Gait Pattern Recognition based on Multi-sensors Information Fusion through PSO-SVM Model

Lie Yu, Gaotong Hu, Lei Ding, Na Luo and Yong Zhang

Abstract—**This study describes a gait analysis system that classifies gait phases using three pressure sensors and one inertial measurement unit (IMU) sensor. The pressure sensors are placed on the insole to measure ground reaction forces (GRF), while the IMU sensor is placed on the tongue to monitor foot angle changes. Gait phases, such as initial contact (IC), mid-stance (MS), terminal stance (TS), and swing (SW), are classified using a support vector machine (SVM). To tackle the problem of low accuracy caused by incorrect SVM model parameters, the study utilized particle swarm optimization (PSO) to optimize the SVM parameters. Three classifiers were constructed using the collected gait dataset while walking，such as a KNN classifier, a SVM classifier, and a PSO-SVM classifier. The experimental results demonstrate that the PSO-SVM algorithm outperforms the others in gait phase classification, achieving an accuracy of 95%. The PSO-SVM approach outperforms both the SVM. This finding illustrates the PSO-SVM approach's superiority in gait phase categorization and indicates its potential utility for classifying gait phases.**

Index Terms—**Inertial Measurement Unit, Gait Phase Classification, Ground Reaction Forces, Particle Swarm Optimization, Support Vector Machine, K-Nearest Neighbor.**

I. Introduction

Human gait phase recognition is a technology that enables the recognition of human motion intent. It is essential for several applications, including medical evaluations, safety identification, and exoskeleton robot control [1-2]. Exoskeleton robots are mechanical devices that allow users to perform physical tasks more adeptly. They have received a lot of interest in fields such as haptic interface [3], military applications [4], strength augmentation [5], and rehabilitation training [6]. The movement of an individual wearing an exoskeleton is essentially a form of human-machine interaction. The process begins with the person moving their body. The exoskeleton system then collects information from the sensors to determine the current gait. Suitable control strategies are then employed to facilitate the entire cooperative process based on the gait data. Failure to detect gait phases may prevent coordination between the exoskeleton device and wearer, hindering the intended assistance. Accurate and reliable comprehension, monitoring, and evaluation of gait parameters at specific time points is essential for synchronizing with the wearer during different physical activities. Observing a patient's gait provides valuable insight into their condition, aiding in accurate diagnosis and treatment. By analyzing patterns of movement and posture during activities such as walking, running, and crawling, caregivers can gain important information about the patient's quality of life.

Traditional methods for recognizing gait phases involve measuring ground response forces using force plates and multi-camera motion capture systems. However, these techniques are limited to laboratory research due to the expensive equipment required and the complex and time-consuming post-processing involved [7]. As a result, they are not suitable for complex situations or everyday use. Wearable sensor systems have become a promising biomedical application due to their affordability, usability, and low impact on human health. These systems consist of accelerometers, gyroscopes, force sensors, and inclinometers, which are placed on the human body to collect data on the subject's movements [8-10]. This data is then used as input for algorithms designed to model factors such as stride length and frequency, and determine the position of segments. However, these algorithms can be complex and vulnerable to intervention.

The popularity of using pressure insole sensors to identify gait characteristics based on ground reaction forces (GRF) has increased. GRF can be converted into moments at the center of pressure (COP) on the sole of the foot and forces along orthogonal axes [11–12]. Proper feature selection is essential before inputting the data into machine learning algorithms to detect various gait phases. Two popular feature extraction techniques for managing continuous data are wavelet decomposition and pattern. For gait analysis, temporal features such as signal mean, variance, skewness, kurtosis, and number of zero crossings [13], and frequency domain features like entropy [14] and fast Fourier transform (FFT) coefficients are commonly considered. Supervised learning algorithms, which use labeled training data for both training and usage [20], include decision trees [15], artificial neural networks [16], K-nearest neighbors [17], and support vector machines (SVM) [18–19]. Although these techniques are distinct, the selection of feature vectors and data size significantly impact their performance. Gait data analysis is

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challenging due to its complexity, temporal dependency, and correlation. In recent years, the SVM has proven to be an effective classifier for pattern recognition, based on nonlinear projection onto high-dimensional feature spaces [21]. When combined with SVM, optimization techniques such as grid search [22], genetic algorithms (GA) [23], and particle swarm optimization (PSO) [24-25] can effectively identify the optimal hyperparameters.

