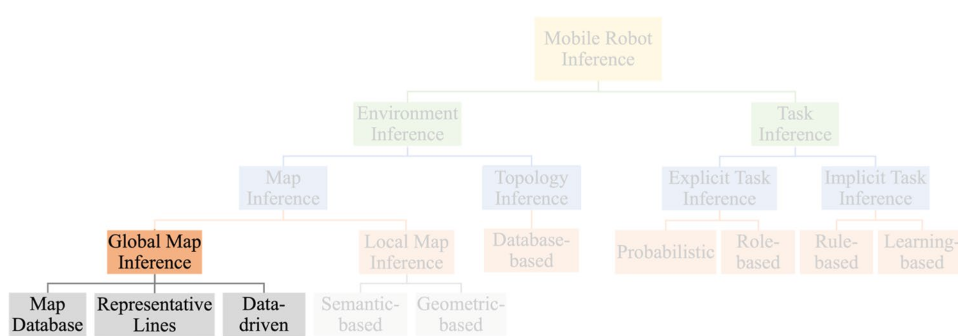


Fig. 3 Mobile robot(s) global map inference methods

their benefits. For example, in [54], the RANSAC-based map inference approach was incorporated with a utility-based single-robot exploration method. This was achieved with the breadth-first search of the underlying Voronoi graph of the environment to find goal locations that lead to potential loop closures to reduce robot state uncertainty with respect to its world during execution. This approach was compared against a traditional nearest frontier approach [74] in simulations of Roman Catacomb environments. The results showed that the nearest frontier approach was not able to complete exploration due to robot sensor drift during mapping which caused the robot to become stuck in a room. On the other hand, the reduced robot state uncertainty with respect to the explored environment in the database map inference-based exploration resulted in less sensor drift, which enabled it to finish the exploration of the entire environment and generate an accurate map.

In [63], an inference method using homogenous transform matrices was combined with a mapping method that uses a Rao-Blackewellized particle filter [75], where the inferred map was used to update the particle weights for robot localization in unknown regions prior to the robot entering these regions. This approach was compared with a non-predictive SLAM approach (using just Rao-Blackewellized particle filter) for mobile robot exploration of structured, indoor office environments. The results showed that map inference was able to: 1) generate a more accurate map in terms of visual similarity with the ground truth of the environment when using the same number of particles for robot state estimation during exploration, and 2) reduce the overall exploration time by 33% by using the predicted map to finish exploration early.

In [64], a Gaussian filtering-based inference method was utilized to estimate the expected information gain at goal locations. This information was used to inform goal selection in an auction-based multi-robot exploration method for real-world office environments. The experiments showed that the mobile robot team could explore and complete mapping using the inference method with the GMappings SLAM approach [55]. Additionally, the authors noted that by using a laser-feature-based approach, they were able to complete the reference map query in real-time, while the visual feature-based approaches used in [54, 63] could not be performed in real-time due to higher computational costs associated with visual feature matching.

Representative Lines Approach The representative lines approach can be used for environments with rectilinear walls, where the wall lines from a partially explored 2D map can be extended to predict the structural layout of unexplored regions [76]. As an assumption, this approach requires the presence of walls in the environment of interest and can be applied for mobile robot exploration in unknown indoor structured environments such as offices and homes. This approach was first presented in [76], where wall lines were forecasted and denoted as representative lines in order to divide a partially explored map by a mobile robot into multiple regions. Each region was either fully observed, partially observed, or unknown. To infer the missing shape of a partially explored region, a set of adjacent regions in the vicinity of the target unknown region were combined to generate the prediction. The prediction was evaluated with respect to the rest of the map using an objective function that considered 1) consistency in terms of the number of walls shared with neighboring rooms, 2) a simplicity metric based on the area and convex hull of the room layout, and 3) the number of walls to determine the final prediction. In this case, map inference can target all unknown regions within a partially explored environment, making the approach a global map inference technique.

The representative lines map inference approach was incorporated to aid with single-robot frontier-based exploration in [53] by accounting for the estimated information gain using the predicted map at each frontier location. Simulations were conducted in indoor structured floor plans and compared against a traditional frontier-based exploration without map inference [77]. The representative lines map-inference-based approach was approximately 12.8% faster in exploration time than the traditional frontier-based approach.

Data-driven Approaches Data-driven approaches can be used to infer the global geometry of a partially explored environment by extracting salient features (e.g., edges and contours) from structural information (e.g.., walls and corners) in the 2D map of the explored environment to make informed predictions about the unexplored regions [9, 51, 69]. Compared to the database and representative lines approaches, data-driven approaches do not require: 1) preloaded map databases to generate predictions during execution, or 2) the presence of walls within the environment. Instead, data-driven approaches utilize representative map data from the environment of interest, to learn to complete partially explored maps during offline training, without searching through a database during online execution. These approaches also target all unknown regions within the environment during inference; thereby, making them global inference strategies. They are based on either: 1) deep learning [44, 51, 52, 65] or 2) matrix completion [45] techniques.

The common deep learning approach used for map inference has been U-Net models [78]. These models include an encoder and a decoder network to generate map predictions for unknown regions within the environment based on 2D map images. The encoder network can utilize either 1) ResNet modules [52], or 2) traditional convolutional layers [44, 51, 65], to downsample and capture the spatial context such as room geometry in the input image. Compared to traditional convolutional layers, the ResNet modules utilize skip connections to enhance the map reconstruction performance in succeeding layers and address the challenges of exploding/vanishing gradients during the optimization process [79]. The decoder network is a mirrored version of the encoder network and is used to generate a prediction for the unexplored regions of the environment by reconstructing the encoded map features from the encoder. To train the proposed U-Net models, the loss function utilized is either: 1) cross-entropy and Kullback–Leibler Divergence [44, 52], 2) a custom topological loss function with persistent homology theory to match the predicted graph with the ground truth [51], or 3) Jensen-Shannon divergence between the U-Net generator and the training data distributions within a generative adversarial network (GAN) framework [65].

As an alternative to using deep neural networks for map inference, a partially completed 2D map can be represented as a matrix where the missing cell values can be recovered using low-rank matrix completion (LRMC) methods [45]. More specifically, an incomplete matrix that has both 1) a rank value smaller than its dimension, and 2) a coherence value close to zero, has been proven to be recoverable by solving the underlying non-convex optimization problem [80, 81]. Using this principle, in [45] a standard iterative-based Singular Value Decomposition [82] solver was applied to recover the missing matrix values within the robot map. While LRMC methods require less training data than deep learning methods [81], deep learning methods can be applied to a wider range of environments as robot maps are not constrained to configurations imposed by the rank and coherence value assumptions. Thus, deep neural network methods are more flexible, given representative training data from the environment of interest.

