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Safety Interaction Mechanisms and Robust Control Methods for Human-Robot Collaborative Systems in Dynamic Environments

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Abstract:

Traditional human-robot collaboration methods primarily rely on rule-based control and physical human-robot interaction, suitable for industrial scenarios with clear rules and relative stability. However, with the advancement of robotics technology, complex environments challenge the rapid adaptability of traditional approaches, limiting system adaptability. We propose a safety interaction framework based on multimodal perception, adaptive safety constraint generation and dynamic adjustment, and collaborative decision-making strategies to address risks arising from dynamic uncertainty. At the robust control level, we integrate adaptive control with intelligent optimization strategies to handle unpredictable human behavior and dynamic environmental changes. This research achieves dynamic obstacle avoidance and conflict resolution through adaptive safety constraints, significantly enhancing the safe operation of human-robot collaborative systems across diverse scenarios.

Keywords: Human-Machine Collaboration System; Dynamic Uncertain Environment; Safe Interaction Mechanism; Robust Control Method

1. Introduction

The scope of research on human-robot collaboration systems continues to expand with technological advancements. Traditional human-robot collaboration methods primarily rely on rule-based control and physical human-robot interaction, which are suitable for relatively stable and well-defined industrial environments. However, with the advancement of robotics technology, its application scenarios have gradually expanded into complex and dynamic open environments such as healthcare, logistics, and service robots, placing higher demands on human-robot collaboration systems. In complex environments, traditional human-robot collaboration methods struggle to make rapid adaptive adjustments, resulting in limited system adaptability. Physical human-robot interaction methods can achieve compliant contact, but they require extremely high precision in dynamic models, and existing safety mechanisms suffer from time delays in high-speed interaction scenarios. Additionally, the uncertainty in dynamic environments primarily stems from environmental changes and human factors, and existing research faces challenges in real-time computation and prediction when addressing these issues. To address the challenges faced by human-machine collaboration systems in dynamic uncertain environments, robust control methods have made significant progress, but most algorithms assume bounded disturbances and lack dynamic adaptability. This paper aims to investigate the safe interaction mechanisms and robust control methods for human-machine collaboration systems in dynamic uncertain environments, focusing on resolving the contradiction between safety and adaptability caused by environmental changes and human factors. By establishing a dynamic safety constraint model and developing intelligent robust control strategies, the paper seeks to achieve safe and reliable operation of human-machine collaboration systems in complex environments.

2. Relevant Theory and Technical Foundations

2.1 Current Status of Human-Robot Collaboration Systems

The scope of research on human-robot collaboration systems (HRC) has expanded with technological advancements. Traditional human-robot collaboration methods primarily rely on rule-based control and physical human-robot interaction [1]. Human-robot collaboration is mainly applied in relatively stable, structured industrial environments with clear rules, which facilitates robots in executing tasks according to pre-set programs. However, with advancements in robotics technology, their application scenarios have gradually expanded into complex and dynamic open environments such as healthcare, logistics, and service robots, where task requirements are flexible and diverse. This places higher demands on human-robot collaboration systems [2]. In complex environments, when faced with sudden obstacles or task changes, traditional human-robot collaboration methods lack flexibility and struggle to make rapid adaptive adjustments, resulting in limited system adaptability.

Physical human-robot interaction methods can achieve compliant contact between robots and humans. For example, impedance control adjusts the robot's impedance parameters to exhibit spring-damping characteristics during human-robot interaction, enabling compliant motion. However, this method requires extremely high precision in the dynamic model, necessitating accurate knowledge of the robot's mass, inertia, and other parameters [3]. Existing safety mechanisms have undergone significant development through a series of updates and iterations. For example, collision detection typically relies on threshold-based triggering, using force sensors or visual systems to detect collisions. However, in high-speed interaction scenarios, there is a time delay between the occurrence of a collision and the sensor detecting it and triggering the protective mechanism, which may result in excessive collisions between the robot and humans or other objects, causing damage. Force/position hybrid control requires an accurate robot dynamics model, but parameter uncertainties in real systems can reduce control accuracy.