The aim is to develop a gait analysis system that can collect gait information and classify different gait phases. A pressure insole with redundancy has been developed, which uses multiple wearable sensors as inputs, due to the random and involuntary nature of human motion. The PSO method optimizes the SVM model to enhance the accuracy of identifying walking gait phases. By optimizing the feature set, each foot can recognize at least four walking gait phases, with the potential to increase the number of recognized gait types. The experimental findings demonstrate that the PSO-SVM classifier accurately identifies gaits with an overall accuracy of 95%.

II. METHODOLOGY

A. Instrumental setup

A system of insoles based on sensors was developed to monitor the GRF and foot angle in real-time, as shown in Figure 1(a). The system comprises of one inertial measurement unit (IMU) sensor and three pressure sensors. Flexible force-sensitive resistors (FSRs) are coated with a nano-functional material that has strong adhesion, bending resistance, and high sensitivity, as illustrated in Figure 1(b). All of the sensors are 15 mm in size and have a maximum capacity of 30 kg with a high resolution of 0.1 N. The resistance of each FSR is greater than 10 MΩ when no force is applied. When a weight of 30 kg is applied, the resistance decreases to about 5kΩ. Calibration of each FSR is done using standard weights. The chosen IMU model is the MPU6050, as shown in Fig. 1(c), which includes a tri-axis accelerometer with a range of ±2g and a tri-axis gyroscope with a range of ±250°/s.

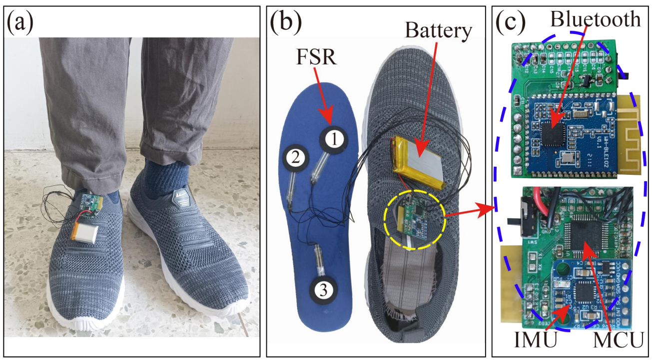

Fig. 1. The insole system with three pressure sensors and one IMU sensor.

Figure 2 illustrates the main operating principle of the system. The voltage of the FSR is digitized using the 12-bit ADC of the STM32. The angle data from the MPU6050 is obtained through I2C communication. The pressure and angle data are then packed and sent to Bluetooth via the serial port. The Bluetooth module forwards the data to the host computer. The collected data has an acquisition frequency of up to 50 Hz. Figure 1 illustrates that the system is powered by a rechargeable 3.3V battery. The diagram depicts the basic workflow of the system.

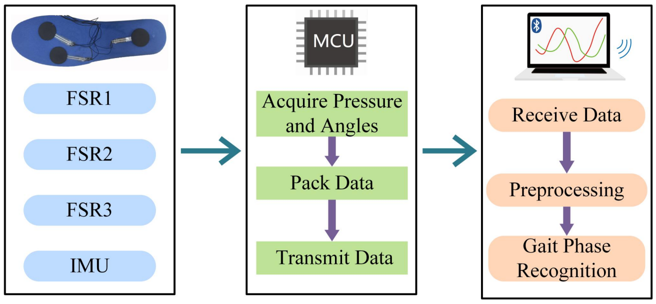

Fig. 2. The working principle and the experimental procedure.

