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Online recognition method for walking patterns of intelligent knee prostheses based on CNN-LSTM algorithm

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Highlights

- In prosthetics, using AI algorithms to identify the fused sensor data as known walking patterns has extremely strong expandability. Moreover, as the learning data continues to expand, the robustness of the model itself also increases accordingly.
- There are numerous AI algorithms currently available. The effective utilization of algorithm combination techniques to learn from each other's strengths can significantly improve the accuracy of identification. The combined model of convolutional neural networks (CNN) and bidirectional long short term memory (LSTM) attempted in this paper has witnessed a significant improvement in its comprehensive recognition rate.
- In the practical application of prosthetics, the real-time performance during the mode switching transition period is particularly important as it can reflect the flexibility of the prosthetics. In this paper, the algorithm optimized by the AI model has controlled the delay rate within one gait cycle, greatly enhancing the safety and reliability of prosthetics in actual use.

Abstract

To enhance the adaptive learning, self-organization, and fault tolerance capabilities of gait pattern recognition in intelligent knee prostheses, an online walking pattern recognition method based on the convolutional neural networks (CNN)-long short term memory (LSTM) model is proposed. Five test subjects wore the intelligent knee prostheses and performed four walking modes: level walking, uphill walking, downhill walking, and stair descent. The preprocessed gait data were fed into four neural network models: CNN, LSTM, CNN-LSTM, and CNN-bidirectional LSTM. Through hyperparameter tuning, the recognition accuracy of these models was compared. Real-time indicator, gait recognition delay, was also measured. Experimental results showed each model had its strengths and weaknesses. Overall, the CNN-LSTM model achieved the best recognition performance with accuracy rates of: level walking 89%±2.5%, uphill 72.8%±3.2%, downhill 71%±3.2%, and stair descent 96%±2.5%. When switching from level walking to downhill, gait recognition delay was 51.7%±15.6%, and vice versa it was 75.8%±11.5%; when switching from level walking to stair descent, gait recognition delay was 47.1%±17.1%, and vice versa it was 38.6%±10.5%. In summary, the application of the CNN-LSTM model for walking pattern recognition in unilateral intelligent knee prostheses is feasible, with accuracy and real-time performance meeting the control requirements of the prostheses.

Keywords: Neural network, walking pattern, gait recognition, recognition delay rate

Introduction

Traditional electronically controlled knee prostheses require the user to pre-select the current walking mode, such as level walking, uphill, downhill, or stairs. Once the walking mode

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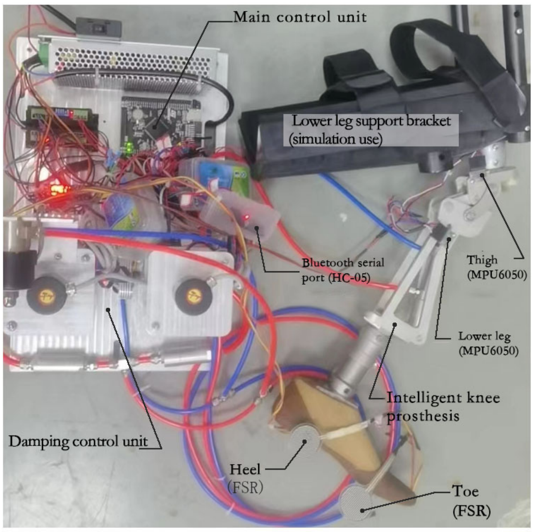

Figure 1. Intelligent above-knee prosthetic prototype.

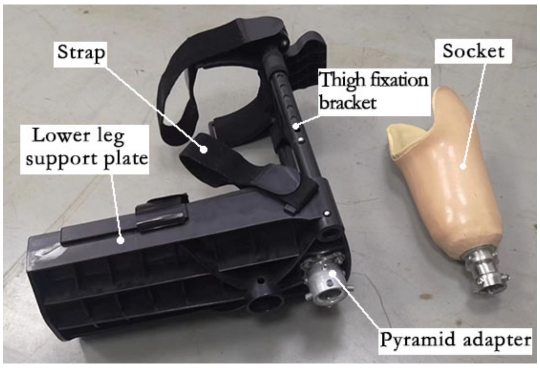

Figure 2. Alternative bracket for prosthetic socket.

is set, the prosthesis follows this predefined mode, and switching modes mid-walk can lead to control failure and an increased risk of falls. Currently, some advanced prostheses worldwide are transitioning from basic electronic control to intelligent systems. For example, the Genium X3 by Ottobock in Germany can intelligently and dynamically respond to various walking modes such as slow walking, fast walking, stair climbing, slope walking, and even obstacle crossing [1]. This indicates that intelligence is the future direction of knee prosthesis development.

