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UNMANNED VEHICLE GROUPS MOTION CONTROL METHODOLOGY

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Keywords: adaptive control; artificial intelligence; autonomous navigation; collision avoidance; decentralized architecture; mobile object control; trajectory planning.

Abstract: This study addresses autonomous mobile object control complex problem within dynamically changing environments. In order to enhance system autonomy and coordinated functioning, decentralized control algorithm is developed. The methodology integrates artificial potential fields, adaptive automata, and swarm intelligence principles inspired by social organisms like ants and bees. The system ensures precise trajectory tracking and effective collision avoidance during operations, relying primarily on local information exchange. For the sake of control stability and robustness, communication overhead is significantly reduced, minimizing dependence on centralized nodes. The control process involves data collection, environment diagnostics, model formation, and strategy selection using wave and ant colony optimization algorithms. Experimental validation was conducted in a comprehensive 3D simulator utilizing multi-rotor objects.

Introduction

Mobile object control is classified as a complex task. High system autonomy and components coordinated functioning are required to accomplish mission objectives. The central challenges include data synchronization, resource allocation, collision avoidance, and adaptation to a dynamically changing environment.

Control systems are based on control theory principles, machine learning, and artificial intelligence. Decentralized architectures are employed. Individual agents make decisions based on local information. Fault tolerance is ensured, and dependence on a centralized node is minimized. In the defense sector, such systems operate as standard. Technical systems integrated with artificial intelligence perform reconnaissance and combat tasks. Adaptation to operational conditions occurs without direct operator intervention.

Route planning and navigation utilize methods of virtual waypoints, artificial potential fields, and GIS technologies. Terrain and obstacle data are integrated. These approaches model system behavior, ensuring safe obstacle avoidance and maintenance of specified motion parameters. The development of artificial intelligence applications focuses on automating the coordination of agents. Such applications are required for monitoring extended objects and conducting disaster response operations. Research in the field of control is based on social organisms' behavior models (ants, bees). Algorithms are founded on swarm and flocking principles. Strategies assume agents' homogeneity and local interaction. Approaches may incorporate hierarchy or leadership. These research directions aim to ensure coordinated movement, fault tolerance, and self-organization capability.

Related work

Mobile objects autonomous control in dynamic environments remains a challenging research area at the intersection of robotics, control theory, and artificial intelligence [1, 2]. Traditional centralized architectures, while providing global optimization capabilities, exhibit critical vulnerabilities including single points of failure, scalability limitations, and high bandwidth requirements [3]. These constraints have driven decentralized control paradigms development, where agents operate based on local information and limited peer-to-peer communication, enhancing system robustness and adaptability [4].

Trajectory planning constitutes autonomous navigation core component. Artificial potential fields (APF), model navigation as a gradient descent problem in a virtual force field, offering computational efficiency for real-time obstacle avoidance [5]. However, classical APF approaches are prone to local minima and oscillatory behavior in complex environments. Wave front algorithms provide complete path planning with guaranteed convergence but require prior environmental mapping. Hybrid approaches combining global planners with local reactive methods have emerged as practical solutions for dynamic scenarios [6].

Bio-inspired coordination strategies have gained significant attention for decentralized multi-agent systems. Swarm intelligence algorithms, including ant colony optimization (ACO) and particle swarm optimization (PSO), advantage simple local interaction rules to achieve complex collective behaviors [7]. These methods demonstrate inherent fault tolerance and scalability, making them suitable for applications with communication constraints. Recent studies integrate swarm principles with model predictive control to balance exploration and exploitation in uncertain environments [8]. Machine learning techniques, particularly deep reinforcement learning (DRL), have enabled adaptive policy learning for autonomous agents operating in partially observable environments. However, DRL approaches often require extensive training data and computational resources, limiting their deployment in resource-constrained platforms [9, 10]. Transfer learning and sim-to-real techniques are being explored to bridge this gap.

