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Gait prediction for lower limb exoskeleton robots based on real-time adaptive Kalman filtering

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Highlights

- The paper develops a gait prediction control strategy for lower limb exoskeleton robots using a real-time adaptive Kalman filtering algorithm, with public gait data from a Clinical Gait Analysis serving as input.
- The model incorporates motor rotation angle, angular velocity, and angular acceleration as core parameters, calculated based on the principles of uniformly accelerated motion. It achieves gait prediction by initializing parameters, calculating Kalman gain, correcting measurements, and updating the covariance matrix.
- A control strategy guided by normal gait parameters enables the exoskeleton to transition efficiently into the desired motion state during startup and gait phase switching. The system employs a microcontroller and Raspberry Pi as its control core, integrated with Bluetooth communication for effective robot control.

Abstract

This paper presents a gait prediction method for lower limb exoskeleton robots using a real-time adaptive Kalman filtering algorithm. The exoskeleton robot targets two user groups: individuals with impaired lower limb motor function requiring rehabilitation training, where the device aids in muscle exercise during walking to facilitate recovery, and healthy individuals using it as a wearable assistive device. To enhance movement intention prediction and improve human-machine coordination, this study focuses on the gait prediction algorithm for walking assistance in healthy users and proposes a gait prediction control strategy based on normal gait orientation. The control system utilizes a microcontroller and Raspberry Pi as its core, enabling functional mode selection through multi-sensor data fusion and effective control of the robot via Bluetooth communication. By comparing the original model algorithm with the proposed real-time updating Kalman filter algorithm, the latter demonstrates feasibility, achieving a prediction error within 1°. This validates the model's effectiveness in real-time gait prediction.

Keywords: Gait prediction, lower limb exoskeleton robot, Kalman filtering

Introduction

Currently, lower limb exoskeleton robots are designed for two primary user groups. The first group includes individuals with impaired lower limb motor function who require rehabilitation. These exoskeletons simulate normal walking gait, assist patients in exercising their leg muscles, and facilitate the recovery of motor functions [1]. The second group includes healthy individuals, where exoskeletons serve as wearable booster devices in fields such as the military, industry, and first aid [2]. These devices enhance user functionality by reducing weight-bearing strain and physical exertion [3].

Commercially mature exoskeletons primarily focus on rehabilitation and employ relatively simple motion control systems. In contrast, exoskeletons for healthy users require real-time stability and improved human-machine interaction, imposing more stringent demands on mo-

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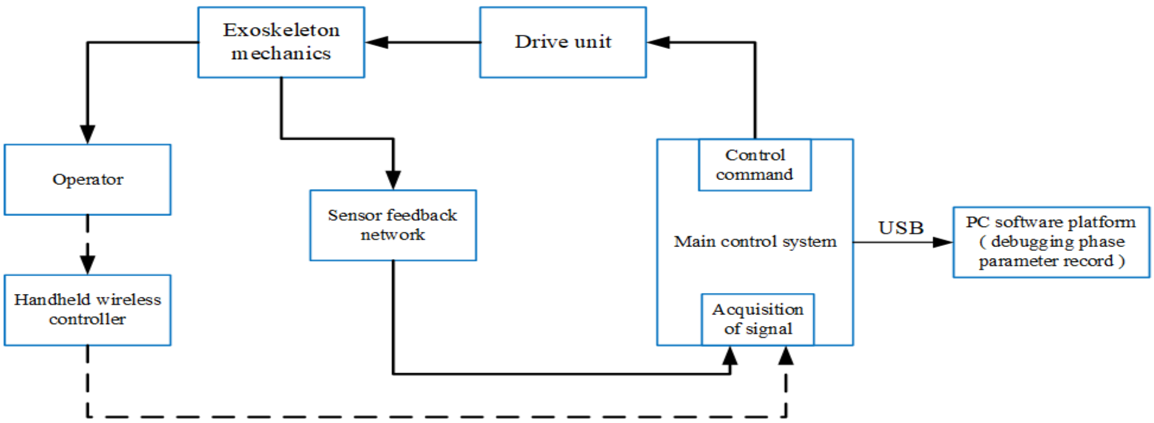

Figure 1. Schematic diagram of the overall composition of the exoskeleton system.

tion control. Qu et al. studied the phase division of normal human gait and proposed dividing motion control into two phases: assisting and following. The control system was developed using fuzzy impedance control and position control based on gait trajectory, with input parameters provided by attitude angle sensors and pressure sensors [4]. Song explored gait predictive control using Kalman filtering and Gradient Boosting algorithms to predict changes in joint angles during robot motion [5]. This approach integrates intelligent modules to estimate current joint angles and predict subsequent changes, enabling precise robot control.