B. Experimental protocol

Figures 1(b) and (c) depict the location of the FSR and IMU sensors on the shoe, which were used to classify the gait phases. The data collection involved eight healthy adults, six males and two females, aged between 21 and 28 years old, with heights ranging from 155 to 176 cm. The participants walked on a treadmill at a predetermined pace of 3 km/h for approximately 30 consecutive gait cycles using their natural gaits.

Before each trial, they were allowed to adjust the position of the sole to evaluate the gait recognition system's resistance to external influences, such as the sole's involuntary movements. The overall correlation of the sole with the pressure sensor changed slightly.

C. Data analysis

During the experiment, we collected several sets of plantar pressure data and translated the voltage signals into digital signals. Additionally, we collected data on plantar pressure during continuous gaits for examination.

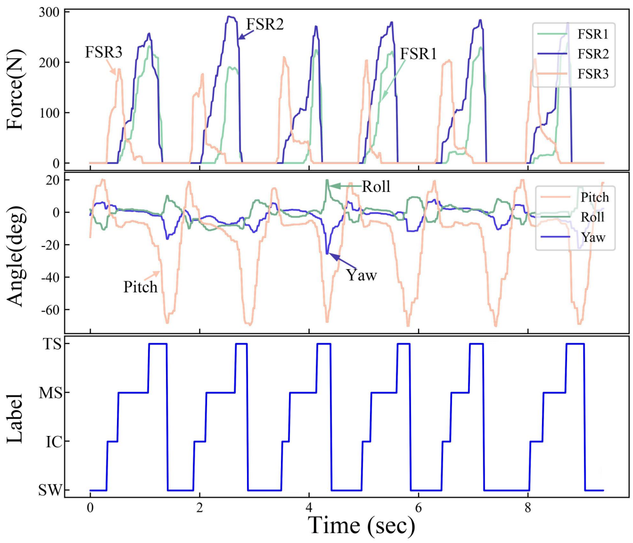

Fig. 3. Plantar pressure data and angle data collected

Figure 3 displays the force value from three FSRs and the angle values from the IMU during normal walking. It is evident that the force from FSR 3 increases dramatically and peaks rapidly when the foot first contacts the ground. Meanwhile, during the full foot contacting phase, the pitch angle reaches its peak and the toes are lifted off the ground.

As the foot progressively flattens, the force from FSR 3 decreases. The three angles then begin to return to their initial values as the force levels of FSRs 1 and 2 on the forefoot start to increase.

Eventually, the force from FSR 3 drops to zero as the walk progresses and reaches the toe support phase. The pitch angle shifts rapidly from its initial value to the valley values at the same time that the pressures of FSRs 1 and 2 reach their maximum.

Subsequently, as the toes push off the ground, the forces of FSR 1 and 2 quickly drop to zero. The swing phase begins when the pitch angle shifts from valleys to peaks. The forces of FSRs 1 and 2 then start to ascend quickly from the ground until they eventually reach zero. As the pitch angle transitions into the swing phase, it shifts from peak to peak.

The data indicates a high level of repeatability in the periodic variations of plantar pressure during normal walking.

D. Reference gait labels

A complete gait cycle refers to a leg's motion from heel strike to toe off, which is divided into four phases. Excessive segmentation can significantly reduce recognition performance. This study considered four gait phases, as shown in Figure 4.

(1) Initial-Contact (IC): Single limb support occurs when the working heel touches the ground first and continues until the toe of the opposing foot lifts off the ground.

(2) Mid-Stance (MS): This phase begins immediately after IC and continues until the heel begins to leave the ground.

(3) Terminal-Stance (TS): This phase begins with heel lift and ends with toe lift.

(4) Swing (SW): This phase is defined as the time between toe-off and the next heel-strike, which marks the beginning of the following cycle.

Figure 3 shows how the labels are connected to the data for each gait phase, while Figure 4 illustrates the relationship between gait phases and actual movements.