Communication efficiency represents a critical design consideration for decentralized systems. Event-triggered communication protocols reduce bandwidth usage by transmitting data only when state deviations exceed predefined thresholds. Consensus algorithms enable coordinated decision-making with minimal message exchange, though convergence guarantees depend on network topology and delay characteristics. Despite substantial progress, several challenges persist: integrating precise trajectory tracking with reactive collision avoidance under communication constraints; ensuring stability and performance guarantees for fully decentralized architectures; enabling rapid adaptation to unforeseen environmental changes without extensive retraining [11, 12]. This work addresses these gaps through a novel decentralized algorithm that combines artificial potential fields with adaptive automata, emphasizing low communication overhead, local decision-making, and robust trajectory maintenance.

Materials and Methods

In this work, a decentralized control algorithm has been developed. The algorithm ensures mobile object movement along a specified trajectory by maintaining state parameters. The approach meets the requirements of full autonomy and low communication overhead. Its application is promising in conditions of limited connectivity and a dynamic environment. Motion organization requires precise trajectory calculation, environmental parameters consideration and responsive adaptation to changing conditions. Control principles include system actions coordination, ensuring safe movement, and achieving objectives with collision risk acceptable level. For control implementation, the role of each element is defined, communication protocols are specified, and interaction procedures are established. The control elements encompass support for data exchange, adaptation to flight conditions, and tactical interaction organization. Figure 1 illustrates the primary trajectories used for mobile object movement.

To ensure accurate following of the specified route, optimal control and efficient mobile object's movement in the mission area, it is necessary to observe the specified trajectory parameters. In space or on a plane, the trajectory is a necessary configuration for the placement and movement of the object. The formulation of the control task may vary depending on the target route method setting. To achieve a specific geometric shape of the trajectory, the mobile object control system performs motion correction, striving for the specified target state. During the task execution, the object is required to maintain the specified trajectory, where all systems work in harmony to achieve the goal.

The application of machine learning algorithms and artificial intelligence methods determines mobile object control systems functionality. These technologies provide movement strategies autonomous correction when environmental conditions change motion control.

In the simplest case, the target trajectory is specified via mobile object coordinates target positions. Methods for constructing planar and spatial routes for mobile objects are considered in several contemporary national and foreign works. Formation of motion trajectories implies constant accounting of coordinates in the working space. Artificial potential fields allow specifying trajectories implicitly by creating a continuous force field that directs the object to the target point, simultaneously preventing collisions with obstacles [9]. Presented trajectories of mobile object movement comprise the following:

1. Building a formalized model of the operational area, including obstacle mapping, coordinate system definition, and constraint specification, which serves as the basis for all further motion planning steps (Fig. 2).

