Proceedings of CONF-CIAP 2026 Symposium: International Conference on Atomic Magnetometer and Applications
DOI: 10.54254/2753-8818/2026.HZ29410

Perception-decision Integration for Air-ground Collaborative Robots

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Abstract. The air-ground collaborative robot system integrates advantages of aerial robots and ground robots to solve task in complex and dynamic environment beyond single robot plat-form limitation. While, the perception-decision integration is important to enhance autonomous and robust of the system. This paper explain the concept of perception-decision integration in air-ground collaborative robot system and explain whole process of perception-decision integration from drone 2D visual perception to ground robot decision making. Firstly, image data of the environment is acquired by the drone. Then, the data is sent to control center and transferred into grid map. Finally, the grid map is used as state space input of Markov decision process (MDP) and value iteration based dynamic programming algorithms are used to solve optimal strategy. The concept explanation in this paper provides a possible technical route to construct efficient and robust air-ground collaborative robot system, and gives theoretical and practice reference for autonomous navigation in complex environment.

Keywords: Air-ground Collaborative Robot, Visual Perception, Markov Decision Process

1. Introduction

With the rapid development of robotics technology, the limitations of a single robot platform in complex tasks have been exposed more and more. In order to meet the complex and dynamic environment and task requirements of disaster relief, environmental monitoring, remote sensing application in agriculture, inspection and maintenance of infrastructure, military reconnaissance, intelligent warehouse and other fields, an air-ground collaborative robot system has been developed.

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Air-ground collaborative robotics system is a combined robotics system constructed by aerial robots (drones) and ground robots. Its core concept is to enhance task execution efficiency and robustness through sharing information, division of roles and complementary advantages.

Divide the role, let the UAV (Unmanned Aerial Vehicle) be “the eye in the sky” and the ground robot be “the executor on the ground”. Only in this way, UAVs can provide global map and obstacle

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DOI: 10.54254/2753-8818/2026.HZ29410

information in the environment in real-time for the ground robot to avoid danger and find the best path; the ground robot can complete precise operation, material transportation, long-term patrol or other tasks. Meanwhile, it can provide a takeoff/landing and charging base for a UAV. In this mode, the control center is the transmission information bridge. It is responsible for receiving the image data acquired by the UAV, transferring it into a grid-based world map and sending it to the ground robot to provide perceptual input for its decision-making. The direct encoding of perceptual information into the decision-making model is the key to enhancing autonomous navigation capability, efficiency, accuracy and flexibility of the air-ground collaborative robot system.

In this paper, the perception-decision integration research of air-ground collaborative robots will be discussed from the following viewpoints: firstly, the architecture of air-ground collaborative robot system will be introduced, and the functions of aerial robot, ground robot and control center as well as their collaborative ways of working will be clarified; secondly, the environmental perception technology will be introduced, that is, how drones use 2D visual perception to get environmental information, and how the information processed by control center to get grid map for use in ground robot will be introduced; at last, this paper will introduce the decision-making scheme, that is, how do use the processed grid map as state space input of Markov Decision Process (MDP) and use dynamic programming algorithm to solve the optimal strategy so as to achieve autonomous path planning and behavioral decision-making of ground robot.

This paper aims to provide a theoretical framework and practical reference for the integrated perception and decision-making design of air-ground collaborative robot systems, with the goal of advancing the application of air-ground collaborative robot technology in broader fields.

2. Air-ground collaborative robot architecture

A composite system, the air-ground collaborative robot system, is composed of aerial, ground robots and a command center. The collaborative working model seeks to amalgamate the strengths of both robot types, surmount their individual drawbacks, and tackle intricate and fluctuating environmental and task demands.

With high mobility and a wide field of view, aerial robots are capable of swiftly accessing target areas for large-scale reconnaissance, monitoring, mapping, and data collection.

Limited endurance and payload capacity render these systems unsuitable for long-duration operations in narrow, enclosed, or cluttered ground environments.

Ground robots are lauded for their stability, substantial payload capacity, extend-ed endurance, and robust maneuverability in complex terrain. They are better suited for precise ground operations, material transportation, inspections, and prolonged stationary tasks. However, ground robots typically move slowly, have limited visibility, struggle to obtain global information, and are inefficient when facing high obstacles or large-scale areas.

