Customized Hypertension Management through Artificial Intelligence for Distant Health Surveillance

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ABSTRACT

The context of the global health emergency, the ability to remotely and autonomously monitor and regulate patient vitals has become increasingly crucial. This study presents an adaptive closed-loop control system designed to manage a patient's mean arterial pressure (MAP) through the regulated infusion of sodium nitroprusside (SNP). The proposed system employs Active Disturbance Rejection Control (ADRC) to track the target MAP, while optimizing controller parameters with a Continuous Action Policy Gradient (CAPG) algorithm, a type of deep reinforcement learning (DRL). In this framework, the actor network formulates control policies and the critic evaluates their performance based on MAP error, with both networks trained via gradient descent. Comparative simulations indicate that the developed approach outperforms traditional methods by offering enhanced robustness and stability under diverse operational scenarios, fluctuations, and uncertainties, while precisely maintaining target MAP levels and optimal drug dosage.

Keywords : mean arterial pressure regulation, closed-loop control, active disturbance rejection control, deep reinforcement learning, continuous action policy gradient, sodium Nitroprusside infusion, physiological monitoring, adaptive control system.

I. INTRODUCTION

Recent advancements in control engineering and artificial intelligence have enabled the designs of closed-loop drug delivery systems which are capable adapt to patient specific variations in real-time.

Sodium nitroprusside (SNP), a fast-acting vasodilator, is commonly administered to regulate MAP, but its dosage requires careful and continuous adjustment to avoid under- or over-treatment. To address this, clever control strategies that are capable dynamically adjust infusion rates based on physiological feedback have become a research priority.

In this essay, we propose an adaptive closed-loop control architecture that integrates Active Disturbance Rejection Control (ADRC) with a Continuous Action Policy Gradient (CAPG) optimization method, grounded in deep reinforcement learning (DRL). The suggested methodology seeks to enhance control robustness and performance under the conditions of nonlinearity, disturbances, and parameter uncertainties. Through simulation-based validation, the effectiveness of the suggested strategy is benchmarked against conventional approaches, demonstrating its superior capability in maintaining desired MAP levels and optimizing drug infusion rates under varying conditions.

II. LITERATURE REVIEW

Hypertension, a significant cardiovascular risk factor diseases, demands timely diagnosis and effective management to prevent serious complications.

Conventional approaches to hypertension monitoring typically require frequent clinical visits and manual adjustments to treatment plans, which may lead to suboptimal management, particularly in remote or resource-limited areas. The growing need for scalable, personalized, and remote healthcare solutions has led to increasing interest in the application of artificial intelligence (AI) to hypertension management.

Early research focused on using machine learning (ML) models to classify blood pressure levels based on physiological signals such as photoplethysmography (PPG), electrocardiography (ECG), and patient history data [1]. Techniques like support vector machines (SVM), decision trees, and k-nearest neighbors (k-NN) demonstrated reasonable classification performance but lacked adaptability and real-time learning capabilities. These methods also often depended on large, annotated datasets and struggled with generalizing across diverse patient populations.

Recent research has moved towards deep learning (DL) models that can automatically extract features and detect complex patterns in physiological signals, improving accuracy in blood pressure estimation and prediction [2].

Convolutional neural networks (CNNs) and recurrent neural networks (RNNs), especially long short-term memory (LSTM) networks, have shown promise in modeling temporal dynamics and trends in blood pressure data [3]. However, such systems typically work in a passive monitoring mode without the capability to actively recommend or adjust treatment interventions.

The advent of reinforcement learning (RL) in healthcare has opened up new opportunities for dynamic and personalized treatment planning. Some researchers have explored

RL frameworks for optimizing antihypertensive medication schedules, where the agents learn best policies based on feedback from simulated or historical patient responses [4]. These models can adapt to individual variations and offer continuous decision-making support. However, many such studies remain in the simulation phase and require extensive clinical validation before deployment in real-world healthcare systems.