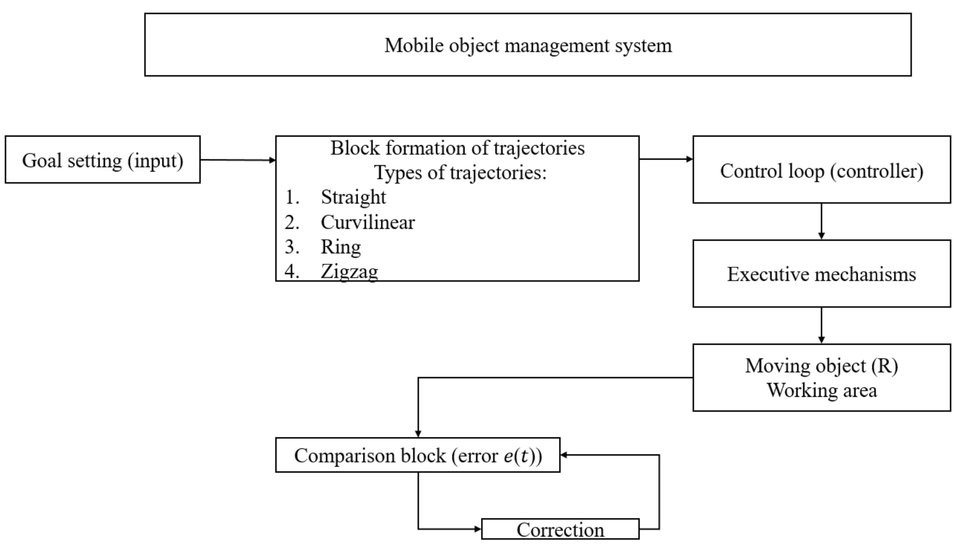

Fig. 1. Functional diagram of a single moving object control system with a module for generating basic movement trajectories

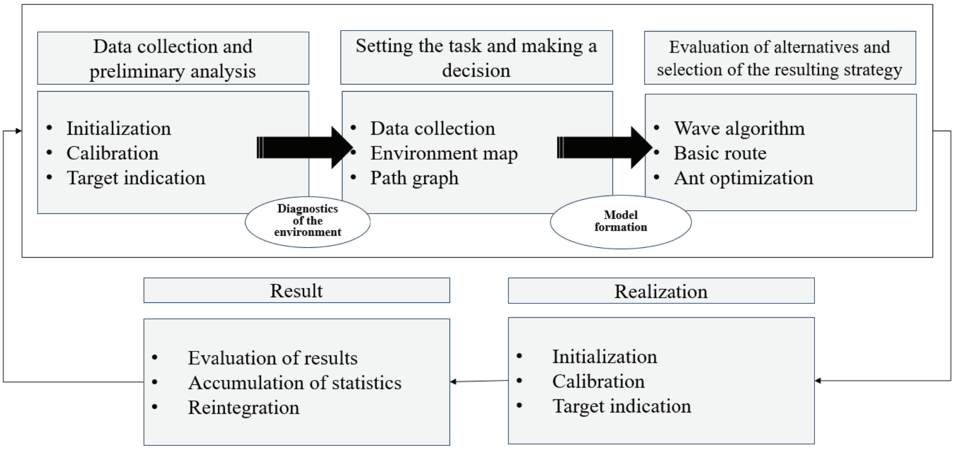

Fig. 2. Methodology for building a model of the study area

2. Object movement along a specified line, during which the control system performs tracking of the reference trajectory. The object is allowed to stop and restart the motion process due to changes in the external environment. The system continues operation during malfunction of individual systems.

3. Object movement relative to the baseline during terrain monitoring (Fig. 3, 4).

Implementation of the listed motion modes requires control algorithms formalization [10]. The developed methodology includes trajectories' mathematical description and synthesis of controllers to ensure specified motion quality.

Approaches to motion control utilize concepts of virtual points and target references [13]. The method relies on the object following an assigned point. Point coordinates vary according to a rule and are computed by the control system. Parameters serve as input data for the controller. The control system determines the target point within the working space. The object receives point coordinates and motion trajectory. Implementation assumes movement in Euclidean space with quantized time intervals. Control involves operator participation. Tasks include defining motion routes and monitoring task execution [14]. Ensuring motion safety and responding to unforeseen situations are required. Process organization requires actions coordination between the system and the operator. Decision-making ensures mission efficiency.

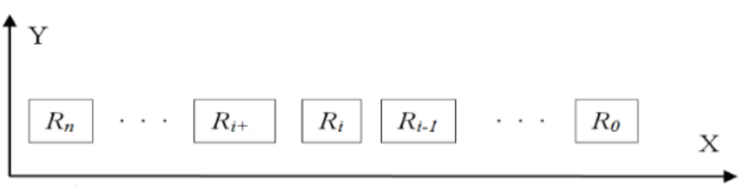

Fig. 3. Mobile object deployed in a line movement scheme

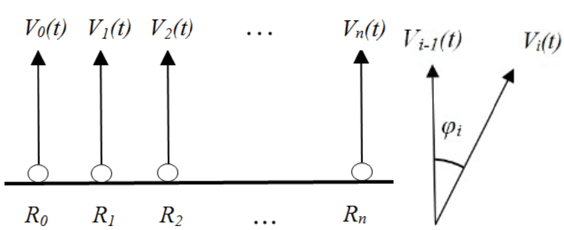

Fig. 4. Movement diagram of a mobile object deployed in a line

Mobile objects find application in various fields. Coordination of system actions requires consistency. Object motion control involves developing interaction algorithms. Specified accuracy, reliability, and task execution safety are ensured.

