

Retraction

Retracted: Athlete Gait Feature Recognition Method Based on Multisource Sensing Information

Security and Communication Networks

Received 15 November 2022; Accepted 15 November 2022; Published 28 November 2022

Copyright © 2022 Security and Communication Networks. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Security and Communication Networks has retracted the article titled “Athlete Gait Feature Recognition Method Based on Multisource Sensing Information” [1] due to concerns that the peer review process has been compromised.

Following an investigation conducted by the Hindawi Research Integrity team [2], significant concerns were identified with the peer reviewers assigned to this article; the investigation has concluded that the peer review process was compromised. We therefore can no longer trust the peer review process, and the article is being retracted with the agreement of the Editorial Board.

References

- [1] L. Xu, C. Xue, and X. Gu, “Athlete Gait Feature Recognition Method Based on Multisource Sensing Information,” *Security and Communication Networks*, vol. 2022, Article ID 2857465, 10 pages, 2022.
- [2] L. Ferguson, “Advancing Research Integrity Collaboratively and with Vigour,” 2022, <https://www.hindawi.com/post/advancing-research-integrity-collaboratively-and-vigour/>.

Research Article

Athlete Gait Feature Recognition Method Based on Multisource Sensing Information

Xu Li,¹ Chunlei Xue,² and Xiaobo Gu³ 

¹Northeast Petroleum University, Heilongjiang, Daqing 163318, China

²Department of Physical Education, Tangshan Normal University, Tangshan 063000, Hebei, China

³Sports Department of Hebei Vocational College of Rail Transportation, Shijiazhuang 050000, Hebei, China

Correspondence should be addressed to Xiaobo Gu; 1921031135@siit.edu.cn

Received 15 January 2022; Revised 27 January 2022; Accepted 4 February 2022; Published 24 February 2022

Academic Editor: Muhammad Arif

Copyright © 2022 Xu Li et al. This is an open access article distributed under the Creative Commons Attribution License, which permits unrestricted use, distribution, and reproduction in any medium, provided the original work is properly cited.

Aiming at the problem of low accuracy of two-dimensional gait recognition at present, a gait feature recognition method based on multisource sensing information is proposed. The multisource sensing information is combined to collect the athlete's gait characteristics, collect the single frame gait image sequence of the human lower limbs during the movement, and extract the human body's three-dimensional feature data during human walking by using the body structure and multisource sensing information, so as to realize the separation of the athlete's gait image background. Finally, it is confirmed by experiments that the recognition rate of athlete gait feature recognition method based on multisource sensing information is significantly improved.

1. Introduction

When athletes walk, everyone has different characteristics from others, so it has become a research hotspot to determine a person's identity according to these characteristics. The current research focus is to find and extract the distinguishable and changing feature information of the corresponding individual from the continuous walking behavior image sequence for identity recognition [1]. However, collecting gait information from typical two-dimensional photographs has limits. The ability to extract three-dimensional gait characteristics from multisource sensing data has become a critical component of effective identification. Gait recognition is a new biometric recognition technique that is gaining traction. Its goal is to recognise people's identities or identify physiological, psychiatric, and psychological features based on their walking pattern. It has a wide range of applications [2]. Therefore, it has aroused the strong interest of many researchers at home and abroad and has become a frontier direction in the field of biomedical information detection in recent years. Gait recognition mainly focuses on the analysis and processing of moving image sequences containing

people, which usually includes three stages: feature extraction, feature training, and classification. In view of this, this paper proposes a gait recognition algorithm based on multisource sensing information and makes an in-depth study on the implementation of gait recognition method.

2. Gait Feature Recognition Method for Athletes

2.1. Athlete Gait Feature Acquisition Based on Multisource Sensing Information. To accomplish human gait classification and recognition, first identify and track the targets in the human motion video, segment the moving human body appropriately, extract the gait characteristics of the moving human body, and then compare the derived gait features with the gait in the database [3]. Human body detection, feature extraction, and acquisition are the three modules that make up the gait recognition system. Figure 1 illustrates the method of acquiring athlete gait features based on multisource sensor data.