The Hybrid Assistive Limb robot, developed by Cyberdyne in Japan, weighs 23 kg, has a 160-minute endurance, and offers two control systems: bioconscious control and autonomous conscious control [6, 7]. The bioconscious control system captures electromyographic signals to infer the user's movement intentions, while the autonomous control system uses pre-stored models to perform assisted movements. Kadone et al. evaluated the HAL robot's effectiveness in patients with gait disorders caused by compressive myelopathy, demonstrating improved gait and restored joint contours after training [8].

Kalman filters have also been widely applied in other domains. For example, Wang et al. used Kalman filtering to process correlated noise and estimate pitch angles [9]. Fan et al. applied a Kalman filter fusion algorithm to eliminate noise and clutter in sowing depth measurements, resulting in more accurate detection data [10]. Li proposed an optimization method based on Kalman filter sensor data fusion, which improved stability, anti-interference capability, and reliability even when some equipment failed [11].

The objective of this project is to develop a wearable exoskeleton robot for assisting healthy individuals during walking. This robot aims to accurately predict the user's movement intentions and provide effective assistance. The control system will use a microcontroller as the central module and integrate multi-sensor data fusion to achieve human-robot synergy. By combining sensing, electromechanical control, information detection, and artificial intelligence, the project seeks to deliver an intelligent wearable assistive device that meets user needs.

Structural design of a lower limb exoskeleton system

The lower limb exoskeleton assistive robot has been independently designed and developed, with its overall configuration illustrated in **Figure 1**. The mechanical structure mainly comprises a sliding hip joint with adaptive length adjustment, a multi-link bionic knee joint, and an electrically controlled backpack module [12-14]. The exoskeleton combines actively powered hip joints with passively assisted knee joints, improving the operator's active control, reducing energy consumption, and extending battery endurance.

As in **Figure 2**, the mechanically adaptive leg features a hip joint transmission module, a bionic knee joint linkage module, ankle and foot components, and additional accessories such as bearings and clasps. The hip joint transmission module includes a disc motor, motor tray, coupling, harmonic reducer, and a disc torque sensor, which is secured using screws. The mechanical leg employs a nested composite design with adjustable and lockable lengths, allowing it to accommodate users of varying heights. By controlling the rotation of the disc motor, electric energy is converted into kinetic energy, pushing the thigh rod to assist movement.

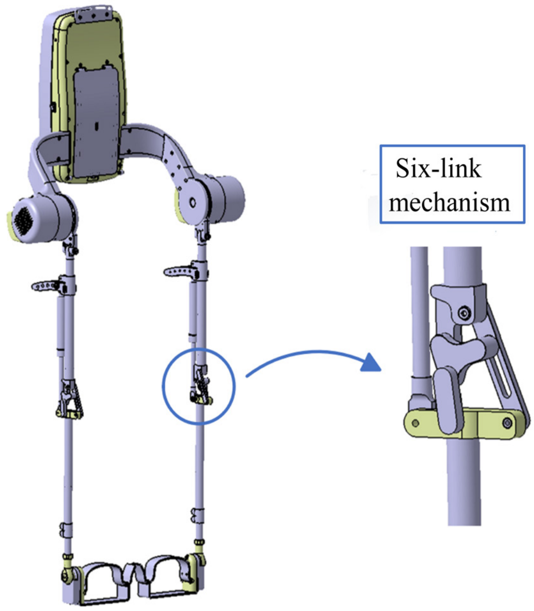

Figure 2. 3D modeling of the exoskeleton robot.