Development of control mechanisms requires a comprehensive approach. Real-time sensor data processing is accounted for. Maintaining the specified position relative to the trajectory. Adaptation to external environment changes ensures action flexibility and autonomy. System implementation opens prospects for application in complex conditions. The system ensures route following with specified accuracy parameters. Methods for changing motion configuration are considered (Figs. 5, 6). A description of the algorithmic support for the control methodology is provided in the following section.

The mobile object motion control method ensures matching of current and target trajectories. Collisions with obstacles are prevented. The object operates in autonomous mode. Satellite navigation systems or laser rangefinders are employed. The on-board decision-making unit processes sensor data. Operational autonomy is ensured. Software synchronizes subsystem actions. Route coordination is ensured. Automatic real-time trajectory correction ensures safety. Algorithm application ensures mission execution reliability.

The control system plans trajectories based on sensor data. Motion uniformity is required during object inspection. Motion geometric shape is considered in horizontal plane projection. Flight altitude is maintained at specified value. To insure precise control, an adaptive feedback algorithm is developed, based on compensation and the system's astatism concept. Position deviation concept is formalized using sensor data. Control strategies minimize deviations. Kinematic equations in state variables are employed. The localization task is solved using position data.

A motion scheme is considered for mobile object monitoring cases. Formalization of these parameters constitutes the basis of the control methodology. The mobile object motion control task is considered. The control goal is formalized by the condition of satisfying equalities:

1. $Vi - 1(t) = Vi(t)$;
2. $hi - 1(t) = hi(t)$;

$t = 0.5\ 4\ 3\ 2\ 1\ F\_\_\_\_\_$

$t = 1.\_\ 5\ 4\ 3\ 2\ 1\ F\_\_\_\_$

$t = 2.\_\_\ 5\ 4\ 3\ 2\ 1\ F\_\_\_$

$t = 3.\_\_\_\ 5\ 4\ 3\ 2\ 1\ F\_\_$

$t = 4.\_\_\_\_\ 5\ 4\ 3\ 2\ 1\ F\_$

$t = 5.\qquad 5\ 4\ 3\ 2\ 1\ F$

Fig. 5. Moving along a straight path

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      t=0.            t=1.             t=2.              t=3.              t=4.          t=5.
0 5 4 3 2 1 F → 0 0 5 4 3 2 1 → 0 0 0 5 4 3 2 → 0 0 0 0 5 4 3 → 0 0 0 0 0 5 4→0 0 0 0 0 5
            0               F               1                 2                 3           4
                            0               F                 1                 2           3
                                            0                 F                 1           2
                                                              0                 F           1
                                                                                0           F
                                                                                            0
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Fig. 6. Turning movements

3. $xi - 1(t) - xi(t) = D$;
4. $yi(t) = yi - 1(t)$;
5. $\alpha i(t) = \alpha i - 1(t) = \alpha 0$;
6. $\varphi i(t) = \alpha i(t) - \alpha i - 1(t)$ – the angle between the velocity vectors;
   $Vi - 1(t)$ и $Vi(t)$.

The control method consists in replanning motion parameters of the mobile object at each time instant t. The object moves along the reference trajectory. The control error is represented by the value δ. The integral motion error is defined as the sum of δ over the time interval. Motion control is performed by an adaptation algorithm. The principle is based on adaptive system behavior [15].