Walking modes are classified based on daily human activities, which can be identified by collecting motion information using advanced sensors and extracting multiple features for classification. With the development of artificial intelligence and big data analysis, these technologies will undoubtedly excel in areas such as human-computer interaction, behavior analysis, rehabilitation, exoskeletons, and prosthetics.

Currently, there are two mainstream methods for human activity recognition: image-based and sensor-based [2]. The former relies on fixed cameras to track target subjects and uses frame sequences to determine walking modes. However, this method has several limitations, such as being susceptible to environmental factors (e.g., poor lighting, background noise), complex image analysis algorithms, difficulty in long-term cross-environment monitoring, and the large, non-wearable nature of the equipment. In contrast, sensor-based methods benefit from advancements in microelectronics, with smaller and more affordable micro inertial measurement unit (MIMU) sensors entering the field of human activity recognition [3]. Due to their compact size and wearability, these sensors have garnered significant attention from researchers and have been widely applied in various fields [4-6].

This paper aims to use a multi-sensor fusion framework (combining MIMU sensors and thin-film pressure sensors) to collect multi-feature variables during the walking process of knee prostheses. Various neural network algorithms are utilized to classify and recognize the walking modes (level walking, uphill, downhill, and stairs) of the intelligent knee prostheses online. The goal is to achieve higher accuracy and stronger real-time performance, enabling intelligent multi-scenario applications for knee prostheses.

Intelligent knee prosthesis prototype

The intelligent knee prosthesis prototype shown in **Figure 1** was developed by the Rehabilitation Engineering and Technology Research Institute of the University of Shanghai for Science and Technology. The prototype mainly consists of a knee prosthesis and a damping control unit. It uses multiple sets of inertial sensors and foot pressure sensors to detect the prosthesis's motion state, enabling intelligent recognition of various walking modes (e.g., level walking, uphill, downhill, stairs). The knee prosthesis achieves swing phase speed-following control during level walking through a particle swarm-optimized backpropagation algorithm, as detailed in recent publications [7].

This prototype is still in a development and debugging stage. For safety considerations, the prototype intelligent knee prostheses were tested in healthy individuals simulating above-knee amputees. Since healthy individuals have intact knees and lower legs, a special support bracket is designed to bind the lower leg and knee, eliminating their respective movement func-