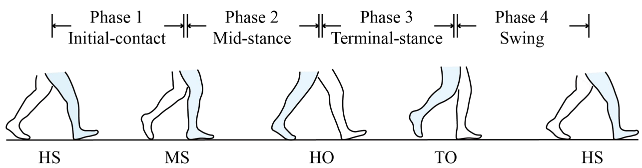

Fig. 4. Division of gait phases

E. Data preprocessing

Normalization is a crucial step in data pre-processing for most situations. Various approaches can be used to normalize data, such as min-max, decimal scaling, z-score, and median. Since the data obtained from two separate types of sensors had different units and ranges, it was normalized using zero-mean and unit variance, as shown in the following equation:

$$x_{norm} = \frac{x-\mu}{\sigma} \tag{1}$$

where μ and σ are the mean and standard deviation, respectively.

III. Gait Phase Recognition through PSO-SVM

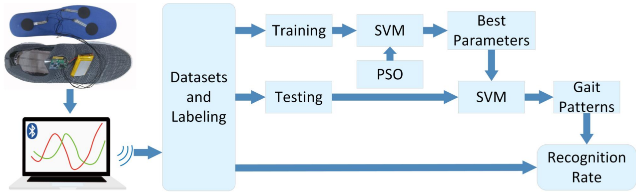

Fig. 5. Flow diagram of PSO optimizing SVM

To tackle the aforementioned issues in gait phase detection, we utilised the SVM algorithm to recognise gait phases. SVM is a widely used pattern identification tool that is a form of machine learning method based on statistical learning theory. Figure 5 illustrates the complete process of applying PSO-SVM to identify gait phases.

The data collected by the sensors in the shoe is transmitted and stored on the computer. The data is then labelled according to the definitions provided in figure 4. 70% of the dataset is used for training, with the remaining 30% serving as testing data. The SVM model is trained using the training data, and the PSO technique is used to optimize it. The best parameters obtained from training and optimization are then entered into the SVM model. The SVM model is used to process the testing data with the optimal parameters to identify the different gait phases. The recognition rate can then be calculated by comparing the identified and labelled findings.

A. Support Vector Machine

The primary concept behind SVM is to transform the vector into a high-dimensional space using a nonlinear transformation and then utilize a kernel function to obtain the optimal linear classification surface in this new high-dimensional space. The rapid expansion of the spatial dimension during the mapping of the low-dimensional input space to the high-dimensional feature space makes it difficult to compute between feature spaces in most cases. The optimization problem for K-class is solved by defining the relaxation variable $\xi = (\xi_1, \xi_2, \ldots, \xi_m)$ and using a single objective function to train all K-binary SVMs simultaneously. The problem can be described as follows:

$$\begin{cases} \min \dfrac{\|w\|^2}{2} + C\sum_{i=1}^{m}\xi_i \\ s.t. \begin{cases} y_i, (\langle w, x_i \rangle + b)^a > 1 - \xi_i \\ \xi_i \geq 0 \end{cases} \end{cases} \tag{2}$$

where w is the vector of weights and b is the bias. C is a positive constant (penalty parameter) and m represents the number of slack variables. $\langle w, x_i \rangle$ denotes the dot product, and a is the constant coefficient (a=1). The optimal classification surface SVM translates this problem into the input space for computation by defining kernel functions to obtain the decision function:

$$f(x) = \operatorname{sgn}\left\{\sum_{i=1}^{n} y_i a_i^* K(x_i \cdot x) + b^*\right\} \quad (3)$$

where a_i is the Lagrange multiplier. There are two training sample sets.

$$D = \left\{(x_i, y_i)\,|_{i=1}^{n}, x_i \in X \subseteq R^n, y_i \in Y \subseteq \{-1,1\},\right\} \quad (4)$$

where n is the dimensionality of the training sample vector, and -1 and 1 are the category numbers. If an optimal classification surface, $w \cdot x + b = 0$, is found to classify the two patterns, then the distance from any point in either sample to this classification surface must be greater than or equal to 1. A support vector is a point in the sample that is exactly one unit away from the classification surface. Any point that is more than one unit away from the classification surface is not a support vector. The classification outcome is determined by the support vectors.