During the investigation of human body feature data sets, we also found some available network data. For example, sports websites often contain athletes' personal information, including athletes' age, height, and weight. BMI

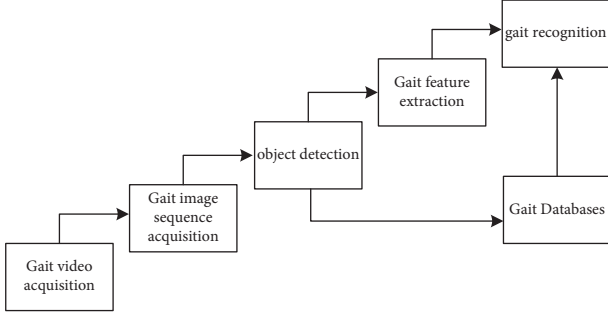


FIGURE 1: Principle of athlete gait feature acquisition based on multisource sensing information.

values can be obtained from height and weight, but the pictures provided are generally athletes' ID photos, not people's whole body photo [4]. This necessitates the use of certificate photographs to identify human traits. As a result, this picture data from documents with BMI values may be utilised. The human BMI value may be identified using the supervised learning approach in deep learning once the motion region has been discovered by motion detection [5]. After analyzing and describing the overall function of the method, it can be obtained as shown in Figure 2.

Gait recognition adopts multisource sensing information technology, which mainly analyzes and processes the video containing human walking [6]. It usually includes three stages: gait detection, gait feature extraction, and gait classification and recognition, involving video/image processing, target tracking, and pattern recognition. The general framework of gait recognition method is shown in Figure 3.

Everyone's stride has its unique features due to variances in bones, muscles, tissues, and organs, which are difficult to modify in a short amount of time. When individuals are moving, the swing angle of their legs may properly represent the human body's movement variations as well as individual differences [7]. However, obtaining the motion characteristics of the human body with precision is challenging. Gait shows people's habits in the process of walking from a psychological standpoint. Thighs, lower legs, feet, and connecting joints make up the human body's lower limbs. The hip, knee, and ankle joints are all moving parts. The pelvis links the upper body to the thigh, while the knee joint connects the thigh to the lower leg [8]. The lower limb joints have three rotational degrees of freedom, according to kinematics research. Each joint has just one rotational degree of freedom throughout the walking process. The lower limb marker point specifications are shown in Table 1.

In order to make the athlete gait feature contour segmentation network more accurate in the output results and more stable in multiscale athlete gait feature contour segmentation, it is necessary to carry out relevant design in the backbone network for feature extraction. At the same time, in order to complete the instance segmentation task of human contour [9], the human body detection frame and athlete's gait feature contour segmentation networks must both be produced at the same time by the athlete's gait feature contour segmentation network. As a result, we must

consider both the function of human body detection and the athlete's gait feature contour segmentation while developing and creating the network. The segmentation of athletes' gait feature contour and multisource sensing information are mostly used to perform this function [10].

2.2. Gait Feature Recognition Algorithm for Athletes. Data is an important element of information, but there is often useless information such as noise in the original data. In addition, the amplitude of the collected data varies greatly between different samples and in different periods or directions of the same sample, and the data dimension is also different [11]. Therefore, before data mining or feature extraction from data, pre- (post-) processing such as data cleaning (denoising, missing value processing), data conversion (data standardization), and data specification (dimension specification, discretization, and data compression) must be carried out. Gait image preprocessing is the first step in the process of gait recognition, and its quality has a very important impact on subsequent feature extraction and recognition. It usually includes human gait motion background modeling, moving target segmentation, binarization, and morphological denoising. The normalized gait image is described by polar coordinate system. Firstly, the following features are extracted: left knee angle θ_{kwe} ; right knee angle θ_{kne} ; left ankle angle $RANKL$ [12]. The right ankle $RANKR$ is because the angle and other features can reflect the dynamic information of gait, and the dynamic features are mainly concentrated in the lower body. In addition, we also extract the angle of the line between the head and shoulder θ_{NAK} ; the angle mentioned above is the angle between the tilt direction of the joint and the vertical line of the ground [13]. The angle can be estimated by formula according to the joint coordinates obtained:

$$\theta = R \arctan Z + \frac{x - a'}{y - b'}, \quad (1)$$

where x and y are the values of joint coordinates, and a' and b' are the values of the previous joint coordinates, which are the estimated angles. In addition, several contour features with good discrimination are extracted from each frame: contour area s , contour centroid ordinate R , maximum contour width f , contour height $f_{p_n, (N-1)}$, and contour aspect ratio Z . The values extracted from the same feature in different frames can be expressed as time series [14]. Finally, we get 10 gait time series, which can well represent the features contained in gait video. Take any point (P) on the cutting line. If the point is located in the human body area, the cutting function value is 1; otherwise it is 0. With m cutting lines and N points on each cutting line, the gait spatial characteristic matrix is

