Gait Recognition Method Based on Wearable Sensor Information Fusion

Ruijie Shao, Hao Wang, Fangyu Liu, Fangmin Sun*
Shenzhen Institute of Advanced Technology, Chinese Academy of Sciences

Introduction

With the rapid development of microelectronics technology and mobile Internet technology, biometric identification methods, such as fingerprints, face, and iris recognition, have been widely used in our daily lives. However, these traditional methods face several limitations, such as requiring direct contact, being affected by environmental factors, and lacking real-time, continuous authentication.

To address these issues, this paper proposes a novel gait recognition method that fuses information from multiple inertial sensors to overcome the limitations of traditional biometric identification technologies. Firstly, gait recognition performance of sensor on different body parts are explored, among which the right wrist was the most significant part of individual difference. Then, decision-level fusion and data-level fusion are performed on various sensor combinations, to verify that the fusion of multi-sensor data can improve accuracy. Compared with decision-level fusion, data-level fusion has a superior overall effect. Finally, the paper tests the model on different numbers of subjects to be recognized and the model's average accuracy 95.06%, proving the robustness and reliability of the model.

Method

The framework of the proposed method mainly includes a data preprocessing module, a model fusion module, and a model evaluation module. Firstly, data preprocessing is conducted to facilitate the needs of subsequent experiments. Then, two types of fusion methods are experimented with. Finally, the model is evaluated to verify its practical value.