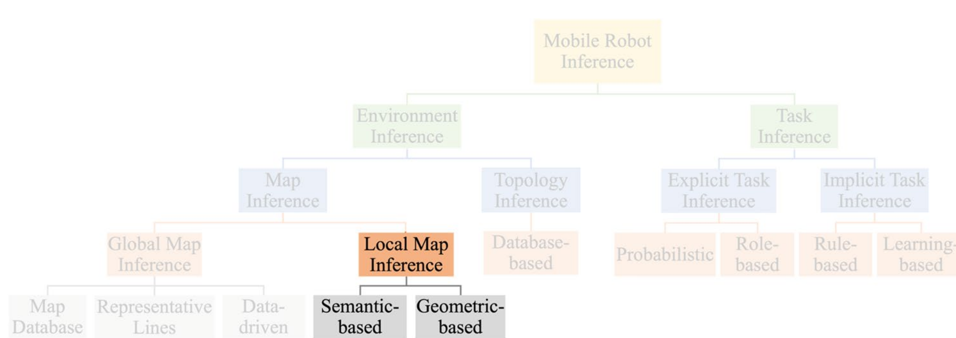
Both deep learning and LRMC methods have been trained with either indoor floor plans of office buildings [44, 52, 65], procedurally generated roads [45], or subterranean tunnel networks for mobile robot tasks such as: 1) exploration [44, 52], 2) mapping [65] and 3) coverage planning [45]. For the exploration tasks, the inferred map was incorporated with existing exploration strategies such as Hector exploration [44], and cost-utility [44, 52] to aid in robot goal selection. Simulations in indoor, domestic environments showed that the deep learning methods from [44, 52], had faster exploration completion time and lower travel distance compared to traditional exploration methods [56, 74, 83]. Furthermore, the inferred map was used for both the mapping and coverage planning tasks, where the map accuracy was improved compared to GMapping [55], and increased environment coverage was achieved with fewer action steps versus existing planners using myopic (short horizon) [84], and non-myopic (long horizon) [85] methods.

3.1.2 Local Map Inference Strategies

Local map inference is used to predict missing sensory information surrounding a robot as a result of occlusions that cause certain regions within this area to be unobservable [12, 71]. Compared to global inference, local inference is conducted at a smaller scale where the goal is to expand the robot's current field of view to gain greater spatial awareness in the immediate vicinity of the robot [12, 49, 67]. Local map inference methods have generally been used for mobile robot tasks such as semantic mapping, exploration, and navigation in unknown structured indoor [12, 49, 66–69] and open space [9, 12, 58, 70], environments. Existing local inference methods, Fig. 4, primarily utilize data-driven techniques that can be further categorized into: 1) semantic-based [49, 66–68] or 2) geometric-based [9, 12, 58, 69, 70] methods.

Semantic-based Approaches Semantic-based approaches have mainly been used in unknown human-centric environments as they use human denotations for objects and regions within the robot's environment to achieve local map inference. Namely, local map inference is achieved in a two-stage manner. In the first stage, mobile robot sensory information such as RGB images [68], RGB-D data [49, 67] and/or 2D laser scan readings [66] are used to predict the semantic label of partially observed 1) objects such as furniture [49, 67] and doors [68], and 2) spaces like offices and corridors [66]. This is achieved using learning-based models such as YOLOv4 [86], U-Net [78], and Sum Product Networks (SPN) [87]. The former two models utilize convolutional layers to perform object recognition [68], and semantic

Fig. 4 Mobile robot local map inference methods



segmentation [49, 67], while the latter utilizes directed acyclic graphs that compute probabilistic distributions over the available semantic spatial categories based on 2D laser scan readings [66]. Then, in the second stage, map inference is performed using semantic cognition from the first stage to infer the missing geometric observations within the local sensory information [49, 67]. This is achieved with 1) a pre-defined dimension estimation heuristic [68], 2) end-to-end reconstruction using the trained convolution-based models [49, 67], or 3) most probable explanation (MPE) inference over the predicted distribution from the SPN [66]. Since semantic-based methods only target occluded information within the mobile robot's sensory range; they are considered local inference strategies. These two-stage local map inference methods have been used in simulated domestic and office environments for mobile robot exploration [68], mapping [49, 66], and navigation [67] tasks.

In [68], YOLOv4 model was used for local map inference during single robot exploration to estimate the expected information gain behind closed doors to enhance robot goal selection. The results showed lower exploration time and distance compared to a Rapidly-exploring Random Tree-based exploration method [83], where goal selection did not anticipate the map in the unobserved region of the environment.

In [49], the U-Net map inference model was combined with active neural SLAM [88] for single robot semantic mapping. This resulted in a higher number of correctly predicted pixels (in terms of semantic labels with respect to the ground truth) when compared to a baseline mapping approach which used the deep high-resolution representation network (HRNetV2) [89] for semantic segmentation without map prediction. In [66], the SPN model was evaluated for its inference accuracy against a common image completion approach using generative adversarial networks (GANs) during single robot mapping [90]. The results showed comparable accuracy between the two approaches; however, SPN utilized 75% less computation than the GANs-based approach as it only required a single up/down pass through the network instead of hundreds of iterations as in GANs, making the SPN-based approach more suitable for real-time robot execution.

In [67], the U-Net map inference model was used to generate an uncertainty map that was subsequently utilized to learn a mobile robot navigation policy with Deep Q Networks (DQN) [91]. Simulation results in unknown, indoor domestic environments showed on average 15 times higher success rate in terms of reaching the desired destination when compared to navigation approaches without map inference, such as the Self Adaptive Visual Navigation (SAVN) [92] and Goal Oriented Semantic Exploration (GOSE) [93] strategies.

Geometric-based Approaches Geometric-based approaches for local map inference have been used for mobile robot exploration and navigation applications in structured, indoor environments [9, 12, 58, 69, 70]. In geometric-based methods, missing occupancy information within an incomplete map is inferred directly from the structural layout and shape of the partially explored map [69]. For mobile robots, local geometric-based inference is utilized to incorporate the predicted occupancy information during path planning and exploration goal selection to anticipate obstacles and potential information gain, respectively, in unseen/occluded regions of the environment. Thus, the focus is on predicting the spatial geometry in regions where the mobile robot will navigate next. This is typically achieved using either: 1) autoencoder networks [12, 58, 69, 70], or 2) conditional neural processes (CNPs) [9]. Similar to the data-driven approaches, autoencoder networks, autoencoder networks used herein also include encoder and decoder networks that utilize convolutional downsampling and upsampling layers for input encoding and decoding to generate missing observations during spatial reconstruction [69]. The input data typically includes partially observed 2D maps [9, 58, 69, 70], and/or RGB-D images from robot egocentric perspectives [12]. On the other hand, CNPs are stochastic processes that have been used to approximate the distribution of occupancy prediction functions on unobserved regions that are conditioned on the occupancy of the explored regions [9]. As a result, CNPs require less training data than autoencoder networks, as they can exploit prior knowledge from training data during testing, which makes them more applicable for mobile robot environments where training data is limited or costly to acquire [94].