2.2 Challenges in Dynamic Uncertain Environments

The uncertainty of dynamic environments primarily stems from two dimensions: environmental changes and human factors. In terms of environmental changes, the appearance of random obstacles and dynamic task adjustments are common issues. For example, in logistics sorting scenarios, the location of target items may change at any time, requiring robots to perceive environmental changes in real time and adjust their movement strategies accordingly [4]. Existing research describes disturbances through environmental modeling, which requires considering random factors in the environment and updating the model in real time, necessitating significant computational resources. However, in complex dynamic environments, the computational cost is high, making it difficult to meet real-time requirements. For example, using stochastic differential equations, where represents the system state, is the control input, is the system drift term, is the diffusion matrix, and is the Wiener process.

In terms of human factors, the uncertainty of the operator's intent poses safety risks for human-robot collaboration. Taking rehabilitation robots as an example, patients may make sudden movements during rehabilitation training [5]. Relying solely on predefined trajectories or rigid constraints cannot adapt to the randomness of human behavior. Therefore, a motion prediction intent prediction algorithm based on neural networks is introduced. Neural networks can learn from a large amount of historical data to establish a mapping relationship between operator behavior and intent, thereby predicting the operator's intent in advance, enabling the robot to adjust its motion strategy in a timely manner, and ensuring the safety and effectiveness of human-robot collaboration.

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2.3 Research Progress in Robust Control Methods

To address the challenges faced by human-robot collaboration systems in dynamic uncertain environments, robust control methods have made significant progress. First, adaptive control compensates for model uncertainty by adjusting parameters online. During robot operation, control parameters are adjusted in real-time based on the system's actual state and changes in the external environment to maintain optimal performance [6]. However, parameter convergence must be ensured during adjustment to prevent oscillations that could impair stability and control effectiveness. Second, fuzzy control employs expert rules to address nonlinear issues, adjusting joint compliance parameters via fuzzy rules to enable robots to adapt better to diverse interaction scenarios. The construction of fuzzy control rule bases relies on experience, making it difficult to comprehensively and accurately summarize all rules for complex systems, thereby limiting their generalization capabilities and potentially resulting in varying application effects across different scenarios [7]. Finally, reinforcement learning (RL) optimizes strategies through trial and error in unknown environments. Reinforcement learning enables robots to continuously learn through interaction with the environment, adjusting strategies based on reward signals to achieve optimal control. However, in practical applications, reinforcement learning faces the issue of low training efficiency, requiring a large number of trial-and-error iterations to learn effective strategies [8]. Additionally, since reinforcement learning relies on trial-and-error learning, unsafe actions may arise during training, potentially causing damage to human-robot collaboration systems.

Most existing robust control methods assume bounded disturbances, but in real-world environments, unmodeled dynamics from sudden impacts may exist, leading to insufficient dynamic adaptability of the algorithms. Furthermore, some computationally complex algorithms require solving an optimization problem within each control cycle, limiting their application in high-speed interaction scenarios and making it difficult to meet real-time requirements.

2.4 Literature Review

Existing literature on human-machine collaboration systems shows a clear trend toward development from structured environments to dynamic open scenarios. Traditional rule-based control and physical human-machine interaction methods have achieved success in industrial applications but exhibit obvious limitations when dealing with complex and dynamic environments. Dynamic uncertain environments reveal real-time computational demands caused by environmental changes and prediction challenges introduced by human factors, while the unpredictability of human factors imposes higher requirements on the system's adaptive capabilities. In terms of robust control methods, current research exhibits a trend toward diversification. Adaptive control, fuzzy control, and reinforcement learning each have their own unique characteristics, but these methods all face gaps between theoretical assumptions and practical applications: most algorithms are based on the assumption of bounded disturbances, while the unmodeled dynamics in real-world environments often exceed this scope. This paper aims to investigate the safe interaction mechanisms and robust control methods for human-machine collaborative systems in dynamically uncertain environments, with a focus on resolving the contradictions between safety and adaptability caused by environmental changes and human factors. By establishing dynamic safety constraint models and developing intelligent robust control strategies, the paper seeks to achieve safe and reliable operation of human-machine collaborative systems in complex environments.