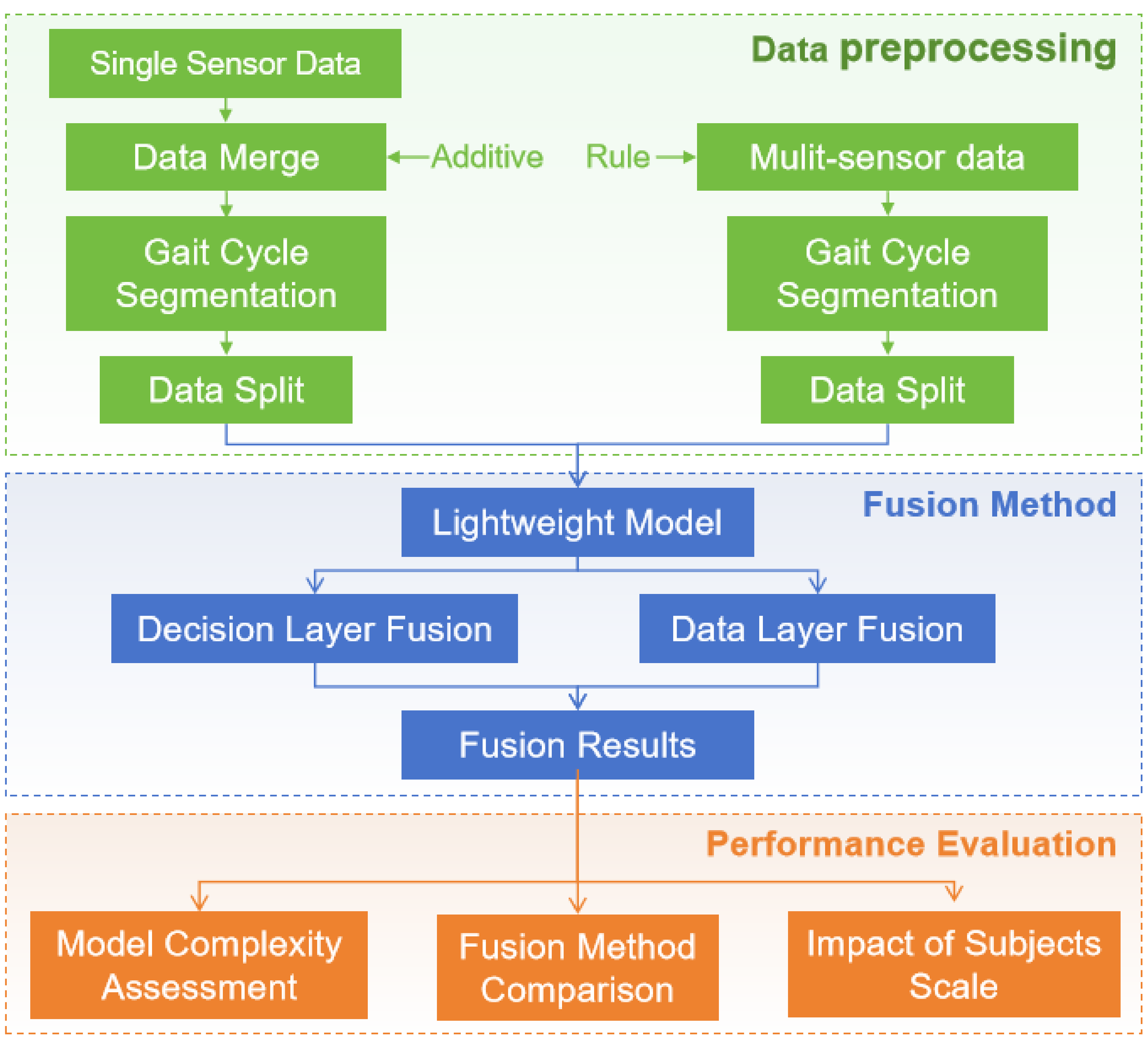

Figure 1 The framework of the proposed method

1. Data-level fusion involves concatenating the acceleration data collected from different body parts using an additive rule from 175 gait healthy participants.

2. We independently designed a lightweight network based on depthwise separable convolution. The model structure is concise with a relatively small number of parameters, offering high computational efficiency and generalization capabilities. By stacking these different convolutional layers, we can progressively extract and transform the features from the input data.

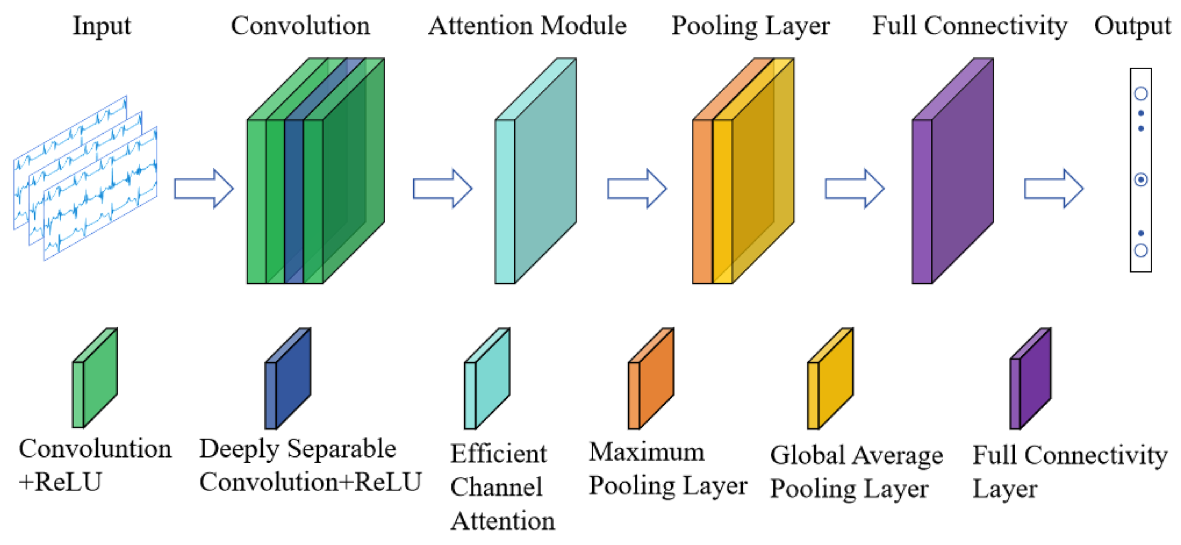

Figure 2 Network model with ECA attention mechanism

Table 1 Network model parameters

Layer (Type)	Kernel Size	Number of Kernels	Feature Map Size
input_1 (InputLayer)	-	-	3×128×1
conv2d (Conv2D)	3×3	8	3×128×8
conv2d_1 (Conv2D)	1×1	8	3×128×8
depthwise_conv2d (DepthwiseConv2D)	3×3	1	3×128×8
conv2d_2 (Conv2D)	1×1	16	3×128×16
max_pooling2d (MaxPooling2D)	1×2	-	3×64×16
global_average_pooling2d (GlobalAveragePooling2D)	-	-	16
fully connected layers	-	-	-