Both types of deep learning models have been trained for local map inference using real-world sensor data of 3D indoor structured environments from publicly available datasets such as Gibson [95], Matterport3D [96], Google Cartographer [57], and KTH [48], and applied for mobile robot navigation [9, 12, 58, 70], and exploration tasks [12, 69]. In mobile robot navigation tasks, the autoencoder-based methods were incorporated within learning-based planners to anticipate the geometry of upcoming regions during navigation using deep reinforcement learning [12], or classical planners that optimized robot trajectory with respect to travel time and localization uncertainty [58, 70]. Whereas CNP has been incorporated with a classical planner to consider dynamic constraints when planning minimal time trajectories [9]. Experimental results showed that navigation with geometric map inference yielded a higher success rate and lower travel time and distance when compared against naïve and conservative path planning benchmarks that anticipated unknown regions by assuming they were occupied. In mobile robot exploration tasks, the inferred map from the autoencoder-based methods has been incorporated with an information-theoretic exploration strategy [69] or within a deep reinforcement learning framework such as Proximal Policy Optimization (PPO) [97] to learn an exploration policy that maps RGB-D images to exploration actions [12]. Simulation results showed higher map accuracy [12], and less travel distance [69], compared to traditional exploration strategies that do not consider the inferred map from unexplored regions of the environment.

3.2 Topology Inference

In topology inference, the environment is represented as an undirected graph where nodes define the semantic categories of spatial concepts with human denotations such as the types of rooms, area, and corridor, while edges define the distance between rooms [50]. Therefore, the topology inference problem can be defined as the prediction of both the semantic labels of nodes in the unexplored portion of an environment and the edges that connect them to the explored environment [48]. As a result, topology inference differs from map inference, as the objective of the former is to predict the spatial relationships between regions in the environment, rather than to predict the overall geometry of the unknown spatial configuration. Therefore, topology inference methods are primarily designed for human-centric environments and are used for mobile robot exploration tasks [60, 71], where spatial semantic labels are critical for mobile robot reasoning. To date, the existing topology inference methods for mobile robotics have primarily utilized a database-based approach for prediction [48, 60, 71], Fig. 5.

Similar to the database approaches used in global map inference strategies database approaches for topology prediction can be applied in environments where a priori knowledge of similar environments (but not necessarily the current environment) is known. Robots make predictions about edit operations (i.e., node and edge additions) for unexplored regions of the environment using a partially explored graph during deployment, which is based on graph-based topological structures stored in a database [48, 71]. Common databases used have typically included 2D indoor floor plans of office environments from the MIT [50], KTH [48], and COLD-Stockholm [98] datasets. Prediction of the semantic labels of nodes and the edges that define how to incorporate new nodes in partially complete graphs has been achieved using three main methods: 1) frequency-based [48], 2) probabilistic-based [48, 60] and 3) sampling-based [71].

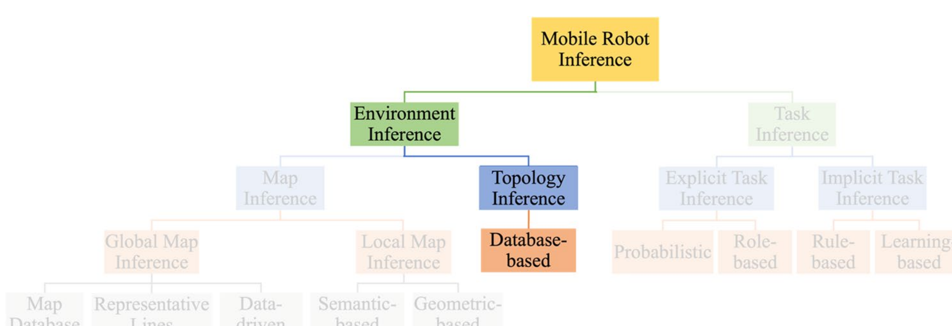
The frequency-based method [48] uses a naïve strategy, where topological map candidates are created by first making eligible edit operations (i.e., the addition of nodes and edges), to the input graph. The frequency of the resultant edited graph within the database is then used to select the final topological map prediction [48].

In the probabilistic-based methods [48, 60], the probability of an edit operation is determined based on statistics from the database in two ways. The first is to decompose the input graph into smaller subgraphs, and then find the discrete probability distribution of each edit operation using a subset of the database with subgraphs from the input graph [48]. Then, the edit operation with the highest probability is selected to generate the final topological map prediction [48]. The second approach uses a probabilistic chain graph to represent the topological structure of the environment and then converts the structure to a factor graph where the prediction is made using Loopy Belief Propagation [60, 99]. Both approaches incorporate the probability of edit operations using existing topological maps within the database.

Lastly, in the sampling-based method [71], the input graph is utilized to first find similar graphs within the database. A similarity index is calculated by the dot product between these graphs [100], using convolutional graph kernels such as Weisfeiler-Lehman Subtree Kernel [101], and Graph Hopper Kernel [102]. Then, prediction of the node and edge additions to the input graph is achieved by sampling subgraphs from clusters of similar graphs within the database using Monte Carlo Markov Chain sampling [103] and then connecting the sampled subgraphs to the input graph to generate the final prediction [71].

The proposed topology inference methods in [48, 71] have been evaluated based on their prediction accuracy for mobile robot exploration in structured indoor environments using the MIT [50] and KTH [48] datasets. The results showed that

Fig. 5 Mobile robot topology inference method



the probabilistic-based approach obtained higher accuracy in terms of correctly predicted semantic labels and edges, compared to the frequency-based approach [48]. In [71], the predicted graphs from the probabilistic approach were compared with the ground truth and found to have negligible differences in terms of the average centrality and standard deviation. In [60], the sampling-based inference approach was incorporated within a mobile robot semantic mapping system that utilized both a support vector machine (SVM) [104] for room shape, size, appearance categorization, and Scale-Invariant Feature Transform (SIFT) [105] for object recognition in structured indoor environments. The results from trials in real-world environments, where a mobile robot was manually driven to complete mapping, showed a successful prediction of room categories in unexplored regions and their relation to the explored regions.