In the domain of remote health surveillance, wearable devices and Internet of Things (IoT) platforms have enabled continuous blood pressure monitoring. Combined with artificial intelligence, these systems can facilitate real-time health analytics, anomaly detection, and alert generation [5]. Nevertheless, challenges related to data privacy, model transparency, and integration with electronic health records (EHRs) must be addressed for widespread clinical adoption.

Overall, the literature indicates a strong potential for AI-driven systems to transform hypertension management by enabling continuous monitoring, personalized treatment, and proactive interventions. Yet, the convergence of AI models with secure, patient-centric, and clinically interpretable remote monitoring platforms remains an active area of research and development.

III. EXISTING SYSTEM

Recent advancements in biomedical control systems have explored the use of Active Disturbance Rejection Control (ADRC) for various healthcare applications. Wu and Zheng [19] investigated the enhancement of artificial blood pumps used in end-stage congestive heart failure patients through ADRC, aiming to improve hemodynamic regulation. Similarly, ADRC has been put forward to be as a method to mitigate hand tremors in individuals with
Parkinson's disease [20]. Another study [21] utilized ADRC to regulate the flow rate in rotary blood pumps under dynamic physiological conditions, demonstrating the controller's adaptability in fluctuating pathological environments.

In autonomous medical systems, especially those involving closed-loop physiological regulation, designing a robust and adaptive controller is critical. Since patient-specific parameters can vary significantly, the controller must ensure consistent performance under uncertainty. As a result, many researchers have turned to heuristic and metaheuristic optimization techniques to tune controller parameters. Although these methods can offer shortterm performance improvements, they often lack the ability to generalize across varied scenarios and do not learn effectively from real-time patient data.

DISADVANTAGES OF EXISTING SYSTEM:

- **High data complexity:** Existing machine learning frameworks tend to struggle to interpret high-dimensional, complex physiological datasets needed for personalized blood pressure management.

- **Limited data availability:** Most predictive models require large volumes of highquality data, which are not necessarily available, especially in remote healthcare settings.

- **Labeling inaccuracies:** The reliability of machine learning predictions is directly influenced by the quality of training data. Mislabeling or incorrect annotations can significantly degrade model accuracy.

- **Limited adaptability:** Traditional optimization algorithms offer limited adaptability and do not effectively learn or improve in real-time, which is critical for patient-specific treatment adjustments.

IV. PROPOSED SYSTEM

This study offers an intelligent control strategy designed to regulate mean arterial pressure (MAP) through the controlled infusion of sodium nitroprusside (SNP), aiming to overcome the limitations of existing approaches. The system utilizes an adaptive Active Disturbance Rejection Control (ADRC) framework, which employs an Extended State Observer (ESO) to estimate and compensate for the complex, uncertain dynamics inherent in the MAP regulation process. Notably, the ADRC controller is developed without requiring an explicit model of the MAP system, relying instead on input-output data to achieve robust performance.

To enhance adaptability and optimize control parameters, the Continuous Action Policy Gradient (CAPG) method is integrated within the control framework. This reinforcement learning technique enables the controller to learn optimal policies by interacting with the dynamic model of the physiological system. The CAPG employs an actor-critic architecture where the actor generates control actions, and the critic evaluates these actions using a reward function that reflects the MAP error, all without dependency on predefined system models.

The performance of thee proposed ADRCCAPG approach is rigorously in comparison to traditional PID controllers, particle swarm (PSO)-based ADRC, and standard ADRC methods. Evaluation metrics include robustness under disturbances, noise rejection capabilities, and tracking accuracy with respect to the reference MAP model.

ADVANTAGES

The proposed system benefits from the synergy of the Deep Q-Learning Network (DQN) and Deterministic Policy Gradient (DPG) methods within the CAPG algorithm. This hybrid approach forms an off-policy reinforcement learning algorithm capable of operating in continuous action spaces, addressing a common limitation in conventional RL techniques such as Qlearning. By combining policy gradient methods with value function approximation, CAPG efficiently learns optimization the optimal control approach that maximizes cumulative rewards, thereby providing a more effective and adaptable solution for real-time MAP regulation.