$$f_p = \begin{bmatrix} f_{p_1,0} & f_{p_1,1} & f_{p_1,2} & \cdots & f_{p_1,(N-1)} \\ f_{p_2,0} & f_{p_2,1} & f_{p_2,2} & \cdots & f_{p_2,(N-1)} \\ \cdots & \cdots & \cdots & \cdots & \cdots \\ f_{p_n,0} & f_{p_n,1} & f_{p_n,2} & \cdots & f_{p_n,(N-1)} \end{bmatrix}. \quad (2)$$

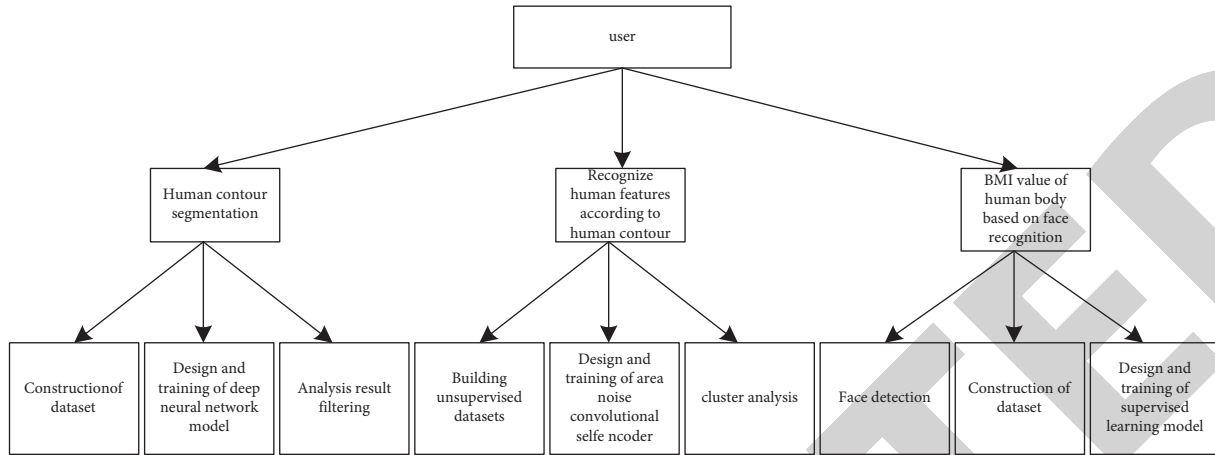


FIGURE 2: Human feature recognition method use case.

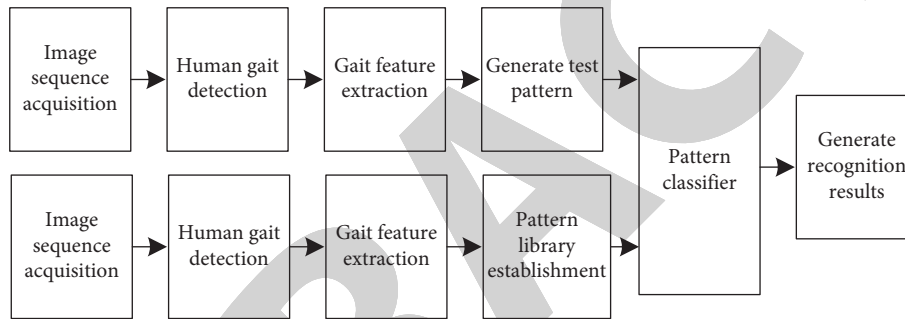


FIGURE 3: Athlete gait recognition framework.

TABLE 1: Marking point parameters.

Serial number	Parameter code	Parameter meaning
A	A1	End of right metatarsal
B	B1	Right heel
C	C1	Lateral right ankle
D	D1	Right tibial shaft
E	E1	Lower right femur
F	F1	Right femoral shaft
G	G1	Anterior spinous process of right iliac bone
H	H1	Anterior part of left metatarsal
I	I1	Left heel
J	J1	Lateral left ankle
K	K1	Lower left tibia
L	L1	Left tibial shaft
M	M1	Anterior spinous process of left iliac bone
N	N1	Sacrum

There are variances in the gait sequences of each individual. For identity detection, just gait spatial data are employed, and the recognition accuracy is low. In the process of detecting a target, the environment is equally significant. Even though the targets are the same in various settings, the target identification approach may need to be drastically altered; otherwise, the implications might be disastrous [15]. Although human vision techniques have a

high level of automation and intelligence, their target identification methods are limited by criteria such as scene, target kind, and application purpose [16]. This is especially true in the case of machine vision. There cannot be any such thing as a universal technique. Figure 4 depicts the process structure for detecting targets in still pictures.