3.3 Discussions on Environment Inference Methods

Environment inference methods provide mobile robots with geometric and topologic information in unknown regions of partially explored environments, using either map and topology inference approaches, respectively. This is beneficial for mobile robot reasoning in unknown environments, as it extends a mobile robot's awareness of the structural layout and semantic knowledge beyond the robot's available sensory range [12]. When compared to traditional methods for navigation (i.e., optimal travel time, distance planners [58, 70]), and exploration (i.e., nearest-frontier [74], utility-based [106, 107]) where mobile robot decisions only consider the observable part of the robot's surroundings, environment inference enables robots to anticipate the spatial configuration in the unobserved (due to sensor range and occlusion) regions beyond the robot's surroundings during planning [48, 51]. Table 1 provides a summary overview of the aforementioned environment inference methods, in terms of their approach, application and environment types.

Global map inference strategies have the advantage of targeting multiple regions within a mobile robot's environment, thereby making them appropriate for mobile robot exploration tasks where the potential information gain of exploration goal candidates can be estimated using the inferred map. Database approaches used in Global map inference are only computationally tractable for simple and repetitive environments as the search space for reference maps is proportional to the number of maps and map features within the database; whereas representative lines are limited to mobile robot applications in environments with rectilinear walls. However, data-driven approaches can be applied to any type of unknown environment; though data collection and labeling for training can be costly and time-consuming due to manually having to label the data. On the other hand, local map inference strategies focus on inferring missing observations due to sensor occlusions within the mobile robot's immediate vicinity. Thus, these strategies are mainly used for mobile robot mapping and navigation tasks in order to predict occluded objects in the environment and anticipate approaching obstacles and turns to achieve safe and smooth robot trajectories. Semantic-based local map inference approaches utilize a multi-stage prediction pipeline; thus, creating opportunities for errors to cascade (i.e., map prediction accuracy is contingent on the semantic classification accuracy) [67]. Similar to the data-driven approaches in global map inference strategies, geometric-based approaches mainly utilize deep learning methods; which can use upwards of 35,000 floor plans during training [58, 70]. Therefore, geometric-based methods have been limited to unknown indoor structured environments where public datasets are available [50, 48].

In topology inference methods, predictions are based on graphical representations of the environment where nodes and edges symbolize spatial semantic categories. Existing methods typically utilize a database-based approach where the unexplored nodes and edges are predicted using statistical methods from similar floor plans that are acquired a priori. Therefore, topology inference methods are well-suited for robot tasks such as semantic mapping [60] and exploration [71] of human-centric environments. As such, existing topology inference methods are limited in their generalizability, since predictions are generated based on the topological graphs available within the robot's database. Thus, topology inference methods cannot be easily applied to unstructured outdoor terrains, as spatial similarities of regions can be non-existent from region to region.

4 Task Inference for Multi-robot System

Multi-robot task inference is defined as the prediction of a robot's expected task by another robot based on complete or partial observations of its behavior during task allocation [46]. Subsequently, multi-robot task inference is closely related to multi-robot task allocation (MRTA), which describes the assignment of tasks to robots working in a team to cooperatively complete a global objective [108]. Mobile robot tasks are typically spatially distributed and require the navigation and exploration of the environment. Traditionally, MRTA describes an explicit cooperation approach as task and teammate information is deliberately exchanged for task allocation [10]. This is typically achieved with market-based [109–111], optimization-based [112–116], and stochastic model-based [8, 117–119] approaches. However, explicit cooperation approaches are dependent on the direct information exchange between robots, and/or with a central controller to create an overall task allocation plan [120]. As a result, mobile robot teams that utilize explicit cooperation

Table 1 Summary of Environment Inference Methods

Inference Type	Approach Type	Approach	Application Type	Environment Type	Ref
Global Map Inference					
Map Database	Heuristics	Spatial alignment with Gaussian filtering	Multi-robot exploration	Structured indoor environments	[64]
		Spatial alignment with RANSAC-based approach	Mobile robot exploration	Structured outdoor environments	[54]
		Spatial alignment with homogeneous transform matrices		Structured indoor environments	[63]
Representative lines		Forecasting wall lines			[53]
Data-driven	Deep learning	Variational Autoencoder			[44]
		Convolutional autoencoder with skip connections			[52]
		Convolutional layers with U-Net architecture		Grid world environments	[51]
		Generative adversarial networks		Structured indoor environments	[65]
	Statistical	Low-rank matrix completion		Grid world environments	[45]
Local Map Inference					
Semantic-based	Deep learning	Multi-modality imagination unit with Resnet18 and U-Net architecture	Mobile robot mapping	Structured indoor environments	[49]
		A deep generative spatial model with sum-product networks			[66]
		A framework of segmentation, completion, and confidence neural networks	Mobile robot navigation		[67]
		Heuristics-based dimension estimation using YOLOv4 for object recognition	Mobile robot exploration		[68]
Geometric-based		A multi-modal model with U-Net architecture			[12]
		U-Net architecture with skip connections			[69]
		Obstacle prediction network with U-Net architecture and Atrous Spatial Pyramid Pooling	Mobile robot navigation	Structured indoor environments	[58]
		Conditional Neural Process			[9]
		Conditional Generative Model			[70]
Topology Inference					
Database-based	Statistical	Frequency-based and probabilistic based approaches	Mobile robot exploration	Structured indoor environments	[48]
		Probabilistic chain graph model with Loopy Belief Propagation	Mobile robot mapping		[60]
	Classical learning	Generative model based on constructive machine learning approach	Mobile robot exploration		[71]

approaches can become uncoordinated if they cannot agree on the team allocation plan when information exchange is unreliable/unavailable due to poor communication infrastructure (i.e., network routers), and/or hardware limitations (i.e., transmission range) [121].

Mobile robot teams that utilize task inference can predict the expected tasks of their teammates (i.e., their intentions) when explicit information exchange is not possible [122]. Therefore, MRTA with task inference describes an implicit cooperation approach, where coordination is maintained by robots that make independent and complementary decisions regarding which task to execute [123]. Task inference is important in mobile robot applications where communication can be limited, unreliable, and/or costly [122]. Additionally, task inference can also improve the scalability of multi-robot systems by reducing the communication and computation overhead associated with increasing robot team size as less information needs to be exchanged and processed if they can be predicted [124]. However, task inference is a difficult problem to solve in an unconstrained environment where the number of tasks and the steps to complete the tasks are extensive and can be unknown prior to deployment [14]. Existing methods for multi-robot task inference, Fig. 6, can be categorized into two main strategies, namely: 1) explicit [122, 124–126], and 2) implicit [10, 123, 127–133].

In explicit task inference strategies, task inference and task allocation are completed separately in a two-stage manner, where robot teammate intentions are first predicted, and then subsequently incorporated for task allocation [134]. In contrast, in implicit task inference strategies, task inference and allocation are completed in an end-to-end manner by mapping robot observations directly to task allocation in the form of robot actions [130]. Thus, in the latter teammate intentions are predicted and incorporated as a property of the resultant task allocation plan. Both strategies utilize the inferred teammate intentions for MRTA, with the difference being 1) explicit task inference strategies are decoupled from MRTA while 2) implicit task inference strategies are coupled with MRTA. Multi-robot task inference has been used for mobile robot tasks such as exploration of unknown indoor environments [125–128], landmark-based navigation [130–133], active monitoring of an environment [122, 124] object search and retrieval [123], and robotic soccer [10, 129].