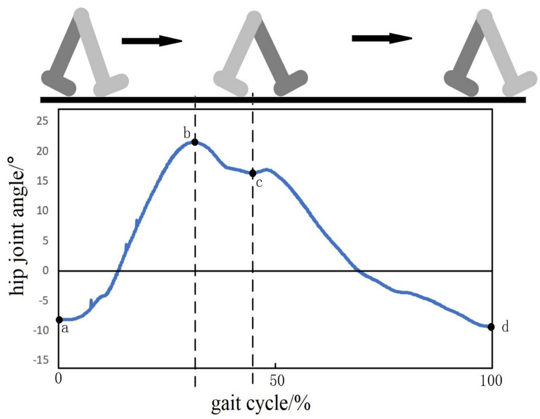

Figure 3. Angular variation curve of the hip joint during a single gait cycle.

The bionic knee joint module features a passive six-link mechanism integrated with an air spring. The air spring stores kinetic energy during knee flexion and releases it during extension, providing a boost to movement. The ankle joint is equipped with an active joint capable of 360° rotation. The footplate connects to the joint via a nested structure, and both components are height-adjustable to adapt to user-specific needs. The unilateral leg, there are 3 degrees of freedom at the hip joint, 1 degree of freedom at the knee joint, and 1 degree of freedom at the ankle joint.

Design of control system for gait prediction based on Kalman filtering

Gait analysis and control scheme design

Normal gait refers to the walking posture that minimizes body energy consumption while maintaining maximum comfort [15]. Gait analysis, a biodynamic research method, studies the human walking process using mechanical principles, specialized treatments, and knowledge of anatomy and physiology [16]. Simplifying the human body into a linkage model facilitates dynamic analysis of motion and force interactions [17]. **Figure 3** shows the angular variation curve of the hip joint during a single gait cycle in normal walking. The curve begins at the initial state (a), where the heel of the right leg contacts the ground, and the left leg's heel is about to lift off, and ends at state (d), where the right leg's heel contacts the ground again. Point b represents the critical transition point where the left leg changes direction, and point c marks the start of left leg support.

The analysis of the gait cycle and hip joint angular variation serves as the foundation for defining the functional requirements of the exoskeleton control system. First, the starting posture and movement speed must be determined. In this study, the two-legged standing position is used as the initial state, and the angular changes in normal gait are utilized to calculate the corresponding movement speeds. This ensures that the robot can rapidly transition into the assistive and following modes. When the motion reaches point b, the exoskeleton must react promptly to change direction and either follow or assist the backward movement of the human leg. At point c, the exoskeleton is required to transfer the user's center of gravity to the supporting leg while assisting the swing leg's motion.

The intelligent control system is designed with a microcontroller as its core, enabling precise control of each joint motor via programmed instructions. The system reads motor parameters and sensor data to determine the motion state of the exoskeleton and performs closed-loop feedback for adjustment and control. Additionally, the system integrates a microprocessor and an electromyography acquisition module to capture the user's leg electromyography signals. These signals are processed to detect the user's movement intentions, assisting the main control system in guiding the robot to the appropriate movement state. The overall design scheme of the exoskeleton control system is depicted in **Figure 4**.

To ensure the normal operation of the robot, a handheld control switch transmits control commands via wireless Bluetooth to manage functions such as startup and reset, ensuring user safety during robot use. The switch conveys