SVM completes complex processes in low-dimensional space and establishes an ideal classification surface in high-dimensional space through nonlinear transformation. The choice of an appropriate SVM kernel function is crucial for the accurate recognition of gait phases. The SVM method commonly employs several kernel functions, including::

Polynomial: $K(x, x_i) = [\gamma(x \cdot x_i)]^a$

Sigmoid: $K(x, x_i) = \tanh[\gamma(x \cdot x_i)]$

Linear: $K(x, x_i) = \gamma(x \cdot x_i)$

RBF: $K(x, x_i) = \exp[-\gamma\|x \cdot x_i\|^2]$

where a is the kernel order of the polynomial, and γ is the width of the kernel function.

B. Particle Swarm Optimization Algorithm (PSO)

PSO is an iterative optimization method that can solve various optimization problems. The particles' position, velocity, and fitness value are their key features. The ideal solution is primarily obtained by combining the experiences of the particles and their environment, with the particles performing the optimization search work. The placements and velocities of the particles are dynamically modified during the search process to discover the global best solution. The velocity and position of the particles are updated by iterations, as shown by the following equation:

$$\begin{cases} V_{id}^{k+1} = wV_{id}^{k} + c_1 r_1 (P_{id}^{k} - X_{id}^{k}) + c_2 r_2 (P_{gd}^{k} - X_{id}^{k}) \\ X_{id}^{k+1} = X_{id}^{k} + V_{id}^{k+1} \end{cases} \quad (5)$$

where w is the inertia weight, and the probing range of the solution is determined by setting the magnitude of its value; d is the spatial dimension, i is the number of particles, and k is the number of current iterations. V_{id}^{k+1} denotes the flight velocity of the *i-th* particle, X_{id}^{k+1} denotes the position of the *i-th* particle, P_{id}^{k} is the individual optimal solution of the ith particle, and P_{gd}^{k} is the global optimal solution. The range of position variation in the *d-th* dimension is $[-x_{\max}, x_{\max}]$ and the range of velocity variation is $[-v_{\max d}, v_{\max d}]$. if X_{id} exceeds the boundary value during the iteration, it is set to the boundary value $-x_{\max}$ or $x_{\max}$. c_1 and c_2 are the learning factors whose values represent the weights of the statistical acceleration terms that push each particle to the individual extreme and global extreme positions. r_1 and r_2 are random numbers distributed in the interval [0,1]. The population size is typically selected through empirical means, while the termination condition for merit-seeking is the maximum number of iterations.

C. Process of PSO optimizing SVM

The SVM was optimized using PSO with the radial basis kernel function. The penalty parameter C and the kernel function radius parameter of the dimensionally optimized support vector machine are selected to obtain a set of penalty parameters and kernel function parameters that result in a superior predictive SVM with the minimum SVM error. Figure 6 illustrates the continuous updating of the positions and velocities of n particles in D-dimensional space according to the equation mentioned above. Iteratively finding the optimal two SVM parameters (C_{best}, γ_{best}).

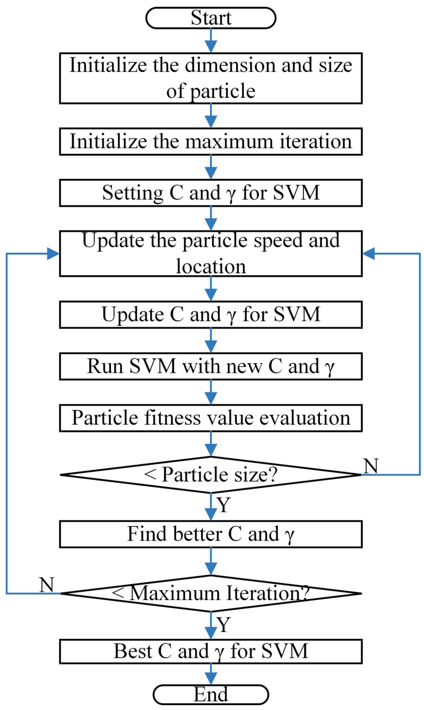

Fig. 6. Process of PSO optimizing the SVM model

PSO optimization SVM procedures primarily involve population initialization, discovering initial extrema, and iterative optimization search. Its procedures are as follows:

Step 1: The program initially randomly initializes m particles and determines their positions and velocities in the D-dimensional parameter space. These positions represent the SVM parameters, including C and γ.