4.1 Explicit Task Inference Strategies

In explicit task inference strategies, the intentions of teammates are explicitly predicted by directly determining the most likely task a robot teammate intends to execute. This is achieved by reasoning about the available tasks based on a priori knowledge of domain information such as the environment size [124, 125], and teammate policies [122, 126]. MRTA is achieved subsequently using the inferred teammate tasks for multi-robot coordination. Explicit task inference strategies, Fig. 7, can be categorized into: 1) probabilistic [124, 125] and 2) role-based [122, 126] approaches, where robots using the former strategy compute a probability distribution over the available tasks, whereas robots in the latter utilize their teammate's policy to directly determine their teammate's intentions.

4.1.1 Probabilistic Approaches

Probabilistic approaches target robot applications with spatially distributed tasks, where task completion is achieved by a mobile robot navigating to a specific location in the environment. Hence, probabilistic approaches typically utilize statistical inference methods to compute a probability distribution over all available locations within the environment in order to predict robot teammate intentions.

Fig. 6 Multi-robot task inference methods

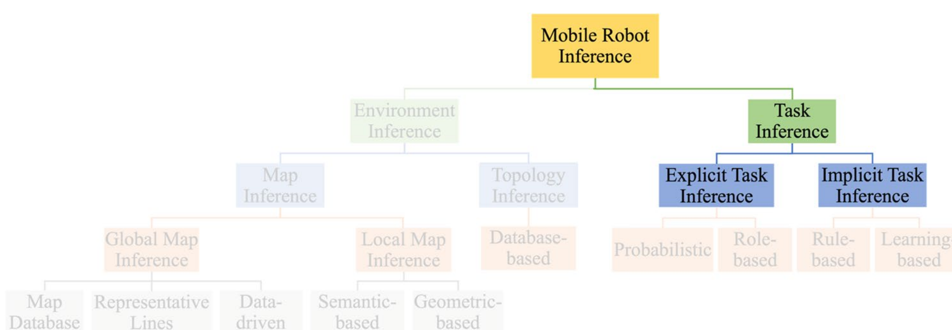
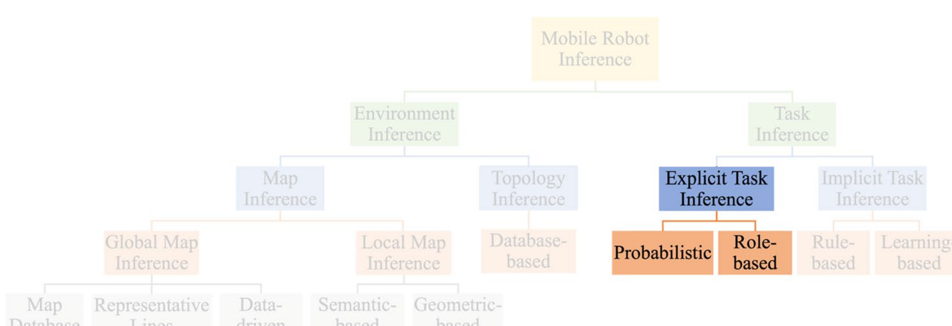


Fig. 7 Multi-robot explicit task inference methods



These probability distributions are determined for teammate goal locations conditioned on either 1) teammates' current states (locations) [124], or 2) the time elapsed since the last observation of teammates' locations [125].

In [124], a presence mass distribution is used to model individual robot locations at a future time step in order to indicate the tasks that they intend to execute, based on the current global state of all teammates. The presence mass distributions for each teammate robot are subsequently combined to create a single statistic measure that embodies the aggregate effect of all teammate intentions. In [125], the likelihood of a teammate robot navigating to a particular goal location is estimated using a wavefront propagation algorithm that iterates over every state within the environment to update future state values based on the last known teammates' positions and the time elapsed since observing these positions. In both of these approaches, the predicted teammates' tasks are subsequently used with planning-based MRTA methods to discount the value of future states for each robot. The planning-based MRTA methods include sequential decision frameworks such as 1) Multiagent Markov Decision Process (MMDP) [124], and 2) Decentralized Markov Decision Process (Dec-MDP) [125], where the policy is solved online using standard MDP techniques (i.e., dynamic programming). The obtained robot policy is then used by each robot to select complementary tasks to execute to cooperatively complete the global task. Thus, probabilistic approaches are explicit task inference strategies, as task inference is completed prior to task allocation based on direct probabilistic estimation of teammates' intentions over the available tasks.

The existing explicit task inference approaches have been used in multi-robot monitoring [124], and exploration [125] of 2D environments, respectively. For the multi-robot monitoring task, "dirt" is randomly placed throughout the simulated environment, and the robots are required to navigate to the dirt locations in order to clean them [124]. The probabilistic task inference method using MMDP showed near-optimal solutions when compared with a standard optimal solver (Stochastic Planning using Decision Diagrams [135]) in terms of the average expected discounted reward for each starting state. Furthermore, the MMDP approach was able to scale to larger 6×6 grid world environments and team sizes of 6 robots, while the standard optimal solver was limited to 3×3 grid world environments with up to 3 robots. The probabilistic task inference approach with Dec-MDP [125], was evaluated in both simulation and real-world structured, unknown environments for multi-robot exploration. Results showed a reduction in both exploration time and local interactions between robots when compared to a traditional utility-based exploration method [136].