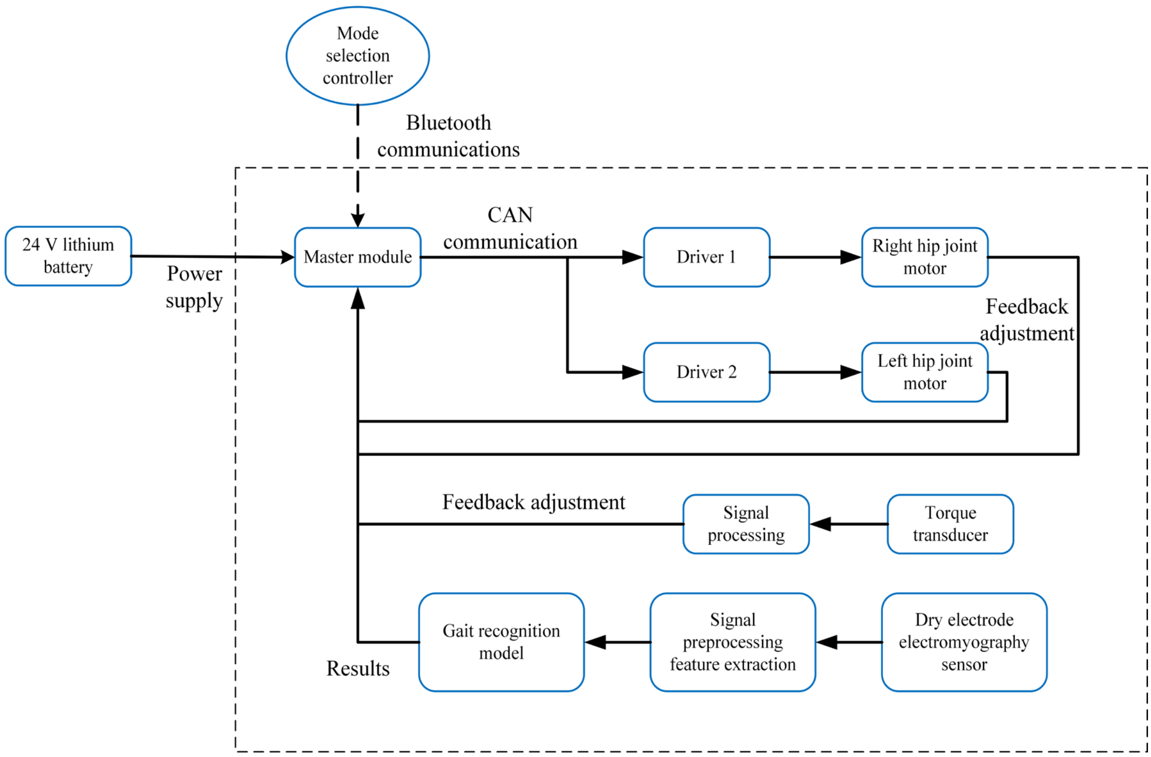

Figure 4. General design scheme of the exoskeleton control system. CAN, Controller Area Network.

commands to the main control module, which analyzes the inputs and transmits corresponding control signals to the joint motor drivers. The motors then execute these commands, enabling the exoskeleton robot to function effectively. During operation, the system primarily controls the speed of each joint motor to provide assistance. Real-time acquisition of motor rotation angles and human-machine interaction data, obtained from torque sensors, allows for precise speed adjustments, reducing resistance and improving control accuracy, safety, and stability.

The exoskeleton robot's control system is built on a comprehensive hardware platform comprising various modules. Key components include:

Power Supply Unit: A lithium battery ensures portability, freeing the system from location constraints.

Main Control Module: Based on the STM32F4 series minimum system, this serves as the core processing unit.

Joint Motors and Drives: Facilitate the robot's movements.

Sensors: Torque sensors provide critical feedback for regulation and control.

Auxiliary System: Built on a Raspberry Pi 4B microcomputer, enabling intention recognition.

These hardware elements collectively form the foundation for implementing the exoskeleton control platform.

Gait prediction based on real-time updated Kalman filtering

Design of the real-time updated Kalman filter gait prediction process

The Kalman filtering algorithm, proposed by R.E. Kalman in 1960, is a recursive filter widely used for solving linear filtering problems in discrete data [18]. It estimates the state of a dynamic system from noisy measurements, minimizing mean-square estimation error, and has been extensively applied across various engineering fields [19-21].

The algorithm consists of two phases: prediction and update [22].

Prediction Phase: The algorithm predicts the system state at the next moment using the prior optimal state estimation and the system model.

Update Phase: The Kalman gain is calculated, allowing the algorithm to compare the predicted value with newly obtained measurements and refine the state estimate for improved accuracy [23].

The core principle involves predicting the state at the Kth moment using the best estimate from the (K-1)th moment. This prediction is then corrected based on observations at the Kth moment, producing a more accurate estimate [24].