3. Data-Layer fusion: The preprocessed multi-sensor data is input into the model for training.

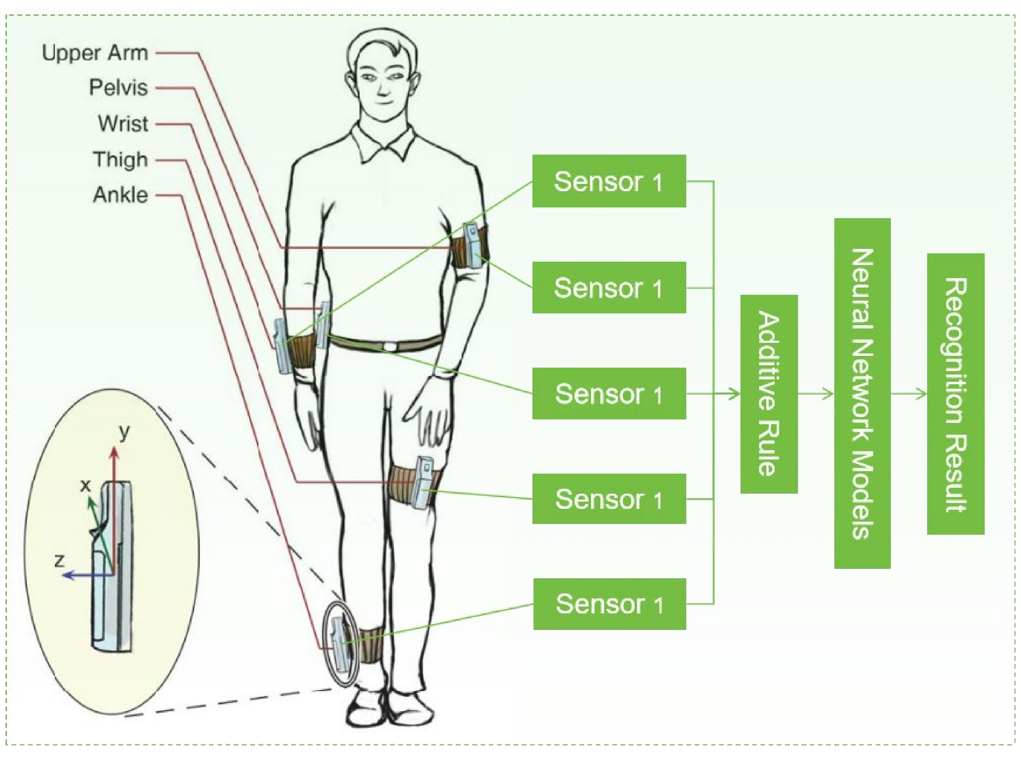

Figure 3 Data Layer Fusion Method

4. Decision-layer fusion: the weighted voting method is adopted based on the accuracy rates of each body part.

The results obtained through voting are compared with the true labels to achieve accuracy rates.