Aerial-ground collaborative robot system can improve the efficiency and stability of task execution by sharing information, tasks and advantages of aerial and ground robots. Drones can provide global real-time maps and target information to the ground robot so that the ground robot can avoid danger or find the best path to proceed, and the ground robot can provide charging, data communication base and take off/landing for drones. Ground robots can be used as a “ground executor” to finish accurate operations or transportation and long-term stationary patrol, while drones can provide information collection and transmission. This mode of “UAV perception and ground execution” has wide application prospects in disaster relief, environmental protection, agricultural detection, building maintenance, military reconnaissance, intelligent warehouse and other fields.

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The control center in the air-ground collaborative robot system is an information transmission bridge between the aerial robot and the ground robot. The control center will receive image data collected by UAVs and then process the image data into a grid world map. After that, the control center will send the grid map to the ground robot, and provide grid perception information for the ground robot in the decision-making process. This method of encoding perceptual information directly into a decision-making model can improve the autonomous navigation ability, efficiency, accuracy and flexibility of an air-ground collaborative robot system in a complex environment.

3. Environmental perception

3.1. Environmental perception of aerial drones

Environmental information gathering is enhanced by visual perception in robots, with aerial robots, benefiting from their broad field of view, adeptly performing large-scale reconnaissance, monitoring, and mapping. The essence of visual perception lies in the acquisition of image data via cameras, which is then employed to extract environmental features. Images undergo processing via image processing algorithms.

UAVs act as the "eyes in the sky" within air-ground collaborative robot systems, delivering overhead imagery essential for ground robots to surmount their height and sensor field-of-view constraints. UAV-acquired images enable environmental perception capabilities, such as obstacle detection and localization, as referenced in [1]. The integration of edge detection, feature point extraction, and image segmentation techniques ensures the efficient identification of environmental obstacles [2]. The application of visual odometry or Simultaneous Localization and Mapping (SLAM) techniques estimates the positioning of obstacles on a two-dimensional plane [3]. Moreover, distinguishable regions are ascertainable via image categorization or semantic segmentation. Delineate zones where ground robots can navigate safely (e.g., with roads and flat terrain, these are distinguished from impassable locations (e.g., water formations, steep gradients, densely obstructed sectors) [2]. The process of environmental feature extraction aids in the identification of notable landmarks and texture attributes. These attributes are employed for the drone's localization and to support ground robots in local navigation [3]. The drone's high-altitude viewpoint facilitates the acquisition of broad-scale data

Utilizing environmental information, ground robots can engage in macro-level path planning, anticipate potential hazards, and optimize global routes, thereby fostering global environmental situational awareness.

3.2. Control center and ground robot perception interaction

In an air-ground collaborative robot system, the control center serves as the core hub for information transmission. Its primary responsibility is to effectively receive, process, and distribute perception data to support the autonomous decision-making and actions of ground robots. The control center first receives raw or preliminarily processed image data from the UAV. Subsequently, the processing modules within the control center convert this image data into a grid-based world map. The depicted map segments the continuous physical space into a grid, each cell being marked with occupancy status, either "occupied" or "unoccupied". For the purpose of addressing sensor observations and environmental uncertainties, the probabilistic occupancy grid representation is generally applied, with occupancy probabilities set between 0 and 1 for each grid cell, and the representation is

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updated recursively. Bayesian updating is the method used to compute the probability based on the sensor model [4, 5].

Post-formation of the grid world map, the control center dispatches the map data to the ground robot via wireless communication. The integration of perception and decision-making is contingent upon the transmission process's pivotal role. Upon obtaining the grid map, the ground robot assimilates it into the state space of its decision-making framework. The method of encoding perception information directly into the decision-making model facilitates the ground robot's capability to utilize the most recent environmental insights for the determination of path and behavior, thereby enhancing the system's autonomous navigation efficacy and robustness in multifaceted and variable environments.

4. Ground robot system decision-making

Robot decision-making schemes are the core component for achieving autonomous behavior and intelligent responses. In air-ground collaborative robot systems, effective decision-making mechanisms are crucial for the collaborative operation, task allocation, and path planning between UAVs and ground robots. With the development of artificial intelligence technology, particularly reinforcement learning (RL), model-based and model-free decision-making methods have been extensively studied. Among these, the Markov Decision Process (MDP) serves as a rigorous mathematical modeling framework, providing a theoretical foundation for sequential decision-making problems in complex environments.

In this paper, the grid map generated by the control center is directly mapped to the state space S of the MDP, with each grid cell treated as an independent state. The occupancy information (free or obstacle) of each cell determines the definition of the state transition function P(s'|s, a) and the reward function R(s, a). For example, attempting to enter an occupied cell will result in restricted state transitions or significant negative rewards, thereby guiding the robot to automatically avoid impassable areas [6,7]. After constructing the state space, action set, and transition and reward models, the path planning problem can be transformed into an optimal strategy problem under the MDP framework, seeking the optimal strategy from the starting state to the target state.