In this study, predictive control of robot motion is implemented using a real-time updated Kalman filter algorithm, with Clinical Gait Analysis data as input. The motion of the robot is primarily determined by motor parameters such as rotation angle, angular velocity, and angular acceleration, calculated based on the principle of uniformly accelerated motion. The detailed construction process of the prediction model is presented as shown below.

The predictive control process using a real-time updated Kalman filter consists of the following steps:

Inputs: Measurement parameter matrix

$$x = \begin{bmatrix} \theta \\ \omega \end{bmatrix}, \quad Q = \begin{bmatrix} D(\theta) & 0 \\ 0 & D(\omega) \end{bmatrix} \quad R = \begin{bmatrix} r_1 & r_2 \\ r_3 & r_4 \end{bmatrix}$$

where Q and R are adjustable parameters.

Outputs: Predictive matrix $y = \begin{bmatrix} \theta \\ \omega \end{bmatrix}$

1. Initialization parameters:

$$H = \begin{bmatrix} 1 & 0 \\ 0 & 1 \end{bmatrix}, \quad A = \begin{bmatrix} 1 & \Delta t \\ 0 & 1 \end{bmatrix}, \quad B = \begin{bmatrix} \frac{1}{2}\Delta t^2 \\ \Delta t \end{bmatrix}, \quad P = \begin{bmatrix} p_1 & p_2 \\ p_3 & p_4 \end{bmatrix}$$

Initially, all elements are set to zero, and angular acceleration a is considered.

2. Calculation of the current initial Kalman gain at Time k :

$$k = \begin{bmatrix} k_1 & k_2 \\ k_3 & k_4 \end{bmatrix} = \frac{P(k) * H^T}{H * P(k) * H^T + R}$$

3. Correction of the measurement value at Time k:

$$x(k) = x(k-1) + K * (y(k) - H * x(k-1))$$

where $x(k-1)$ represents the measurement value at the previous moment and can be initially set to 0.

4. Update of the covariance matrix at time k :

$$P(k) = (I - K * H) * P(k)$$

where I is the two-dimensional identity matrix.

5. Prediction of the state at time $k+1$:

$$x(k+1) = A * x(k) + B * a$$

where a is the acceleration at time k , calculated from the velocity at time k and the time interval.

6. Predictive update of the covariance matrix:

$$P(k+1) = AP(k)A^T + Q$$

7. Recording of current time data: This step prepares the data required for calculating a .

Implementation of gait prediction algorithm

In this study, a control strategy for the exoskeleton robot is designed based on normal gait parameters. The control scheme uses human walking parametersas a guide, enabling the exoskeleton to quickly transition to the corresponding motion state when switching between startup and gait phases [25]. The booster function is achieved by controlling the robot's speed to exceed human motion through real-time feedback adjustment.

The development environment for the control system program is KEIL MDK, where C language is used. **Figure 5** illustrates the flowchart of the main control program. During the debugging phase, after the robot system is powered on, the master control system's clock, interrupt, serial port, and mode selection controller are initialized. The parameters of each motor and driver are then verified by connecting to a computer to ensure they function correctly.

Since the relative operating angle of the robot must be tested in real time, the initial starting state is defined as a two-legged standing position. If the robot deviates from this state after the motors are operational, it can be restored by selecting the abnormal reset mode, ensuring the initial gait data is ready for execution. The communication protocol between the mode selection controller and the master control system is AA000xBB, transmitted wirelessly via the Bluetooth module. The variable x ranges from 1 to 4, representing the following instructions: 1: Normal operation; 2: Abnormal reset of the right hip joint; 3: Abnormal reset of the left hip joint; 4: Normal reset.

In the normal reset mode, the operation stops after returning to the initial two-legged standing position.