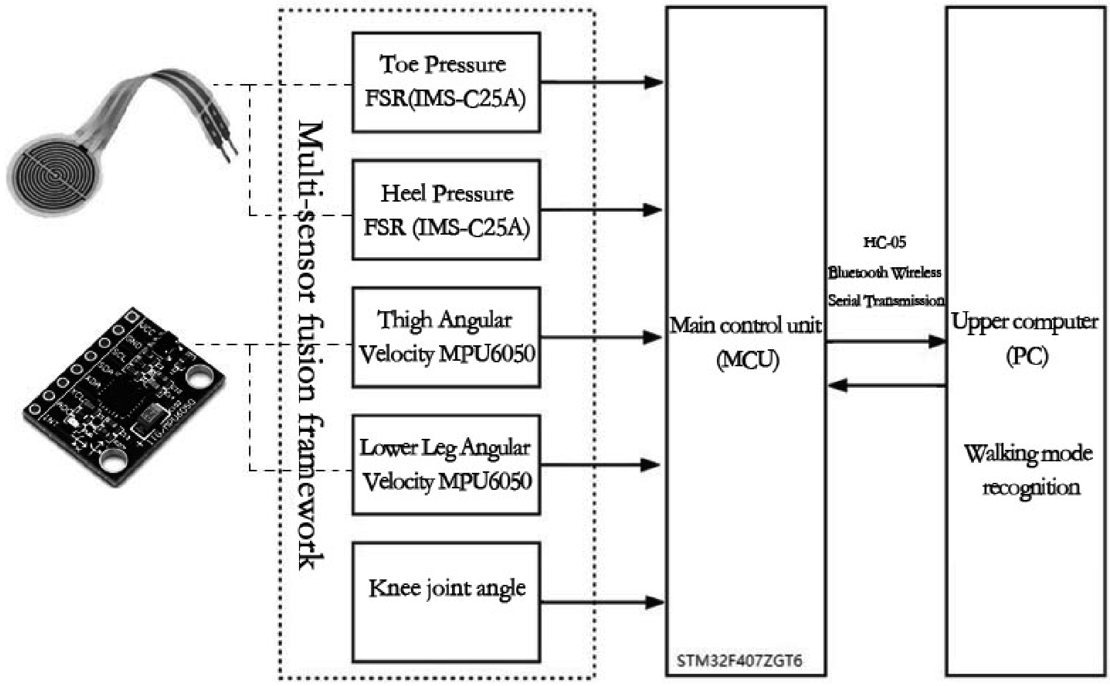

Figure 3. Main control unit framework.

Table 1. Information of test subjects

No.	Gender	Age	Height (m)	Weight (Kg)	Thigh length (m)	Lower leg length (m)	Stride length (m)
1	Male	53	1.70	70	0.42	0.48	0.63
2	Male	43	1.65	61	0.40	0.47	0.61
3	Male	29	1.78	75	0.44	0.51	0.66
4	Female	41	1.52	55	0.37	0.43	0.56
5	Female	55	1.60	57	0.39	0.46	0.59
Mean		44.2	1.65	63.6	0.404	0.47	0.61
Standard Deviation		10.45	0.098	8.59	0.027	0.029	0.038

tions. The structure of the lower leg support bracket is shown in **Figure 2**. The lower end of the bracket is equipped with a pyramidal interface, which connects to the knee prosthesis. The front and rear of the bracket have straps that secure it to the thigh, forming a unified structure that acts as a thigh prosthetic socket.

As shown in **Figure 3**, based on the characteristics of human walking and different road conditions, the selected lower limb kinematic parameters include thigh swing angular velocity, lower leg swing angular velocity, knee joint angle, heel pressure, and toe pressure. The thigh and lower leg angular velocities were collected using MIMU sensors (model MPU6050). The knee joint angle was obtained by integrating the differences between the angular velocity sensors of the thigh and lower leg. The foot pressure information was collected by thin-film pressure sensors Force Sensing Resistor [8, 9]. The main control unit operates using an STM32F407 embedded microcontroller [10, 11], and communication between the main control unit and the upper computer is achieved via a wireless Bluetooth serial port (model HC-05). The upper computer processes the data using a neural network model algorithm and returns the final recognition results. The hardware configuration of the upper computer includes a CPU (Intel i3-4160®), GPU (GeForce GT430®), 8GB RAM, and runs on a 64-bit Ubuntu 18.04 operating system with a Python-Anaconda 3.6, TensorFlow 1.7.0 neural network learning environment.