4.1.2 Role-based Approaches

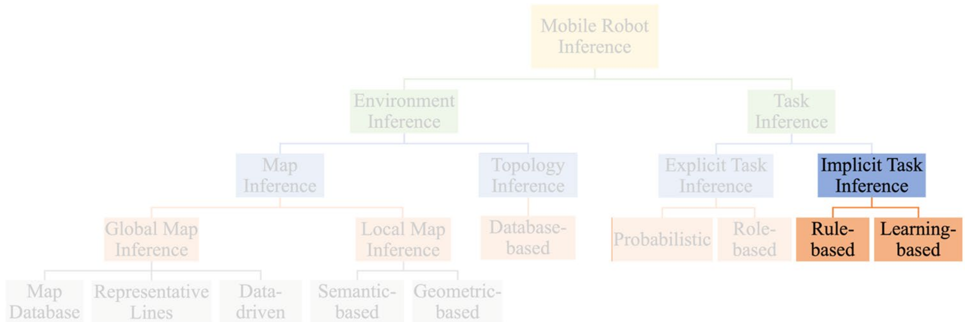
Role-based approaches for task inference have been designed for heterogeneous robot teams, where individual robot members can have different sensory, computation, and/or actuation systems to fulfill their distinct roles [137]. Each robot's role is described by a policy, which determines the robot's behavior by mapping robot observations to actions. Thus, role-based approaches achieve explicit task inference by first using teammates' policies to directly predict teammates' intended tasks to execute and then complete MRTA thereafter using the predicted tasks of the teammates. This is achieved using two sequential decision-making methods; namely, Partially Observable Markov Decision Process (POMDP) [122] and Decentralized Multi-policy Decision Making (D-MPDM) [126]. In both methods, a fixed set of manually designed policies based on a priori domain and task knowledge is available to all robots within a team. For task inference, individual robots first estimate their teammates' belief states and locations by using Bayesian estimation [122], or a particle filter [126]. This allows the robots to obtain their teammates' expected tasks to execute through forward simulation by passing the estimated belief states and locations through the respective teammates' policies to obtain their action outputs. The predicted tasks of the teammates are then utilized for MRTA by either using a policy: 1) that takes as input the robot's observation as well as teammates' expected task to execute [122], or 2) with the minimal time to goal after performing multiple forward simulations across all available policies [126]. Since task allocation is achieved separately from task inference, role-based approaches describe an explicit task inference strategy.

Similar to probabilistic approaches, role-based approaches have also been used for multi-robot monitoring and exploration tasks under communication limitations in 2D environments [122, 126]. In both applications, the role-based POMDP and D-MPDM based methods achieved higher task completion rates and needed fewer timesteps than traditional POMDP and depth-first search methods which do not consider teammate intentions during communication dropouts.

4.2 Implicit Task Inference Strategies

In implicit task inference strategies, mobile robot intentions are indirectly predicted and incorporated as part of the MRTA process; without directly predicting the expected tasks of robot teammates [129]. This can be achieved through rule-based and learning based methods, Fig. 8. For rule-based strategies, robot intentions are implicitly inferred using handcrafted heuristics based on what robots have already completed (i.e., their progress) or how well they can accomplish a given task (i.e., their performance) [123,

Fig. 8 Multi-robots implicit task inference methods



127–129]. Furthermore, for learning-based strategies robot teammate intentions are learned from both robot experiences and labeled data from human demonstrations during offline training [10, 130–133]. In both rule-based and learning-based approaches, task inference is achieved as part of task allocation where robot observations are mapped directly to action selection. Thus, individual robots make decisions regarding the tasks to execute while teammate intentions are incorporated implicitly within the resultant task decision; thereby, coupling task inference and allocation. Compared to explicit task inference strategies, implicit task inference strategies are advantageous in that they do not: 1) need to iteratively compute a probability distribution over the available tasks, which thus reduces the computational burden with the increasing number of tasks compared to probabilistic approaches (Sect. 4.1.1), and 2) require a priori knowledge of teammate policies for task inference that can limit robots to simple manually designed behaviors as in role-based approaches (Sect. 4.1.2).

4.2.1 Rule-based Approaches

In rule-based approaches, task inference is achieved via manually designed heuristics that leverage teammate information using progress [127, 128], and performance [123, 129] measures, as a proxy for their intended task to execute. Namely, robot progress describes the tasks that have been completed [128], while performance describes a robot's ability to complete an incomplete task [123]. Rule-based approaches have been used in multi-robot exploration [127, 128], search and retrieval of objects [123], and robotic soccer [129] applications, to predict future robot intentions. In multi-robot exploration [127, 128], each robot uses a greedy heuristic to select an exploration goal candidate from unknown regions within the generated maps of other teammates in order to reduce overlap in mapping effort. Teammate intentions are implicitly inferred during goal selection as coordination is achieved by robots selecting complementary goals based on what their teammates are likely to explore next (conditioned on what they have already explored) in order to maximize coverage. Mobile robot performance measures are typically represented by a travel cost, which includes either: 1) travel distance [123] or 2) travel time [129], required to complete a task. In object search and retrieval applications, travel distance cost can be estimated using an A* graph search between an observed teammate position and the known task location [123]. Whereas, in robotic soccer, travel time cost to regain ball possession can be estimated using machine learning models such as model trees and neural networks, trained with manually collected data including robot velocity, distance, and heading angles [129]. Since robots are expected to minimize cost during execution, their intention to execute a task is indirectly predicted based on their ability to complete the task. As a result, a robot selects a task to execute, based on knowing that its teammates cannot complete the selected task at a lower cost using the estimated performance measure.

In terms of experiments, the proposed rule-based approaches have been evaluated in 2D simulation environments [123, 127, 128], real-world structured indoor lab environments [128], and soccer fields [129]. For multi-robot exploration, the progress-based approach showed successful exploration to complete coverage of the unknown environment [127, 128]. In the robot object search and retrieval application [123], colored blocks were randomly distributed throughout an initially unknown environment, where a multi-robot team was expected to locate the blocks and return them to a designated area. The performance measure approach using travel distance as a cost [123] yielded a faster completion time when compared to a traditional auction-based approach [138]. A 95% success rate was achieved in assigning the correct robot to regain ball possession in robotic soccer when using travel time as a cost for the performance measure [129]. Furthermore, in [129], the choice of travel time versus travel distance as the performance measure was investigated to facilitate effective coordination without explicit information exchange. The results showed that using travel distance, the robots only achieved an 81% success rate in correct allocations.

4.2.2 Learning-based Approaches

In learning-based approaches, task inference is learned using Learning from Demonstration (LfD) [10], or Deep Reinforcement Learning (DRL) [130–133], techniques. In both techniques, task inference and allocation are completed in an end-to-end manner, where robots make action selection decisions directly from observations. Compared to rule-based approaches, learning-based approaches do not require handcrafted heuristics but instead rely on training data to learn robot action selection. More specifically, in LfD methods, human operators remotely control each robot in parallel within a team to complete different tasks. During training, each robot learns from human demonstration the necessary actions for multi-robot coordination, using observations of teammate positions/locations and actions to implicitly learn their intentions. Namely, in [10], the LfD approach utilized Case-Based Reasoning (CBR) [139], which describes a high-level planning approach that generates the tasks to execute based on past experiences obtained from observations and human control during training. For the DRL methods, mobile robots directly interact with the task environment repeatedly to learn an end-to-end policy that maps sensory inputs directly to robot actions [140]. In DRL, the policy is parameterized by a neural network function approximator, where the weights are optimized with respect to a manually defined reward function designed to encourage robots to achieve the desired cooperative behavior in the given task environment [141]. Therefore, teammates' intentions are implicitly predicted and incorporated as a property within the hidden states of the robot's policy [47]. The DRL techniques considered in implicit task inference include Dueling Deep Q Networks (DDQN) [130, 131], and Deep Deterministic Policy Gradients (DDPG) [132, 133]. The learned policy utilizes sensory inputs including the robot's position and speed, as well as partial observations of teammate positions and their goal locations to generate discrete [130, 131] or continuous [132, 133] robot actions; thereby, achieving task allocation without directly predicting teammates' intended tasks. This is true for both LfD and DRL methods, where task inference is achieved implicitly and incorporated as a property of the task allocation plan; therefore, learning-based approaches are implicit task inference strategies.