Next, the shortest path is solved using dynamic programming methods. Under the conditions of known state transition models and reward functions, dynamic programming (DP) is an effective solution method that guarantees a globally optimal solution [8]. This paper adopts the Value Iteration algorithm based on the Bellman Optimality Principle as the core path planning strategy [9]. This method first assigns an initial value function V(s) to each state and utilizes the Bellman equation:

$$V_{k+1}(s) = \max_{a \in A} [R(s,a) + \gamma \sum_{s'} P(s's,a) V_k(s')] \tag{1}$$

Here, $V_{k+1}(s)$ denotes the value function of state s at the (k+1)-th iteration, which evaluates the expected cumulative return when taking the optimal action in state s. The operator $\max_{a \in A}$ indicates that the action a is selected from the action set A to maximize the expected return. The function R(s, a) represents the immediate reward obtained by executing action a in state s. The parameter γ in [0,1) is the discount factor, which balances the importance of current versus future rewards and ensures the convergence of infinite-horizon return calculations. The transition probability function P(s'|s, a) describes the probability of transitioning to state s' when action a is taken in state s. Finally,

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$V_k(s')$ is the value of successor state s' at the k-th iteration, which recursively contributes to the computation of the expected return. Through iterative updates, this process converges to the globally optimal value function.

Iteratively update across the entire state space until the value function converges. The converged value function can be directly used to derive the optimal policy:

$$\pi^*(s) = \underset{a \in A}{argmax} \left[R(s,a) + \gamma \sum_{s'} P(s's,a) V(s') \right] \tag{2}$$

Here, π (s) denotes the optimal policy at state s, i.e., the decision rule that prescribes the action yielding the maximum expected return. The operator $\underset{a \in A}{argmax}$ specifies the action that achieves the maximum value of the target function, rather than the maximum value itself. The expression inside the brackets is structurally consistent with Equation (1), consisting of the immediate reward R(s, a), discount factor γ , transition probability P(s'|s, a), and the value function V(s'). However, in this context, V(s') refers to the converged optimal value function. By applying this formula, the optimal decision rule can be extracted for every state, thereby forming the globally optimal policy π *.

Generate an optimal path from the current position to the target position for a ground robot [6, 7]. Compared to greedy search or heuristic algorithms, dynamic programming offers global optimality and stability under known environmental models [10, 11]. However, its computational complexity increases significantly with the size of the state space, leading to excessive computational overhead in large-scale grid map scenarios. To enhance real-time planning capabilities, strategies such as state aggregation and hierarchical planning can be introduced to compress the search space [12], combined with heuristic pruning methods to reduce redundant computations.

5. Discussion

The perception-decision integration design of air-ground collaborative robot systems is a promising research field. However, this field currently faces numerous challenges. Perception uncertainty is a major issue. The precision of image processing and grid map conversion may be compromised by UAV-captured 2D images affected by lighting, weather, and occlusion. Ground robots' path planning can be compromised when UAVs fail to gather clear ground data in dense forests. Subsequently, the process of real-time map updating is elaborated upon.

Robustly persists as a subject meriting additional inquiry. The real-time aspect of the perception-to-decision transition poses a significant challenge. Rapid decision-making by ground robots is contingent upon the utilization of the most recent perception information in changing environments.

The exploration of enhanced planning algorithms, such as Monte Carlo Tree Search (MCTS) and deep reinforcement learning, is deemed necessary for addressing decision-making complexities in large-scale and intricate environments.

6. Conclusion

The application prospect of the air-ground collaborative robot system is promoted by the synergy value of the drone and ground robot. Perception and decision are the key technologies to support an autonomous and robust air-ground collaborative robot. In the paper, the mechanism of perception-decision integration in air-ground collaborative robots is studied. Drone plays the role of a 2D vision sensor in the air and transfers image information to a grid-based world map through the control

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center. The grid map is selected as the state space input of the Markov decision process and the dynamic programming technique, including value iteration, is adopted to design the optimal path of the ground robot.

This paper aims to offer a reference for the design of an effective and robust air-ground collaborative robot, and enhance the collaborative perception and decision of the air-ground collaborative robot. There are still some challenges in perception uncertainty, real-time performance and solving the large-scale state space. These problems will be further optimized in the algorithm and hardware. This paper expects that air-ground collaborative robot technology will be widely applied in disaster response, environment monitoring, smart agriculture and other fields in the future and provide a new solution for complex real-world problems.

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