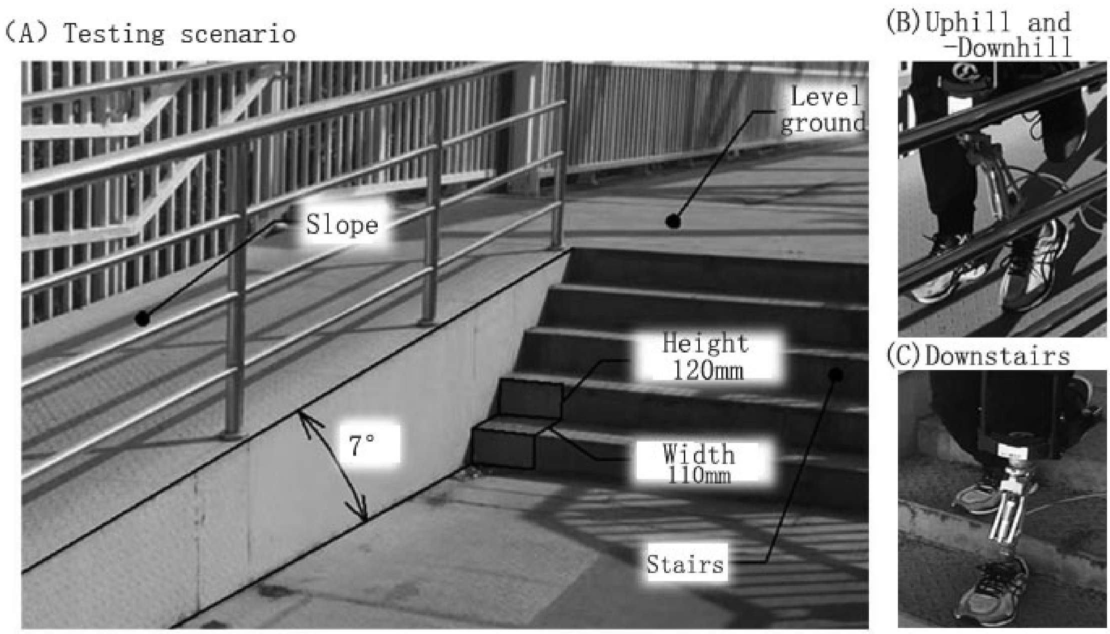

Figure 4. Gait testing in different walking modes. (A) Testing scenario; (B) Uphill and Downhill; (C) Downstairs.

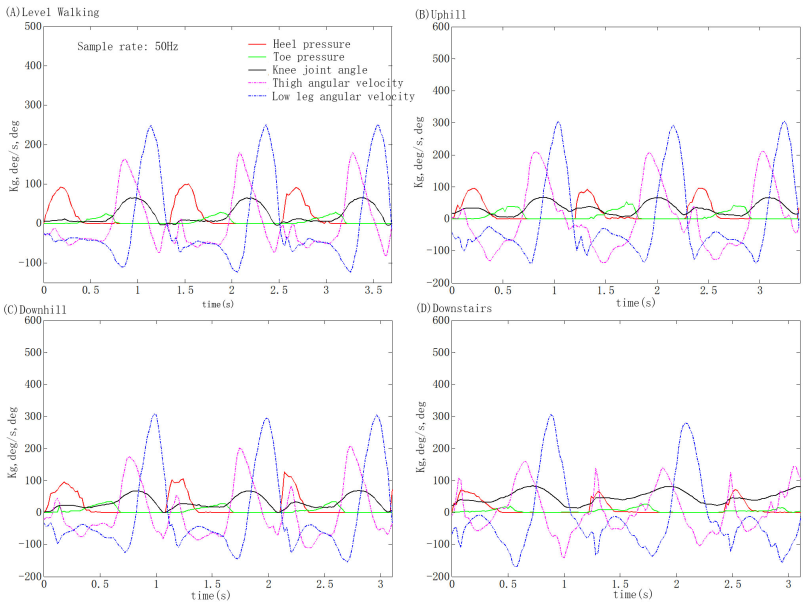

Figure 5. Gait data of test subjects. (A) Level Walking; (B) Uphill; (C) Downhill; (D) Downstairs.

Experimental methods

Experimental subjects

The gait data collection involved 5 healthy volunteers whose specific physical parameters are shown in **Table 1**. All participants were informed about the details of the experiment and the intended use of the collected data, and they signed informed consent forms.

Experimental conditions and procedure

1. The length of the lower leg section of the knee prosthesis was adjusted according to the height and leg length of the test subjects to ensure that both lower limbs were of equal height

2. Since the test subjects were healthy individuals (not above-knee amputees), they underwent a period of adaptive training to get used to wearing the prosthesis. However, during actual testing, subjects were allowed to hold onto handrails to prevent accidental falls.