3. Safety Interaction Mechanisms in Human-Machine Collaborative Systems under Dynamic Uncertainty

The core characteristic of a dynamic uncertain environment lies in the unpredictability of environmental states and human-machine behaviors, which prevents the system from pre-planning safe paths or accurately predicting interaction outcomes, thereby leading to risks such as collisions and task failures. Therefore, the design of safe interaction mechanisms must be based on a closed-loop framework of "real-time perception-risk assessment-decision adjustment-execution feedback," utilizing multi-modal perception, dynamic constraint modeling, and collaborative decision-making strategies to ensure the system maintains safe boundaries even under uncertainty.

3.1 Modeling and Analysis of Dynamic Uncertain Environments

When conducting safety interaction research on human-robot collaboration systems in dynamic uncertain environments, the primary task is to accurately model and analyze the environment, as environmental uncertainty directly threatens the safety of human-robot collaboration. Environmental dynamics introduce uncertainty, primarily manifested in three aspects. First, sensor noise severely interferes with the robot's accurate perception of environmental information. When sensors measure the distance to obstacles, ranging errors may cause the distance information received by the robot to deviate from the actual value, leading the robot to misjudge the position of obstacles and plan a path that invades the safety zone, thereby increasing the risk of collision [9]. Second, dynamic changes in tasks can disrupt the system's original task parameter settings, causing the robot to fail to complete collaborative tasks due to inability to match new task parameters, and potentially triggering safety incidents due to misoperations. Third, the trajectories of dynamic obstacles are difficult to predict.

Uncertainty in human-robot interaction exacerbates environmental complexity. For example, errors in predicting operator behavior can complicate the robot's motion planning [10]. Human operators exhibit high flexibility and uncertainty in their behavior, potentially suddenly altering their operational intent or action amplitude during actual operations. Ambiguity in collaborative intent may cause the robot to execute actions unrelated to the task objective. During human-robot collaboration, operators may fail to explicitly indicate the task objective or provide unclear or inaccurate instructions. Response delays require the robot to maintain a safe state during the delay period [11]. There is a certain physiological delay from perception to response in humans. In human-robot collaboration, this delay may prevent operators from providing timely feedback on the robot's actions.

To effectively address the challenges posed by dynamic uncertain environments, environmental modeling must integrate multi-source data to enhance environmental perception accuracy and use dynamic update mechanisms to real-time correct environmental models. By promptly correcting errors through dynamic update mechanisms, safety risks caused by delayed or incorrect environmental information can be avoided.

3.2 Key Issues in Safe Interaction

Real-time risk assessment quantifies the deviation between the current state and safety constraints to provide early warnings of potential hazards. Risk assessment must address two key issues: risk indicator definition and dynamic threshold setting. Risk indicators should comprehensively reflect factors such as human-machine distance, relative velocity, and obstacle density. They can be defined as:

$$R(t)=\alpha\cdot\frac{1}{d_{safe}(t)}+\beta\cdot v_{rel}(t)$$

where $d_{safe}(t)$ is the current human-robot distance, $v_{rel}(t)$ is the relative speed, and α and β are weighting coefficients (adjusted according to the task's safety level). When the human-robot operating distance is close and movements are precise, the weight of α should be increased to make the distance's impact on risk more significant; When the robot and operator's movement speeds may be high, the weight of β should be increased to make the impact of speed on risk more prominent. The design logic of this formula is to reflect the urgency of a collision through a weighted combination of distance and speed. The closer the distance and the higher the speed, the higher the risk value, thereby more accurately quantifying collision risk [12]. The dynamic threshold must be adjusted according to the task scenario. In high-precision collaborative tasks, the threshold *R(t)* must be stricter because such tasks have extremely high safety requirements, and even a minor collision could lead to serious consequences; in low-risk tasks, *R(t)* warnings can be appropriately relaxed. The warning mechanism can effectively address safety risks in different scenarios through real-time monitoring and dynamic adjustment, ensuring the safety of human-machine collaboration.