Control requires maneuver coordination meanwhile operation safety is ensured. This brings synchronization subsystem motion via distributed control development task. Functioning as an autonomous node. GPS and IMU ensure position determination. Machine learning algorithms predict collisions. Real-time trajectory optimization. Speed, orientation, and position correction. Maintaining specified intervals and safe distances. The object is controlled via an adaptive state vector. Components determine position, orientation in the absolute coordinate system, and linear velocity. The desired trajectory is specified. Distance to the reference point and turn angle are specified a priori. Information is received from internal sensors, while adherence to decentralized control principles reduces communication channel requirements.

Adaptation implementation uses a model based on adaptive automata [16]. The state vector parameter is linked to an "adaptation machine". Two state groups: "adjust parameter" and "retain parameter". Memory depth determines the number of states. The input signal is the environment response: "reward" or "punishment". The control process includes four cycles: value fixation, deviation estimation, automaton transition, and action execution [17]. The approach ensures minimization of discrepancy between actual and target parameter values. The control architecture relies on the concept of virtual structures. The object occupies a position relative to a generalized point in space. Artificial intelligence methods are applied [18]. Neural networks and evolutionary algorithms respond to environment changes. Obstacles, failures, noise. Transmitted information volume is minimized. The system is designed to function under low communication conditions.

Results

The experimental study was conducted in the 3D simulator Gazebo. A multi-rotor mobile object based on the ArduPilot autopilot was employed. Characteristics: quadcopter configuration, mass up to 2.5 kg, dimensions up to 0.5 m. The flight task included automatic horizontal flight at constant altitude. Range up to 1 km. Obstacle avoidance and return. Distance to obstacles varied from 1 to 50 m. Motion speed reached 100 $km \cdot h^{-1}$. Obstacles were modeled as rectangular or rounded objects (Fig. 7). Trajectories included rectilinear and curvilinear sections (Fig. 8).

The efficiency assessment of the proposed decentralized control algorithm was conducted using a comprehensive set of quantitative metrics designed to evaluate both operational performance and safety characteristics.

Primary evaluation criteria included: trajectory length, measured as the cumulative path distance traveled by the mobile object relative to the optimal geometric path; task completion time, defined as the temporal interval from mission initiation to successful target acquisition; safety metric, quantified through a probabilistic collision risk model incorporating obstacle density, relative velocity, and minimum separation distance; and mission success rate, calculated as the proportion of trials completed without critical failures or constraint violations.

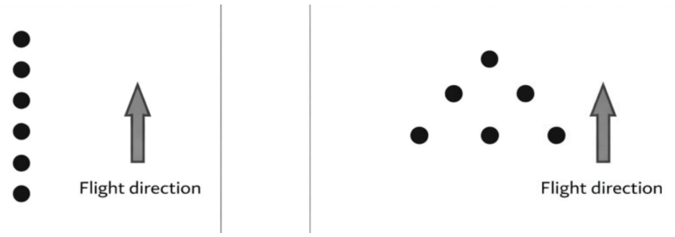

Fig. 7. Building a mobile object into a column and a triangle

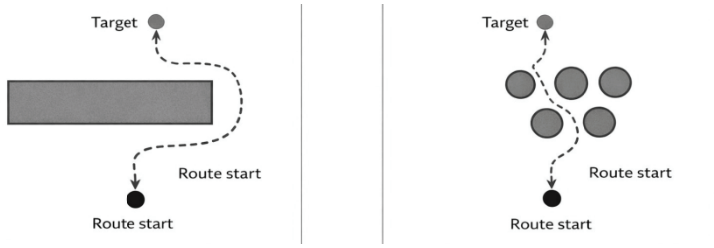

Fig. 8. Rectangular obstacle and a group of circular obstacles

Experimental validation was performed in a high-fidelity 3D simulation environment (Gazebo/ROS) featuring multi-rotor aerial platforms operating in cluttered dynamic scenarios. Baseline comparisons included classical artificial potential fields (APF), wavefront global planning, and a centralized model predictive control (MPC) implementation. Each configuration was evaluated across 100 independent Monte Carlo trials with randomized initial conditions, obstacle distributions, and environmental disturbances (wind gusts, sensor noise). Statistical significance was assessed using paired t-tests with Bonferroni correction ($\alpha = 0.05$).