3. The walking sequence for the test subjects

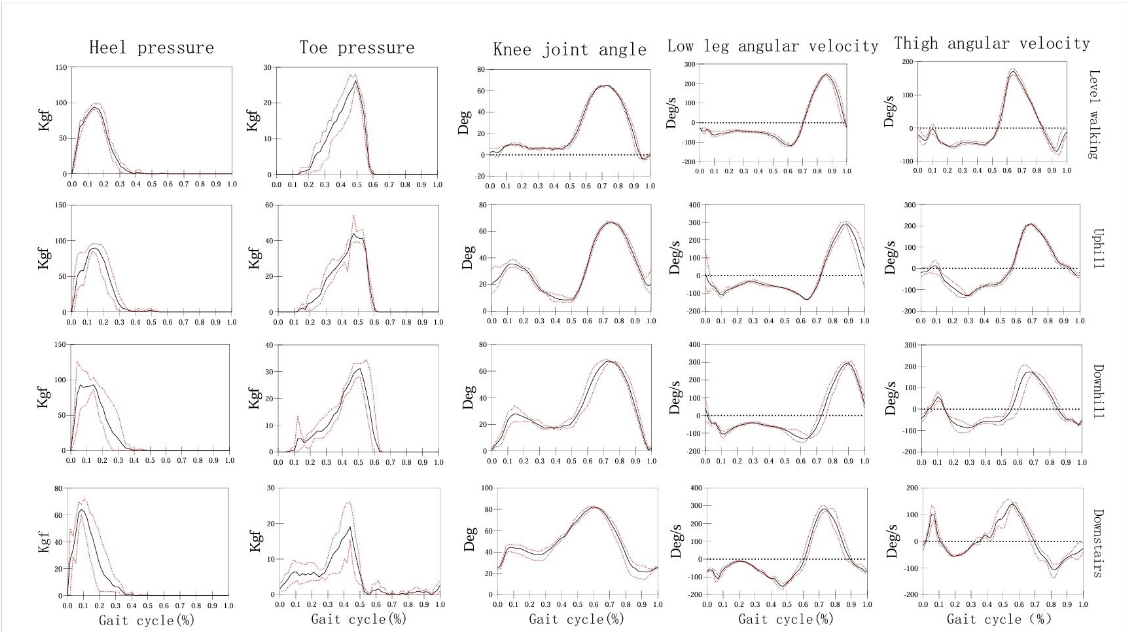

Figure 6. Statistical analysis of gait data.

Table 2 Gait Data Samples of Test Subject (#1)

Samples (N)	Toe force (kgf)	Heel force (kgf)	Knee angle (deg)	Thigh velocity (deg/s)	Leg velocity (deg/s)	Label
1	0	0	6	-25	-26	WE
596	0	0	18	3	-42	UR
929	0	0	1	-22	-32	DR
1,232	0	0	68	0	-29	DS

Note: WE, walking on even ground; UR, uphill walking; DR, downhill walking; DS, stair descent.

was level walking, uphill and downhill walking (**Figure 4B**), and stair descent (**Figure 4C**). To ensure an adequate sample size, each walking mode required at least 30 steps.

4. There were no specific requirements for the walking speed; subjects could walk at their preferred pace.

5. The testing environment is shown in **Figure 4A**, with a slope angle of 7°. The stairs had a width of 110 mm and a height of 120 mm, with handrails on one side.

6. There were no restrictions on which leg the prosthesis was worn on, so either the left or right leg could be used.

Data collection and analysis

Figure 5 shows the gait data from the prosthetic side of the test subjects, collected at a frequency of 50 Hz. It can be seen that different walking modes exhibit distinct gait characteristics, including the swing angular velocity of the thigh and lower leg, foot pressure, and the flexion-extension angle of the knee joint [14, 15]. All gait data from the test subjects were first normalized and then imported into GraphPad Prism 8.4 for statistical analysis. The mean and variance distributions are shown in **Figure 6**.

Neural network models

In this study, we utilized various neural network models to classify and recognize the four different walking modes: convolutional neural networks (CNN), long short-term memory (LSTM), CNN-LSTM, and Convolutional Neural Network - Bidirectional Long Short-Term Memory (CNN-BiLSTM) hybrid [16-19]. The classification performance of these models was compared through iterative learning.

Training set and test set

During the learning process of the neural network model, 80% of the data from each test subject in every walking pattern is used as the training set, while 20% is reserved as the test set. See **Table 2**.

Table 3. CNN-LSTM related parameters

Category	Subcategory	Parameter	Optimized value
Model	LSTM	Layers	2
	Conv1D	Units	64
		Kernel size	1×3
		Filters	64
	MaxPooling1D	Pool size	1
	Hyper	Batch size	25
	parameter	Epochs	500
		Dropout	0.2
		Learning rates	0.001

Note: CNN, convolutional neural networks; LSTM, long short-term memory.

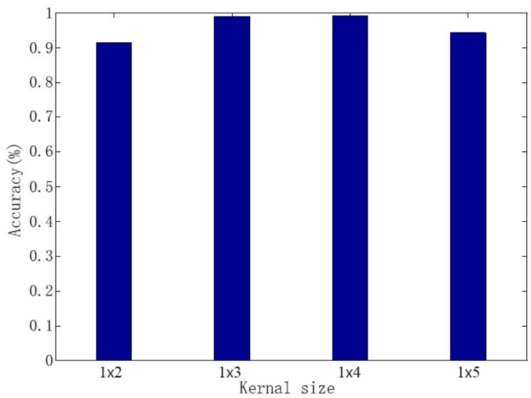

Figure 7. The Impact of CNN Convolution Kernel Size on Gait Pattern Recognition. CNN, convolutional neural networks

Parameter settings

Hyperparameter optimization included the number of LSTM layers and nodes, the size of CNN convolution kernels, dropout rates, and learning rates [20]. The walking modes were recognized using four neural network models: CNN, LSTM, CNN-LSTM, and CNN-BiLSTM, with the Mini SGD optimizer [21]. To balance the real-time performance and accuracy of recognition, a CNN convolution kernel size of 1×3 was chosen, and the test results are shown in **Figure 7**. **Table 3** presents the final optimized values for the convolution kernel size, the number of LSTM layers, and the learning rates for the CNN-LSTM model.