In human-machine collaboration, conflicts may arise from ambiguous action priorities or violations of safety constraints. Collaborative decision-making must address two issues: conflict detection and conflict resolution. Conflict detection is achieved through a safety constraint model, with safety distance constraints:

$$d_{safe}(t)=\|x_h(t)-x_r(t)\|\geqslant d_{min}+v_{max}\Delta t$$

where $x_h(t)$ and $x_r(t)$ represent the positions of the human and robot, respectively; d_{min} is the minimum safe distance; v_{max} is the maximum relative velocity; and Δt is the system response time. The design logic of this formula is to dynamically expand the safe distance to address collision risks caused by system response delays. Traditional safe distances only consider the static minimum distance, but in dynamic environments, humans and robots may continue moving within the system response time, resulting in a reduced actual distance. Conflict resolution requires selecting strategies based on conflict type. For action priority conflicts, solutions can include priority allocation or action adjustments. For safety constraint conflicts, dynamic safety potential fields can guide robots to detour.

3.3 Safe Interaction Framework Design

A framework for human-machine safety interaction is designed based on dynamic uncertain environments and critical issues. First, environmental state monitoring is conducted using multimodal perception. Accurate perception of environmental states and human-machine behavior is a prerequisite for safe interaction. Multimodal perception integrates data from lidar, cameras, force sen-

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sors, and wearable devices to construct a high-precision environmental model. Data fusion reduces the impact of errors from individual sensors and enhances the robustness of environmental perception. Multimodal perception integrates the advantages of different sensors to provide a more comprehensive and accurate reflection of environmental states and human-machine behavior, offering reliable data support for safe interaction. Second, adaptive safety constraint generation and dynamic adjustment. The adaptive adjustment mechanism enables safety constraints to flexibly adapt to different scenarios and task requirements, enhancing collaboration efficiency while ensuring safety. When task pace accelerates, the system can appropriately reduce safety distances to improve productivity; conversely, during precise tasks, the system strictly maintains larger safety distances to ensure safety.

4. Robust Control Method Design

4.1 Modeling Uncertain Systems for Robust Control

The core objective of robust control is to ensure that systems maintain stability and expected performance even in the presence of uncertainty. Its theoretical foundation is based on three pillars: Lyapunov stability theory proves the asymptotic stability of systems under uncertainty by constructing energy functions; the small gain theorem ensures that disturbances do not cause system instability by analyzing the gain boundaries of the system's input-output relationships; and μ-analysis quantifies the impact of structured uncertainty on system performance, providing quantitative tools for robust design [13]. The effectiveness of robust control depends on precise modeling of uncertainty. First, external disturbances are typically modeled as bounded energy signals to reflect their physical constraints; Sensor noise is classified as Gaussian white noise or colored noise based on its statistical characteristics, and its effects are suppressed through filters. Second, parameter variations are modeled as time-varying parameters fluctuating within known intervals or described through multiplicative uncertainty to represent deviations between the model and the actual system. Finally, unmodeled dynamics are constrained within a frequency band range via a weighting function to prevent interference with low-frequency control performance.

4.2 Robust Control Strategies for Human-Machine Collaboration

In human-machine collaboration scenarios, the system must simultaneously address the unpredictability of human behavior and dynamic changes in the environment. Therefore, adaptive control and intelligent optimization strategies must be combined to achieve dynamic adjustments.

Adaptive control addresses time-varying uncertainties by adjusting controller parameters online. In other words, adaptive control dynamically adjusts the gain matrix to balance response speed and overshoot, thereby adapting to time-varying uncertainties. Its core formula is:

$$u(t) = K_p(t)e(t) + K_i(t)\int_0^t e(\tau)d\tau + K_d(t)\dot{e}(t)$$

where $K_p(t)$ adjusts the proportional gain in real time to quickly reduce the error, $K_d(t)$ suppresses overshoot through the error change rate, and $K_i(t)$ eliminates steady-state error; When system parameters change or human operating forces undergo sudden changes, the gain matrix $K_p(t)$, $K_i(t)$, and $K_d(t)$ are updated online via an adaptive algorithm, dynamically adjusting based on the product of error and its rate of change. This ensures the system maintains critical damping response under uncertainty, keeping the closed-loop system stable during parameter adjustments and preventing oscillations caused by sudden gain changes.