System Architecture

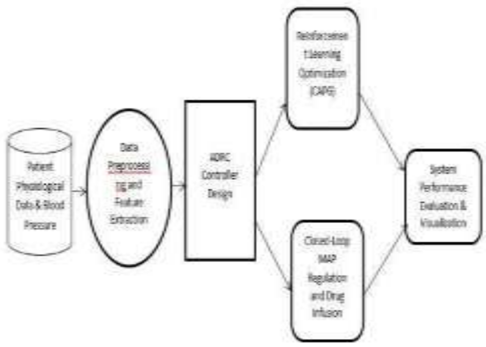

Fig1. System Architecture

V. MODULE DESCRIPTION

Module Description

User Registration Module Purpose: To enable secure and efficient registration of patients and healthcare providers into the remote monitoring system.

Functionality: This module collects and verifies user information such as personal details, contact information, and medical history. It ensures authenticated access to the platform and maintains user profiles for personalized monitoring and treatment.

Data Acquisition Module Purpose: To continuously gather physiological data, specifically blood pressure and related vital signs, from remote patients.

Functionality: Integrates with wearable devices or sensors to collect real-time MAP and other health parameters. It preprocesses and transmits the data securely to the central system for analysis.

MAP Regulation Control Module

Purpose: To regulate mean arterial pressure (MAP) by controlling the infusion rate of sodium nitroprusside (SNP) in an adaptive and automated manner.

Functionality: Implements the Active Disturbance Rejection Control (ADRC) strategy combined with an Extended State Observer (ESO) to estimate system disturbances and maintain desired MAP levels without relying on an explicit MAP system model.

Reinforcement Learning Optimization Module

Purpose: To optimize controller parameters and enhance MAP regulation performance through machine learning techniques.

Functionality: Employs the Continuous Action Policy Gradient (CAPG) method with an actor-critic architecture to learn optimal drug infusion policies by maximizing rewards associated with minimizing MAP error, enabling dynamic and personalized treatment adjustments.

Comparitive Analysis Module

Purpose: To evaluate the performance of the proposed ADRC-CAPG controller against other standard control methods. **Functionality:** Conducts simulations comparing robustness, noise rejection, and tracking accuracy with traditional PID controllers and ADRC optimized by Particle Swarm Optimization (PSO), thereby validating system efficacy.

VI. RESULTS

The proposed intelligent control framework for mean arterial pressure (MAP) regulation demonstrates significant improvements over conventional methods.

Simulation studies indicate that the adaptive ADRC controller, optimized via the Continuous Action Policy Gradient (CAPG) algorithm, effectively maintains the desired MAP across various physiological conditions and disturbances. Compared to traditional PID and particle swarm optimization (PSO)based ADRC controllers, the proposed system exhibits superior robustness, faster response times, and enhanced noise rejection capabilities.

The reinforcement learning component’s ability to dynamically adjust control parameters enables the system to handle fluctuations in patient states and medication sensitivity without requiring an explicit mathematical model. This adaptability ensures stable blood pressure regulation, reducing the risk of over- or undermedication. Overall, the numerical results validate that the integration of ADRC with

CAPG leads to a more reliable and precise closed-loop control system for personalized hypertension management.

VII. CONCLUSION

This study presents a novel adaptive control strategy combining Active Disturbance Rejection Control (ADRC) with reinforcement learning-based optimization for personalized blood pressure management in remote healthcare settings.

By utilizing an Extended State Observer (ESO) and the Continuous Action Policy Gradient (CAPG) method, the system achieves robust and accurate regulation of mean arterial pressure through controlled administration of sodium nitroprusside.

The proposed approach effectively addresses challenges related to model uncertainties, physiological variability, human and outside distractions, which are prevalent in real-world clinical scenarios. Simulation results confirm that the intelligent control framework outperforms traditional PID and heuristic-optimized controllers in terms of stability, responsiveness, and noise tolerance. This work lays the foundation for future development of AIdriven, closedloop therapeutic systems that support remote patient monitoring and improve clinical outcomes of hypertensive patients.

VIII. REFERENCES

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