Model evaluation results

To evaluate the performance of the walking mode recognition algorithm, accuracy was used as the performance metric [22]. The formula is as follows:

$$Acc = \frac{TP+TN}{TP+TN+FP+FN}$$

where true positive is the correctly identified positive samples, true negative is the correctly identified negative samples, false positive is the incorrectly identified positive samples, and false negative is the incorrectly identified negative samples. Using this formula, the confusion matrices for the four neural network algorithms in recognizing the four different walking modes were plotted, as shown in **Figure 8** [23].

The recognition accuracies for the four different walking modes of all test subjects were imported into GraphPad Prism 8.4 for statistical analysis. The final statistical results are shown in **Figure 9**.

Testing the four neural network models revealed that the CNN-BiLSTM model had a recognition rate of 94.8%±1.6% for level walking and 98.6%±1.3% for stair descent, but only 37%±4.2% for downhill walking, leading to its exclusion. The remaining three neural network models have their own advantages and disadvantages:

- The CNN model achieved a recognition accuracy of 99%±1.4% for stair descent but only 78.6%±3.6% for level walking and 47%±6.8% for downhill walking.
- The LSTM model improved the downhill recognition rate to 60.2%±1.9% compared to the CNN model.
- The CNN-LSTM hybrid model further increased the downhill recognition rate to 71%±3.2%, although the recognition rates for other walking modes decreased slightly.

Overall, the CNN-LSTM model was determined to be the most advantageous compared to the other models.

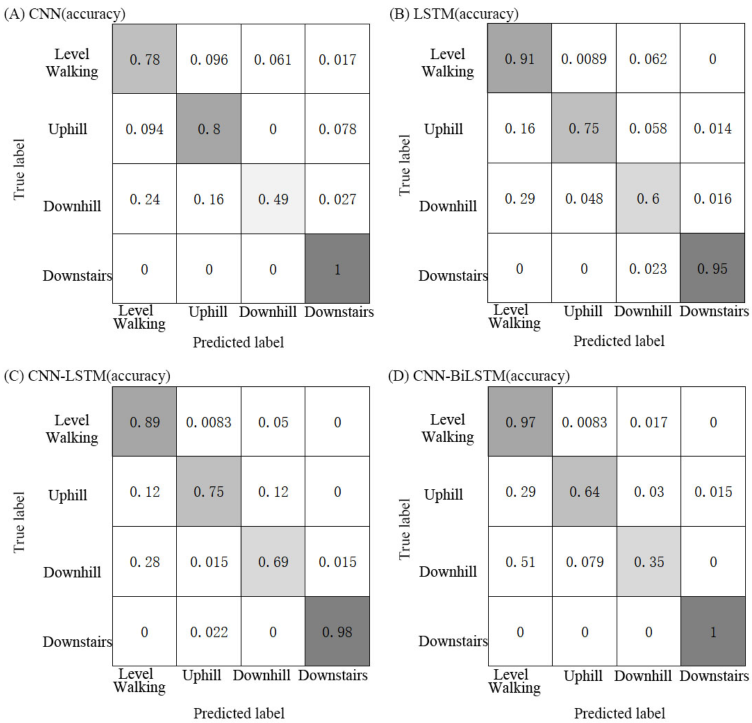

Figure 8. Accuracy evaluation of neural network models. A. CNN (accuracy); B. LSTM (accuracy); C. CNN-LSTM (accuracy); D. CNN-BiLSTM (accuracy). CNN: convolutional neural networks; LSTM: long short term memory; CNN-LSTM: convolutional neural networks-long short term memory; CNN-BiLSTM: convolutional neural networks-bidirectional long short term memory.