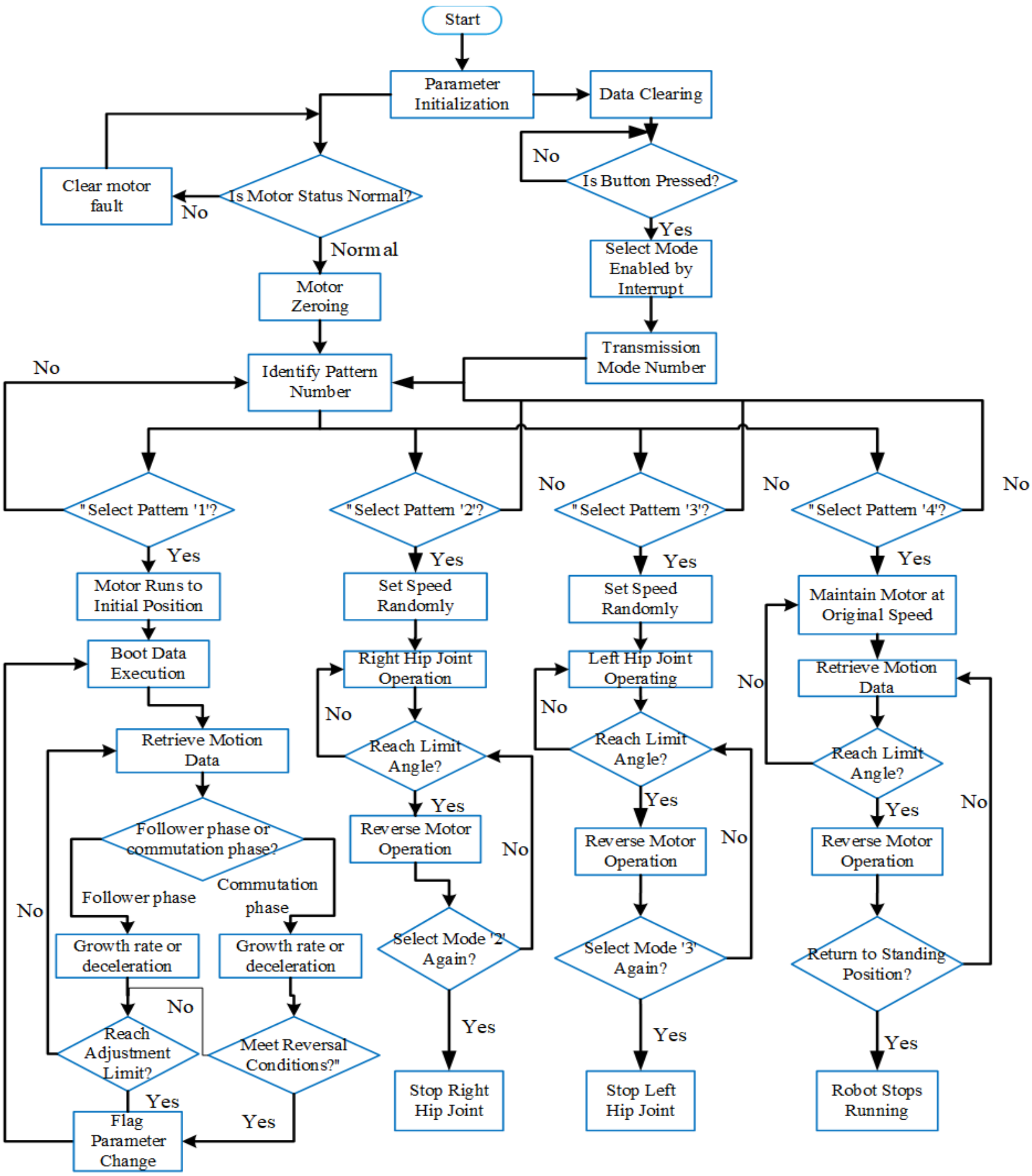

Figure 5. Main control program flow chart.

This study employs Profile Velocity Mode for robot control, focusing on the operational speed. The process is as follows [26]:

Retrieve the control index of the selected mode.

Activate the Profile Velocity Mode control mode via Service Data Object communication.

Clear any errors, enable the drivers and motors, and wait for the controller to select the working mode and transmit the corresponding control data.

In normal operation mode, the main control module transmits the initial guidance gait data to start the robot, entering the following phase. During this phase, the robot assists the human body in walking, with the torque sensor enabling users to adjust the operational speed of the robot.