Step 2: The new position of the particle is calculated and updated based on its acceleration, velocity, and other relevant parameters.

Step 3: The parameters for particle position are used as input to construct the SVM model. The fitness values of the particle parameters are then evaluated based on the classification results of the SVM model. Steps 2 and 3 are repeated until all particles have been calculated.

Step 4: To determine the optimal global parameters, consider all particles.

Step 5: If the number of iterations has not been reached, proceed to step 2 to begin the next iteration. Once the termination condition is met, the optimal particle parameters are obtained. These parameters are then used to retrain the SVM model, which is then used to evaluate the final classifier for recognition and classification.

The PSO technique is used to optimize the penalty parameter C and the kernel function radius parameter γ that minimize the SVM error. The optimized values are then used for SVM training and classification prediction.

IV. Result and Discussion

A. Selection of SVM kernel function

The penalty factor C and kernel function parameters for the SVM binary tree classification model were selected using an empirical technique. The values of C and γ were set to 2 and 1, respectively, and t was defined to represent the type of kernel function. A dataset of gait features was selected and divided into 30% for training and the remaining for testing. The test results for the various kernel functions are presented in Table I.

TABLE I
Recognition results of different kernel function

Kernel Function	Parameter	Accuracy
polinomia	C=2, γ=1	92.03%
RBF	C=2, γ=1	91.09%
linear	C=2, γ=1	88.9%
sigmoid	C=2, γ=1	58.9%

When comparing the test results of several kernel functions, it is evident that polynomial and RBF kernel functions have higher recognition accuracy. In terms of response time, the RBF kernel function outperforms the polynomial kernel function. Therefore, for the PSO optimization SVM multiclassification model, the RBF kernel function was selected as the kernel function.

The SVM classification model comprises of two parameters, namely C and γ. Therefore, we utilized the PSO method with a population size of 20 and particle dimension of 2. The number of iterations was limited to 100, and the coefficients for the local and global acceleration factors were set to 1.5 and 1.7, respectively.

A ten-fold cross-validation procedure was employed to optimize the parameters and minimize parameter errors. The training and optimization data were randomly separated into ten groups, each containing an equal number of samples. During each iteration, nine groups were used as the training set, while the remaining group was used as the test set. The average recognition rate from the ten-fold cross-validation was calculated after ten iterations to validate each group of data, thus increasing the algorithm's dependability.

B. Optimization of SVM model based on PSO

Figure 7 illustrates the iterative process of the PSO algorithm, following the algorithm flow depicted in Figure 6. The objective function's average value for all particles in each generation is represented by Fmean, while Fbest denotes the maximum value of the objective function for all particles in each generation. As the number of iterations increases, the average fitness of each particle eventually converges towards the fitness value of the best parameters. The optimization procedure concludes with a fitness of 94.375% after meeting the termination condition. The optimal parameter values were found to be C_{best} = 9.58 and γ_{best} = 3.4.

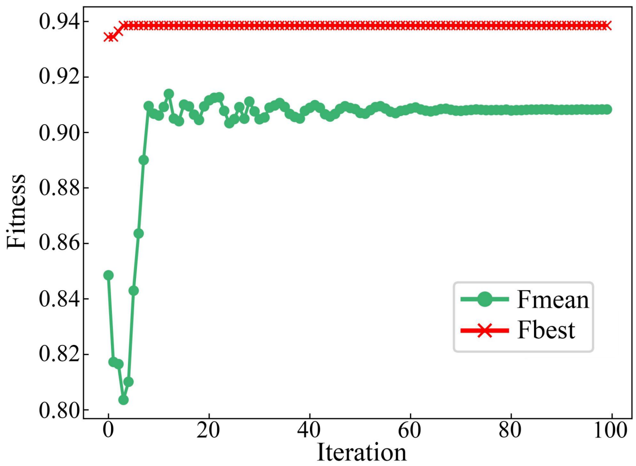

Fig. 7. Change curve of the optimal fitness with increasing iteration by using PSO.