Learning-based approaches have been used for robotic soccer [10] as well as landmark-based navigation [130–133]. In robot soccer, the LfD task inference approach was evaluated in a 2D simulated soccer field [10]. The results showed successful cooperation behaviors between mobile robots in a team in evading defender robots and scoring. In landmark-based navigation, goal locations were distributed throughout 2D open space environments, where the objective of each mobile robot was to navigate to unique locations using either DDQN or DDPG DRL methods without arriving at other robots' goals [130–133]. Experiments were conducted with both static and dynamic obstacles with fixed boundaries. In general, the DDQN and DDPG based task inference approach resulted in lower travel distances and higher success rates in terms of cooperatively arriving at unique locations when compared against traditional planning-based navigation approaches [142] and alternative DRL architectures such as DQN and DDQN [143].

4.3 Discussions on Task Inference Methods

The objective of task inference for multi-robot systems is to predict the task intentions of robot teammates in order to achieve effective task allocation without the continuous exchange of information between robot teammates [46, 47]. Therefore, MRTA methods using explicit [122, 124–126], or implicit [10, 123, 127–133], task inference strategies allow robots to make independent decisions regarding the tasks to be executed while accounting for what their teammates are likely to do next, in order to complete complementary tasks in communication-limited environments. Thus, enabling robot teams to operate in realistic environments where information exchanges between robots are neither permanent nor free of cost [144]. In addition, task inference also reduces the computation and communication overhead in multi-robot systems, leading to better scalability of robot team size as a result of lower communication bandwidth, and information processing [126]. Table 2 provides a summary overview of the task inference methods discussed herein, in terms of their approach, application and environment types.

In explicit task inference strategies, teammates' intended tasks are first predicted, and then incorporated for task allocation. This is achieved using either probabilistic or role-based approaches. Both approaches have the advantage of interpretability in terms of the prediction result being quantitative and understandable to the human designer [145]. However, as mobile robot tasks are spatially distributed, probabilistic approaches are only computationally tractable for small environments. This is due to the number of robot tasks increasing proportionally with environment size, making iterating over every possible task to obtain a probability distribution computational expensive. Conversely, role-based approaches require a priori knowledge of all robot teammate policies to predict their intentions. However, existing policies have been limited to manually designed heuristics, where predictions are centered around high-level robot intentions such as whether a robot will act greedily or randomly or a binary classification of whether a robot has completed a task that is defined by its role. This limits the classification of teammate intentions to a predefined selection of high-level intentions which are independent of environment size. As a result, role-based approaches are better suited for larger environments (i.e., higher number of

Table 2 Summary of Task Inference Methods

Inference Type	Approach Type	Approach	Application Type	Environment Type	Ref
Explicit Task Inference					
Probabilistic-based	Heuristics	Presence mass distribution	Multi-robot task cooperation	Grid world environments	[124]
		Wavefront propagation algorithm	Multi-robot exploration	Structured indoor environments	[125]
Role-based	Statistical	Bayesian estimation of belief state		Grid world environments	[122]
		Forward simulation of policy with particle filter estimation			[126]
Implicit Task Inference					
Rule-based	Heuristics	Locally shared 2D maps	Multi-robot exploration	Structured indoor environments	[127, 128]
		Travel cost estimation with A*	Multi-robot task cooperation		[123]
		Travel cost estimation with model trees and neural networks	Multi-robot task cooperation	Structured outdoor environment	[129]
Learning-based	Classical learning	Case-based reasoning			[10]
	Deep learning	Deep Q Network and Dueling architecture	Multi-robot navigation	Grid world environments	[130]
		Enhanced deep deterministic policy gradient			[132]
		Multi-modal Deep Q Network and Dueling architecture		Unstructured outdoor environments	[131]
		Deep deterministic policy gradient		Structured indoor environments	[133]

tasks) compared to probabilistic approaches, where the number of teammate intentions are dependent on the environment size.

In implicit task inference strategies, task inference and allocation are coupled, as teammate intentions are captured as a property of task allocation. Rule-based and learning-based approaches have been used to map robot sensor observations directly to robot action in an end-to-end manner. Rule-based approaches require domain expert knowledge to select appropriate robot features such as the progress and performance measures used to achieve implicit task inference, resulting in the loss of critical information regarding the true underlying robot and environment states [146]. Conversely, learning-based approaches can learn complex task inference strategies from high-dimensional sensory data; however, they require offline training which can be time-consuming and require expert knowledge to obtain and create labeled datasets.

5 Open Challenges and Future Research Directions

To date, existing environment and task inference methods have been used to address single robot and multi-robot system challenges in unknown environments. While environment inference has aided with navigation [58], exploration [54], and mapping [66] tasks, task inference has focused on improving robot coordination and cooperation for task allocation in scenarios where robots have limited communication and perception [10, 122], highlighting the potential of using inference for mobile robotics and MRTA problems. However, many open challenges still remain. For example, current environment inference methods have focused on single robot applications, and have not yet been extended to multi-robot systems. Furthermore, they have mainly considered static features such as walls and corners for map and topology inference in unknown indoor structured environments [52]; and have not considered features that can be obtained from teammate robot actions. Similarly, existing task inference methods do not yet account for task abandonment during robot execution where a robot's actions can be suboptimal due to environmental (i.e., stochastic action outcome) and hardware (i.e., perception uncertainty) factors [147]. We discuss these two important challenges below and propose potential research directions that can be explored to address them.

5.1 Challenge 1: Multi-robot map inference using teammate actions

In existing map inference methods, a single robot's prediction of unknown regions is contingent solely on the geometric information obtained via its onboard sensors (i.e., camera, rangefinder) from the observed regions within the partially explored environment [69]. In general, multi-robot systems provide improved robustness, reliability, and overall performance gains in terms of task completion efficiency due to better spatial distribution compared to single robot systems [148]. Therefore, map inference methods should leverage information from multiple robots that operate in a shared space by using observations of their actions to provide high-level contextual information for map inference [149]. Consider a navigation task, where observations of a teammate robot emerging from behind an obstacle can be used to infer the existence of a traversable pathway behind the obstacle [150]. Similarly, in an exploration task, observations of a teammate robot making a U-turn at the end of a corridor suggest the absence of information gain at the end of the corridor (i.e., dead-end). In both of these examples, teammate robot actions contribute contextual information for map inference that enables a high-level understanding of the robot's environment which can reduce robot replanning efforts during execution [151]. To our knowledge, there exists only one multi-robot map inference method [64], however, the method only utilizes geometric information from 2D laser scans of the robot's static environment to infer the spatial layout of the unexplored regions. Teammate robots were considered subsequently during the goal assignment stage for multi-robot exploration, which utilized an auction mechanism for explicit cooperation. Thus, map inference was achieved without the consideration of teammate robots deployed within the shared space.