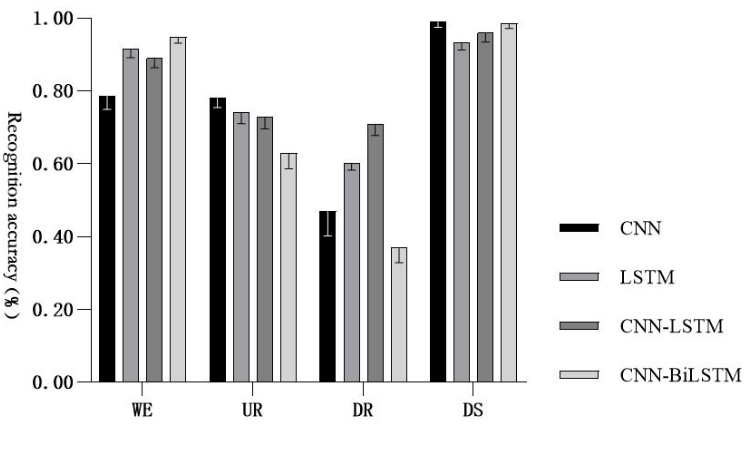

Figure 9. Statistical results of recognition accuracy. WE, walking on even ground; UR, uphill walking; DR, downhill walking; DS, stair descent.

Table 4. Delay Rate Test Results

Walking mode transition state	GRD
WEDR	51.7%15.6%
DRWE	75.8%11.5%
WEDS	47.1%17.1%
DSWE	38.6%10.5%

Note: WE, walking on even ground; DR, downhill walking; DS, stair descent; GRD, gait recognition delay.

Calculation of online recognition delay rate

The CNN-LSTM model, trained offline, has preliminary walking mode recognition capabilities. When one walking mode transitions to another, the online gait recognition system can promptly send the recognition results to the main control unit, identifying the current walking mode in real-time.

The formula for calculating the recognition delay rate is as follows:

$$GRD = \frac{T_s}{GC} \times 100\%$$

where GRD represents the recognition delay rate, GC represents the gait cycle, and Ts represents the system's recognition time, i.e., the time from when the gait data are sent to when the recognition result is returned [24].

There are 12 possible combinations for the transitions between the four walking modes: WE-UR, WE-DR, WE-DS, UR-DR, UR-DS, DR-DS. Considering the daily usage scenarios of the knee prosthesis prototype, this experiment only measured the delay rates for transitions between level walking (WE) and downhill (DR), and between level walking (WE) and stair descent (DS). The results, shown in **Table 4**, indicate that the recognition delay meets the usage requirements, allowing mode transitions to be recognized within one gait cycle. Among the four transitions, the delay is greatest when switching from downhill to level walking. The system can only recognize the mode transition near the end of the downhill step, further indicating that these two walking modes have less distinct features and require more classification time. In contrast, the delay is smallest when switching from stair descent to level walking, suggesting that these two walking modes have more distinct features and are easier to classify.

Conclusion

This paper proposes an exploratory solution to the problem of real-time walking mode recognition faced in fields such as prosthetics, exoskeletons, rehabilitation engineering, and behavior analysis [25]. By utilizing a unilateral knee prosthesis walking mode recognition system constructed with MIMU and Force Sensing Resistor sensors, we successfully collected gait data for level walking, uphill, downhill, and stair descent. The gait data for these four walking modes were classified using CNN, LSTM, CNN-LSTM, and CNN-BiLSTM models. Comprehensive evaluation confirmed that the CNN-LSTM model provided the best recognition results, with the highest relative accuracy. To verify the real-time performance of online recognition, we calculated the recognition delay rates for transitions between level walking and stair descent, and between level walking and downhill. The results showed that the delay time was less than one gait cycle, meeting the real-time requirements for knee prosthesis control.

Currently, the walking mode recognition system still uses a master-slave architecture, where unilateral lower limb gait data are sent via a wireless Bluetooth serial port to a more powerful PC for processing by neural network models. The processed classification results are then returned to the main control unit via the serial port. Future research will involve porting the code to the main control unit, eliminating the master-slave architecture, and facilitating the independent application of the prosthesis [26]. Additionally, the experiment did not include stair ascent testing because the current knee prosthesis prototype is still a passive type (unable to provide additional assistive power), making it difficult to achieve such a walking mode [27].

Author contributions: Yibin Zhang was responsible for the hardware design of the prosthetic prototype and the construction of the experimental scenario. Yan Wang undertook the hardware design of the data acquisition system and also carried out the gait data collection and organization of the prosthetic during the testing process. Meanwhile, Hongliu Yu focused on the algorithm optimization of the road condition recognition model.

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