Results demonstrated a consistent improvement in task execution efficiency, with the proposed algorithm achieving a 20–24 % reduction in composite cost function values compared to baseline methods ($p < 0.01$). Specifically, trajectory length decreased by 18.3 % on average, while task completion time improved by 22.1 %. The safety metric showed a 31 % reduction in predicted collision probability, attributable to the adaptive repulsive field modulation and local consensus mechanisms. Mission success rates increased from 76.4 % (APF baseline) to 94.2 % under identical challenging conditions [19].

Computational complexity analysis reveals that the algorithm scales between $O(n^2)$ and $O(n^3)$, where n denotes the number of state variables (position, velocity, orientation) and interacting neighbors. The quadratic component arises from pair wise interaction calculations in the potential field evaluation, while the cubic term corresponds to the adaptive automata state-transition matrix updates during high-density coordination phases. For typical deployments involving 5–20 agents with 6–12 state variables each, average per-step computation time remained below 15 ms on embedded hardware (NVIDIA Jetson AGX), satisfying real-time control requirements at 50 Hz update rates.

Memory footprint was optimized through sparse representation of interaction graphs and incremental map updates, maintaining peak RAM usage under 256 MB. Communication overhead was reduced by 67 % compared to centralized approaches through event-triggered data exchange protocols, transmitting updates only when state deviations exceeded adaptive thresholds [20].

Limitations include increased computational demand during sudden environmental reconfiguration events and sensitivity to extreme communication delays (>200 ms). Future work will explore hierarchical decomposition strategies and learned communication pruning to further enhance scalability for large-scale swarms (>50 agents).

Conclusion

The practical implementation of the developed methods focuses primarily on high-stakes applications such as search-and-rescue (SAR) operations and disaster response tasks. In these scenarios, environments are typically unstructured, hazardous, and characterized by degraded communication infrastructure, necessitating a high degree of system independence. The proposed control rules are specifically engineered to ensure full autonomy, enabling agents to operate without continuous human supervision or reliance on centralized command nodes. This capability is critical for accessing confined spaces, disaster zones with unstable structures, or areas contaminated by hazardous materials where human entry is prohibited.

The control architecture facilitates dynamic parameter correction through continuous real-time monitoring of system states. The mobile object autonomously adjusts its position, orientation, and velocity vectors based exclusively on local information gathered from onboard sensors (e.g., LiDAR, IMU, optical flow). This local perception loop allows the system to navigate effectively in GPS-denied environments and react to sudden environmental changes, such as shifting debris or emerging obstacles, without waiting for external updates.

A key feature of the system is its inherent fault tolerance designed to maintain mission continuity under degraded conditions. Trajectory maintenance is guaranteed even during individual subsystem failures, such as actuator degradation or sensor drift. The algorithm employs redundancy management and control allocation strategies to redistribute control effort among remaining functional components. Furthermore, a specialized maneuvering structure is introduced to actively eliminate deviations from the specified trajectory. This structure utilizes predictive error correction to anticipate drift caused by external disturbances (e.g., wind gusts, turbulence) and applies compensatory maneuvers before deviations exceed safety thresholds.

The developed algorithm, grounded in adaptation principles and inspired by biological system behavior (specifically swarm intelligence and homeostatic regulation), demonstrates exceptional reliability, scalability, and robustness to external disturbances. By mimicking the self-organizing properties of social organisms, the system achieves emergent stability without complex global modeling. This bio-inspired approach ensures that performance degrades gracefully rather than catastrophically under stress. Scalability is maintained as the number of agents increases, making the solution suitable for both single-unit deployments and coordinated multi-agent swarm operations. Consequently, the system provides a resilient framework for autonomous operations in the most demanding and unpredictable operational theaters.