C. Results of gait phase recognition

A comparison study was conducted to test the feasibility and effectiveness of the PSO-optimized SVM algorithm for gait identification. The study compared the PSO-SVM, SVM, and K-nearest neighbors (KNN) classification methods.

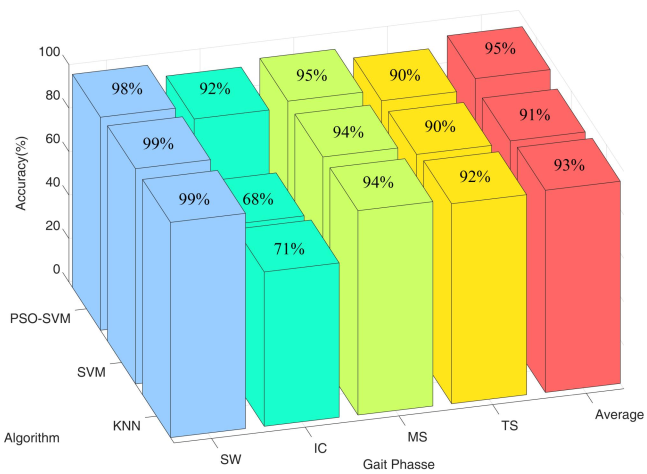

Fig. 8. Accuracy of three different classifiers for four different phase classifications

A comparative experiment was conducted using 1280 sets of gait data samples. The samples were divided into four phases of gait: HS, MS, HO, and TO. After pretreatment, the samples were used for comparative analysis. The dataset was divided into a 70% training set for the model and a 30% test set for evaluation.

For the purpose of comparison and performance evaluation, we applied the trained SVM classification model, PSO-optimized SVM classification model, and KNN classification model independently to the test set.

Figure 8 shows the accuracy of three different classifiers in classifying the four unique gait phases, as well as the average accuracy of each classifier. When comparing the recognition rates of the three algorithms, it was found that they all achieved high recognition rates for phases one, three, and four. PSO-SVM achieved the highest recognition accuracy of 92% in phase two classification, while SVM and KNN achieved 68% and 71% recognition rates, respectively. In this experiment, PSO-SVM achieved the highest average recognition rate of 95% compared to SVM and KNN, which achieved average recognition rates of 91.09% and 92.8%, respectively. The PSO-optimized SVM method outperformed both the SVM multi-classification model and KNN in recognizing all four gait phases. The experiment's dataset included six dimensions, resulting in similar classification and recognition accuracies for both KNN and SVM. Integrating PSO to optimize SVM parameters further increased the gait recognition rate.

The results demonstrate that the gait samples obtained through our experimental equipment and the PSO-optimised SVM multi-classification model can accurately identify various gait phases with high recognition accuracy and practicality. This approach is crucial for creating stable gait transitions and adjusting smart prostheses.

V. Conclusion

This study analyses walking patterns and classifies the gait cycle into four categories. Motion information of individuals during walking can be collected by using pressure sensors to gather GRF data and IMUs to gather foot angle data. This method provides a more comprehensive understanding of the mobility status of the lower limbs during walking by overcoming the limitations of single data sources.

The article introduces the concept, parameters, and implementation of the PSO method, which is integrated into the SVM model for gait recognition. The experimental results demonstrate that the PSO-optimized average fitness ranges from 90% to 92%, effectively eliminating local optima in kernel parameter selection. Consequently, the recognition rate of the SVM multi-classification model increases from 91.09% to 95%. The PSO-SVM technique demonstrates superior recognition accuracy compared to SVM and KNN, highlighting its practical value and usability.

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