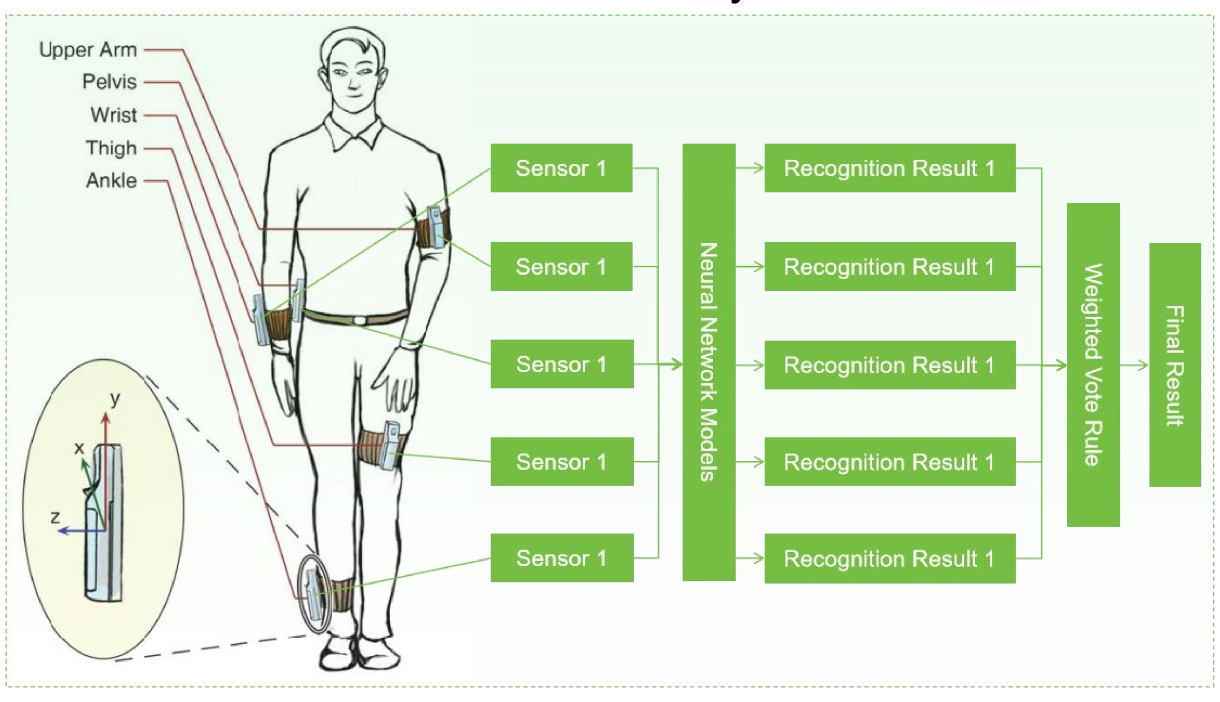

Figure 4 Decision Layer Fusion Method

Results

Train the model on single-part data to obtain the size of individual differences in the training set for different parts. The most significant individual differences to the smaller differences is as follows: right wrist, right pelvis, left upper arm, left thigh, right ankle.

Table 2 Network model parameters

Sensor Location	CNN	SPs
1-wrist	***0.8510***	0.564
2-upper arm	0.7727	0.639
3-pelvis	0.8136	***0.734***
4-thigh	0.7568	0683
5-ankle	0.7484	0.688

The accuracy rate for the fusion using the voting method based on the results obtained from the five body part sensors is 0.9633. It can be seen that the accuracy has significantly improved compared to that of single sensor method.

Table 3 Gait Recognition Accuracy When Four Sensors Were Used

Sensor Locations	Accuracy
2-Upper Arm + 3-Pelvis + 4-Thigh + 5-Ankle	0.9425
1-Wrist + 3-Pelvis + 4-Thigh + 5-Ankle	0.9445
1-Wrist + 2-Upper Arm + 4-Thigh + 5-Ankle	0.9147
1-Wrist + 2-Upper Arm + 3-Pelvis + 5-Ankle	0.9487
1-Wrist + 2-Upper Arm + 3-Pelvis + 4-Thigh	***0.9501***

The model with the ECA attention mechanism introduced achieved higher accuracy rates compared to the models without attention mechanisms.

Table 4 Accuracy of Decision Level Fusion Method

Sensor Locations	Accuracy (Without ECA)	Accuracy （with ECA）
1-Wrist + 2-Upper Arm + 3-Pelvis + 4-Thigh + 5-Ankle	0.9418	***0.9751***
1-Wrist + 2-Upper Arm + 3-Pelvis + 4-Thigh	*0.9556*	**0.9577**
1-Wrist + 3-Pelvis + 4-Thigh	0.9404	**0.9459**
1-Wrist + 3-Pelvis	**0.9383**	0.9238
Average Accuracy	0.9440	**0.9506**

Conclusion

This paper proposes a novel gait recognition method that fuses information from multiple inertial sensors. The main contributions of this article can be summarized as follows:

1) A novel lightweight network model integrating an attention mechanism is designed to reduce the number of parameters and improve recognition accuracy, making it suitable for resource-constrained wearable devices.

2) By comparing the gait recognition performance of sensors placed on different body parts, the most individual-differentiating sensor locations are identified, enhancing the accuracy of the recognition system.

3) The study explores both decision-level and data-level fusion methods, finding that data-level fusion outperforms decision-level fusion, thus improving the overall system performance.

Although certain research results have been achieved, there are still some limitations in practical applications. In future research, we will further enhance the robustness of gait recognition models to adapt to different application scenarios, enhance the real-time performance of the models, and improve their ability for continuous learning.

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