Additionally, intelligent optimization strategies combining fuzzy logic or reinforcement learning can further enhance system performance: Fuzzy logic converts human experience into fuzzy rules to handle nonlinear uncertainties, with the advantage of enabling rapid decision-making through linguistic variables, making it suitable for scenarios with high real-time requirements; reinforcement learning learns optimal control strategies through trial and error, defining robust performance metrics as reward functions:

$$J = \int_0^t [e^T Q e + u^T R u + \delta^T S \delta] dt$$

where the weight matrices *Q, R,* and *S* penalize uncertainties such as error, control energy, and human operation deviations, guiding the controller to balance response speed and energy consumption in dynamic environments. By optimizing u(t) through interaction with environmental data, the strategy gradually approaches the global optimal strategy, overcoming traditional methods' reliance on model accuracy[14]. Additionally, a sufficiently trained RL model can adapt to unseen collaborative scenarios, enhancing system robustness. The advantages of this strategy are threefold: first, dynamic adaptability, where adaptive control combined with intelligent optimization enables the system to real-time perceive environmental changes and adjust control strategies, significantly improving tracking accuracy in dynamic environments; second, model flexibility, where fuzzy logic and RL do not rely on precise models, requiring only data or empirical rules, making them suitable for highly nonlinear and uncertain scenarios in human-robot collaboration; Third, enhanced safety: by limiting control energy and the impact of uncertainty, dangerous collisions between the robotic arm and humans caused by overcompensation are avoided.

4.3 Methodological Advantages Analysis

Robust control strategies for human-machine collaboration overcome the limitations of traditional control methods in terms of adaptability, disturbance rejection, and overall performance, demonstrating significant advantages in dynamic environments. Compared to PID control, which relies on fixed parameters, this strategy uses an adaptive adjustment mechanism to update the gain matrix in real time, enabling rapid response to dynamic events such as sudden changes in load or human operating force during human-machine collaboration. It effectively suppresses overshoot and oscillation, significantly enhancing disturbance rejection capability; Compared to optimal control (LQR), it explicitly handles bounded uncertainties, eliminating the need for precise models and assumptions about Gaussian white noise disturbances. It maintains stable control even in complex scenarios such as model parameter deviations and human operation nonlinearities, significantly expanding its applicability. In terms of dynamic environmental adaptability, this strategy integrates adaptive adjustment and intelligent optimization techniques: on one hand, it employs an online parameter update mechanism to ensure the system maintains critical damping response even when parameters change; on the other hand, it introduces nonlinear decision-making capabilities to the system. Fuzzy logic rapidly adjusts control parameters based on empirical rules, while reinforcement learning optimizes control strategies through trial-and-error learning. The two work together to handle complex uncertainties such as human intent prediction and operational deviations, significantly enhancing the system's generalization ability in unknown scenarios. Additionally, system stability is strictly maintained during dynamic adjustments, avoiding the risk of instability caused by sudden parameter changes. Through the synergistic effects of adaptive adjustment, intelligent optimization, and stability assurance, an efficient balance is achieved between stability, disturbance resistance, and dynamic performance.

5. Conclusion

Traditional human-robot collaboration methods mainly rely on rule-based control and physical human-machine interaction, which are suitable for relatively stable industrial environments with clear rules. However, with the advancement of robot technology, complex environments make it difficult for traditional human-robot collaboration methods to adapt quickly, resulting in limited system adaptability.