When transitioning to the commutation phase, the system integrates direction switching functionality. The program evaluates the torque information from human-machine interaction and the current operating speed. Once the predefined conditions are satisfied, the system

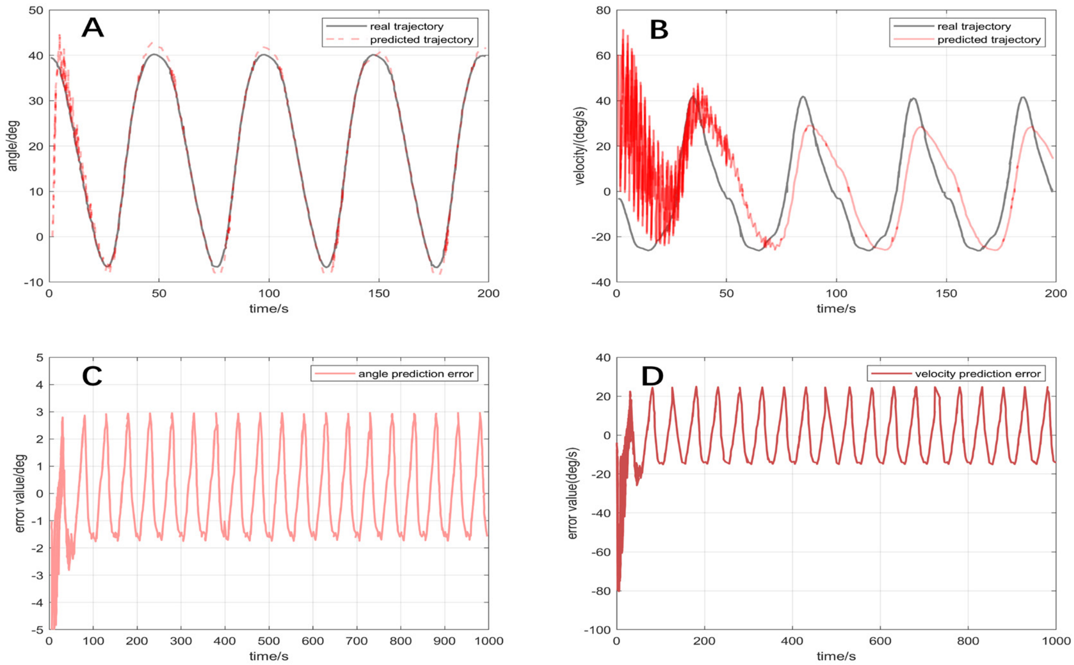

Figure 6. Simulation results of conventional Kalman filter prediction. (A) Angle change curve; (B) Velocity change curve; (C) Angle prediction error curve; (D) Speed prediction error curve.