In order to incorporate teammate actions for the purpose of map inference, teammates can be modeled as dynamic sensors that take as input the environment geometry and output their actions, respectively. Therefore, a robot can treat its teammates as mobile sensors in the environment and incorporate both environmental contextual and geometric information from them during inference. This concept has been recently explored in self-driving car applications with nearby drivers modeled as sensors using K-means clustering and conditional variational autoencoders to map discrete driver action classes (i.e., slowing down, speeding up) [152], and past vehicle trajectories in order to make geometric predictions for occluded regions. However, since the proposed methods have focused on autonomous driving, they are limited by: 1) simple and controlled traffic scenarios where road agents (i.e., vehicles and pedestrians) follow specific navigation rules, 2) predictions focused only on pre-defined regions that are commonly occluded due to incoming traffic at crosswalks and intersections, and 3) driver actions constrained by vehicle kinodynamics. As a result, these methods cannot be easily transferred to address the map inference problem in cluttered and unknown environments. Potential research fields include image [153–155] and video inpainting [156–158] to address the problem of incorporating static and dynamic features from the known environment during prediction. Namely, image inpainting completes a partially occluded image by predicting missing pixel values based on spatial and semantic context from the non-occluded regions of the image [153]. Thus, image inpainting methods can target arbitrary regions during prediction by considering static features (i.e., obstacle placement/geometry) from the known environment. On the other hand, video inpainting methods extend the image inpainting task to incorporate spatial and temporal coherence with respect to prior consecutive image inputs during prediction. Therefore, video inpainting methods can be utilized to incorporate dynamic information (i.e., teammate trajectories) within the robot's environment during map prediction. However, existing video inpainting methods have not been applied in robotics, as they are limited to scenes without significant appearance changes where the subject (i.e., robot teammate) experiences simple linear motion across consecutive frames [159]. Therefore, a promising research direction is to address temporal consistency with complex motions from challenging mobile robot trajectories in unstructured and cluttered environments, where the spatial configuration can change significantly between consecutive decision timesteps during robot navigation/exploration tasks.

5.2 Challenge 2: Multi-robot global plan inference to predict robot task abandonment

Task inference methods for multi-robot teams have mainly focused on the prediction of teammate robot goals by assuming all observed actions contribute to the completion of their predicted tasks [14]. However, several reasons can prevent rational mobile robots from executing optimal actions such as mechanical and electrical failure, being flipped over, uncertainty, stochastic action outcomes, and noisy sensor readings [160]. In these scenarios, robots can execute sub-optimal actions that deviate from their plan without changing their intended task. Therefore, robots in the team need to be able to infer whether a teammate robot intends to complete their original predicted task or has abandoned it for another task due to failure, by considering observations of the robot's actions and its plan. This is especially critical for multi-robot cooperation, where successful completion of the overall global task by the team requires individual robots to be committed to completing their delegated tasks [147]. As a result, knowing whether a robot has abandoned a task is vital for replanning and maintaining team performance.

In order to predict task abandonment or deviation, individual robots must be able to infer the tasks and plans of teammates [161]. In mobile robotics, a robot's plan to complete a task is described by the global trajectory it intends to execute to arrive at its goal location. Thus, addressing the proposed challenge requires solving global robot trajectory inference conditioned on the robot's goals using observations of its action history as well as the environment configuration. This is a complex problem as: 1) robot trajectories depend on a multitude of factors from interaction with the environment itself and other robots [162], and 2) robot trajectories are multi-modal, where given the same action history, goal, and environment configuration, there can exist several trajectories [163]. Addressing the multi-robot trajectory inference problem, allows robots in a team to replan in order to reduce performance loss (i.e., the time elapsed and energy consumed) incurred from teammates abandoning their tasks [147]. For example, a mobile robot with a warning of a low battery may suddenly take an alternative route that is less demanding in terms of power requirements, towards its goal during exploration, or go back to its home base. An observing robot that does not have direct communication with this robot can infer this robot's future global trajectory conditioned on its goal, to decide whether the robot has abandoned its goal and if replanning of the team is necessary to maintain global team performance.

Trajectory inference methods have been proposed for both autonomous vehicles and pedestrians to account for the semantic context of an environment [164–166], and interactions between road agents (i.e., vehicles and pedestrians) [162, 167–170] in controlled traffic scenarios. However, autonomous vehicle inference methods focus only on short-term trajectory predictions (up to 5 s) to avoid immediate collisions with nearby vehicles and pedestrians [171] due to the dynamic nature of the environment. They do not consider inference for global plans towards achieving long-term goals (destinations) such as travel between destinations in different cities, etc. [172]. On the other hand, pedestrian-based methods have considered global goal conditions [168, 173–175]; however, they typically require either a static overhead (i.e., surveillance camera) or birds-eye-view perspectives with a fixed frame of view [176], with pedestrians following social norms [177]. These requirements are distinctly different than for mobile robot teams deployed in unstructured environments where predictions must account for: 1) camera ego-motion from first-person perspectives, 2) unconstrained goals and plans based on robot task-specific objectives (i.e., optimal time vs. coverage), and 3) varying environment traversability configurations. Potential future research fields in multi-robot global plan inference include: 1) multi-robot trajectory forecasting [167, 175, 179] to infer short-term trajectories of future teammates to avoid imminent collisions, and 2) multi-robot trajectory planning [177, 178, 180] to plan long-term team trajectories between initial and final robot positions. However, both research fields individually cannot address the global plan inference problem as existing forecasting methods are limited to short-term trajectories, while planning methods require access to global information (i.e., environment configuration and teammate states). Thus, a promising research direction includes integrating multi-robot trajectory planning during trajectory forecasting to extend the inference horizon to long-term global team trajectories for prediction of task abandonment.

6 Conclusion

In this survey paper, we present a novel mobile robot inference taxonomy to classify both environment and task inference for single and multiple robots deployed in partially observable and communication-limited unknown environments. For each inference class, we identify and discuss the existing problems, applications, and solution methods. While there has been significant progress made in the past decade in the area of mobile robot inference, existing inference approaches are still in their early stages and have been limited in their implementation on mainly robots navigating, exploring, and mapping structured indoor environments with unknown regions. Therefore, we provide an analysis of open research challenges in the context of multi-robot coordination for unstructured environments and provide future research directions to tackle these challenges for this promising field.

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