This paper proposes a safe interaction framework based on multimodal perception, adaptive safety constraint generation and dynamic adjustment, and collaborative decision-making strategies to address the risks posed by dynamic uncertain environments, thereby enhancing the safety and reliability of human-machine collaboration systems. In terms of robust control methods, this paper proposes a strategy combining adaptive control with intelligent optimization to address the unpredictability of human behavior and dynamic environmental changes. This strategy achieves system stability and expected performance under uncertainty by online adjustment of controller parameters and utilization of intelligent optimization methods such as fuzzy logic or reinforcement learning, thereby enhancing the adaptability and robustness of human-machine collaborative systems in complex environments. This research is of significant importance for achieving dynamic obstacle avoidance and conflict resolution through dynamic adjustment of safety constraints, ensuring the safe operation of human-machine collaborative systems across various scenarios.

References

[1] Kao, I., & Gong, C. (1997). Robot-based computer-integrated manufacturing as applied in manufacturing automation. Robotics and Computer-Integrated Manufacturing, 13(2), 157-167.

[2] Dixit, A. K., Kumar, T. V., Joshi, A., Bedi, H. S., Chakravarthi, M. K., & Singh, D. P. (2022, December). Trends in robotics and computer integrated manufacturing. In 2022 5th International Conference on Contemporary Computing and Informatics (IC3I) (pp. 212-216). IEEE.

[3] İç, Y. T. (2012). An experimental design approach using TOPSIS method for the selection of computer-integrated manufacturing technologies. Robotics and Computer-Integrated Manufacturing, 28*(2), 245-256.*

[4] Urhal, P., Weightman, A., Diver, C., & Bartolo, P. (2019). Robot assisted additive manufacturing: A review. Robotics and Computer-Integrated Manufacturing, 59, 335-345.

[5] Rodriguez-Guerra, D., Sorrosal, G., Cabanes, I., & Calleja, C. (2021). Human-robot interaction review: Challenges and solutions for modern industrial environments. Ieee Access, 9, 108557-108578.

[6] Sheridan, T. B. (2016). Human–robot interaction: status and challenges. Human factors, 58(4), 525-532.

[7] Robla-Gómez, S., Becerra, V. M., Llata, J. R., Gonzalez-

ISSN 2959-6157

Sarabia, E., Torre-Ferrero, C., & Perez-Oria, J. (2017). Working together: A review on safe human-robot collaboration in industrial environments. Ieee Access, 5, 26754-26773.

[8] Karuppiah, K., Sankaranarayanan, B., Ali, S. M., & Bhalaji, R. K. A. (2023). Decision modeling of the challenges to human–robot collaboration in industrial environment: a real world example of an emerging economy. Flexible Services and Manufacturing Journal, 35(4), 1007-1037.

[9] El-Shamouty, M., Wu, X., Yang, S., Albus, M., & Huber, M. F. (2020, May). Towards safe human-robot collaboration using deep reinforcement learning. In 2020 IEEE international conference on robotics and automation (ICRA) (pp. 4899-4905). IEEE.

[10] Cai, J., Du, A., Liang, X., & Li, S. (2023). Prediction-based path planning for safe and efficient human–robot collaboration in construction via deep reinforcement learning. Journal of computing in civil engineering, 37(1), 04022046.

[11] Iucci, A., Hata, A., Terra, A., Inam, R., & Leite, I. (2021, December). Explainable reinforcement learning for human-robot collaboration. In 2021 20th International Conference on Advanced Robotics (ICAR) (pp. 927-934). IEEE.

[12] Li, W., Hu, Y., Zhou, Y., & Pham, D. T. (2024). Safe human–robot collaboration for industrial settings: a survey. Journal of Intelligent Manufacturing, 35(5), 2235-2261.

[13] Liu, Z., Liu, Q., Xu, W., Liu, Z., Zhou, Z., & Chen, J. (2019). Deep learning-based human motion prediction considering context awareness for human-robot collaboration in manufacturing. procedia cirp, 83, 272-278.

[14] Wang, P., Liu, H., Wang, L., & Gao, R. X. (2018). Deep learning-based human motion recognition for predictive context-aware human-robot collaboration. CIRP annals, 67(1), 17-20.