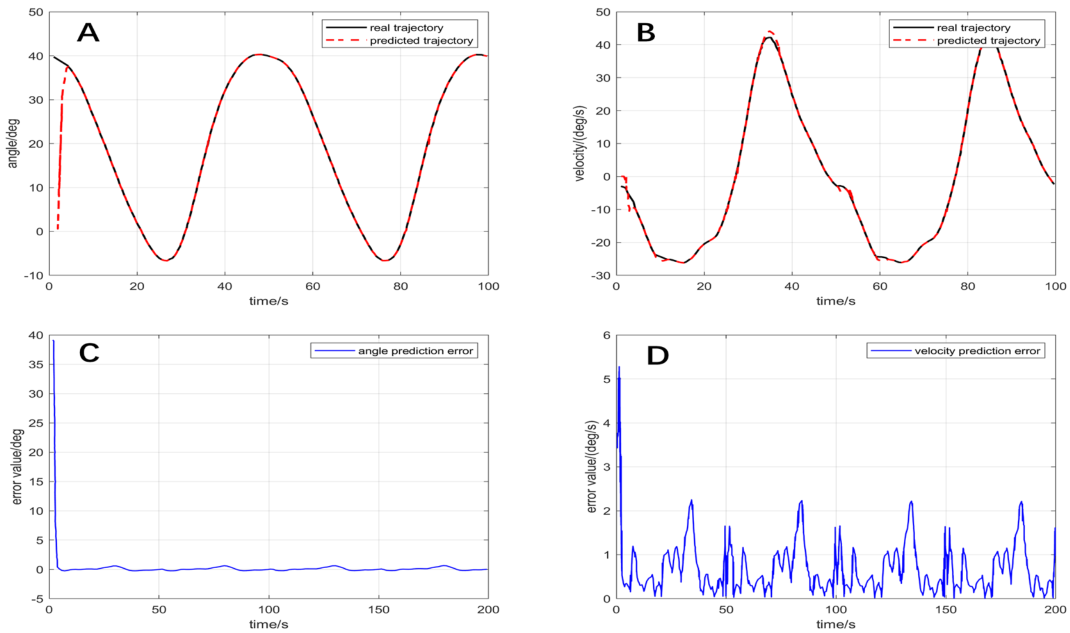

Figure 7. Simulation results of real-time updated Kalman filter prediction. (A) Angle change curve; (B) Velocity change curve; (C) Angle prediction error curve; (D) Speed prediction error curve.

transitions to the next stage of speed guidance control. To further ensure safety, the program includes limits on both the running speed and operating angle.

Result analysis

The model prediction simulations were conducted using MATLAB, with the results presented in **Figure 6** and **Figure 7**. **Figure 6** displays the prediction results of the conventional Kalman filtering model, while **Figure 7** shows the simulation results of the real-time updated Kalman filter model.

The results indicate that the real-time updated Kalman filter achieves gait predictions for lower limb exoskeleton robots that align more closely with actual motion parameters, demonstrating superior accuracy and stability. Compared with the conventional Kalman filter, the updated model achieves higher prediction accuracy, with reduced errors in both angle and velocity predictions and smaller fluctuations in the error curves.

In particular, the joint velocity change curves reveal significant jitter in the initial stage when using the conventional Kalman filter, requiring a stabilization period before aligning with the walking gait. In contrast, the real-time updated Kalman filter stabilizes much faster, effectively avoiding the jitter observed in the conventional model and adapting more rapidly to gait changes.

When stabilized, the real-time updated Kalman filter achieves a prediction error of no more than 1°, outperforming the conventional model's error range of 0°–5°, which only considers angle predictions with H=[1 0]T. This smaller error range further confirms the feasibility and effectiveness of the real-time updated model in gait prediction.

Conclusions and outlook

This study investigated a gait prediction method for lower limb exoskeleton robots using a real-time updatable Kalman filtering algorithm, aiming to enhance human-machine coordination and predict user motion intentions. A control strategy based on normal gait orientation was implemented using a microcontroller and Raspberry Pi as the core, combined with multi-sensor data fusion. The system achieved functional mode selection via Bluetooth communication. Experimental results showed that the real-time updated Kalman filter outperformed the conventional model in prediction accuracy, achieving a prediction error of no more than 1°.

Future research can focus on the following directions:

Algorithm Optimization: Enhancing computational efficiency to improve real-time performance, making the prediction algorithm more suitable for practical applications.

Integration of Additional Sensor Data: Incorporating biofeedback signals, such as electromyography, to enhance prediction accuracy and adaptability.

Broader Applications: Expanding the use of the system to military, industrial, and first-aid scenarios to meet diverse needs.

AI Integration: Leveraging advancements in artificial intelligence and machine learning to further improve gait prediction performance, enabling more intelligent and personalized support for users.

These developments will provide a robust technical foundation for the commercialization and clinical application of lower limb exoskeleton robots, advancing their utility and accessibility across various domains.

Author Contributions: Haonan Geng was responsible for writing and editing the whole paper, proposing the research idea and theoretical framework, designing the corresponding research program and implementing it. Xudong Guo was responsible for reviewing the draft paper and supervising the research work. Fengqi Zhong is responsible for the operation of the project and data analysis. Haibo Lin collected the necessary materials for the study and did some experiments. Guojie Zhang supervised the research and provided technical support. Qin Zhang provided the necessary resources and supervised the research work. Jiaheng Chen performed part of the data analysis and collected the required materials.

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