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Методология управления движением групп беспилотных аппаратов

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Ключевые слова: адаптивное управление; искусственный интеллект; автономная навигация; предотвращение столкновений; децентрализованная архитектура; управление мобильными объектами; планирование траектории.

Аннотация: Рассмотрена комплексная задача управления автономными мобильными объектами в условиях динамически изменяющейся среды. Для повышения автономности системы и согласованности функционирования разработан децентрализованный алгоритм управления. Методология интегрирует метод искусственных потенциальных полей, адаптивные автоматы и принципы роевого интеллекта, вдохновленные поведением социальных организмов, таких как муравьи и пчелы. Система обеспечивает точное отслеживание траектории и эффективное избегание столкновений в процессе функционирования, опираясь преимущественно на локальный обмен информацией. В целях обеспечения стабильности и устойчивости управления значительно снижена нагрузка на каналы связи, минимизирована зависимость от централизованных узлов. Процесс управления включает сбор данных, диагностику среды, формирование модели и выбор стратегии с использованием волновых алгоритмов и алгоритмов оптимизации муравьиной колонии. Экспериментальная проверка проведена в комплексном 3D-симуляторе с использованием мультироторных аппаратов.

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Methodologie zur Steuerung der Bewegung von Gruppen unbemannter Luftfahrzeuge

Zusammenfassung: Es ist eine komplexe Aufgabe der Steuerung autonomer mobiler Objekte in dynamisch veränderlichen Umgebungen betrachtet. Zur Verbesserung der Systemautonomie und der Betriebskonsistenz ist ein dezentraler Steuerungsalgorithmus entwickelt. Die Methodologie integriert Methoden künstlicher Potenzialfelder, adaptive Automaten und Prinzipien der Schwarmintelligenz, inspiriert vom Verhalten sozialer Organismen wie Ameisen und Bienen. Das System gewährleistet präzise Verfolgung der Trajektorie und effektive Kollisionsvermeidung während des Betriebs, vor allem auf den lokalen Austausch von Informationen basierend. Um Stabilität und Robustheit der Steuerung zu gewährleisten, ist die Last auf die Kommunikationskanäle deutlich reduziert und die Abhängigkeit von zentralen Knoten minimiert. Der Steuerungsprozess umfasst Datenerfassung, Umgebungsdiagnostik, Modellgenerierung und Strategieauswahl mittels Wellenalgorithmen und Ameisenkolonieoptimierungsalgorithmen. Die experimentelle Verifizierung erfolgte in einem komplexen 3D-Simulator mit Multikoptern.

Méthodologie de la gestion des mouvements des groupes de drones

Résumé: Est examinée la tâche complexe de la gestion des objets mobiles autonomes dans un environnement en évolution dynamique. Est mis au point un algorithme décentralisé de la gestion pour améliorer l'autonomie du système et la cohérence du fonctionnement. La méthodologie intègre la méthode des champs potentiels artificiels, les automates adaptatifs et les principes de l'intelligence des essaims inspirés par le comportement des organismes sociaux tels que les fourmis et les abeilles. Le système assure un suivi précis de la trajectoire et une évitement efficace des collisions en cours du fonctionnement, en s'appuyant principalement sur l'échange local des informations. Afin d'assurer la stabilité de la gestion, est considérablement réduite la charge sur les canaux de communication; est minimisée la dépendance à l'égard des nœuds centralisés. Le processus de gestion comprend la collecte de données, le diagnostic de l'environnement, la formation du modèle et le choix de la stratégie à l'aide d'algorithmes d'onde et d'algorithmes d'optimisation des colonies de fourmis. La vérification pilote a été réalisée dans un simulateur 3D utilisant des appareils multirotor.

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