The frequency feature of gait is stable. The frequency feature can be used to supplement the gait feature, and the

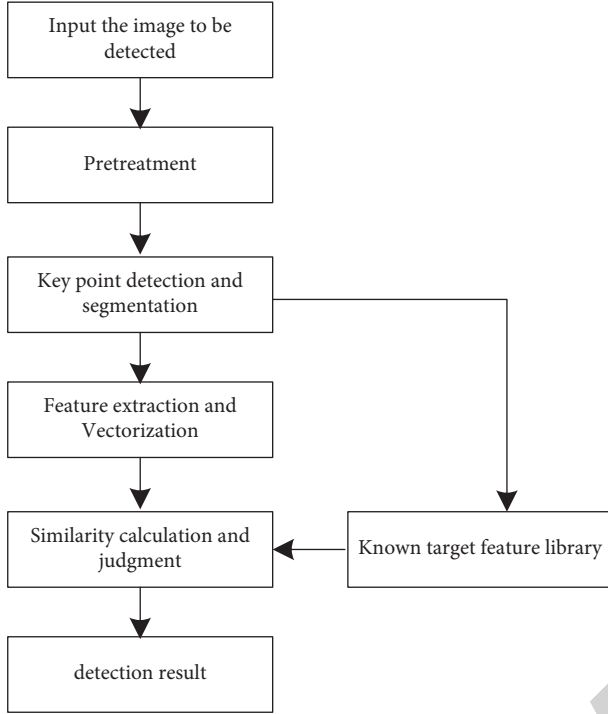


FIGURE 4: Still image object detection framework.

frequency feature of gait image can be extracted by Fourier transform.

$$V(\rho, k) = \sum_{j=0}^{N-1} f_{\rho}(\theta_j) - 1. \quad (3)$$

In the feature extraction step, holes and ghosting are easy to occur. Therefore, it is necessary to eliminate pseudo-feature points E . For the initial motion foreground extraction, the front and rear frame difference method U is adopted, as shown in

$$\lambda = V(\rho, k) + |E_{i+1} - U_i|. \quad (4)$$

Since there are many noise points in the initial foreground, these noise points are easy to be regarded as feature points. Therefore, the pseudo-feature point elimination algorithm is used for judgment [17]. The specific judgment process is as follows: if you want to calculate the distance from each connected domain to the image center, you need to calculate the image centerline coordinates first.

$$R(a) = \lambda - \frac{\sum_{i=1}^M a_i}{M}, \quad (5)$$

$$R(b) = \frac{\sum_{i=1}^M b_i}{M}. \quad (6)$$

In the formula, a_i, b_i , respectively, represent the central coordinates of the connected area, and $R(a), R(b)$ are the center coordinates of the horizontal axis and the vertical axis, respectively. The windowing method is used to process the processed human behavior signal. The sensor signal is

taken from a rectangular window that covers half of the window factory. Following the proper window factory, a feature vector representing human behavior is formed by extracting a range of characteristics from a single window factory signal [18]. The background subtraction method is based on the dynamic background model; that is, the parameters of the background model are obtained through a series of image training, the image to be processed is input into the established background model for comparison to detect the moving target, and the model parameters can be updated dynamically according to the changes of the scene. Its flowchart is shown in Figure 5.

The standard deviation is one of the statistical features, which effectively reflects the dispersion degree of sensor data. When people are in the static behavior state, the acceleration data is basically unchanged, and the standard value is 0, while the acceleration data changes constantly during people's movement, and the standard value is greater than 0. The specific calculation formula is

$$D = \sqrt{\frac{1}{\lambda} \sum_{i=1}^S A_i + (R(a) - R(b))^2}. \quad (7)$$

If S indicates the number of samples, \bar{A} represents the average value of the sample. According to the formula, the static and dynamic behavior of human body can be distinguished. Skewness can measure the skew direction of acceleration sensor data distribution, analyze the schematic diagram of gravity direction, and identify human behavior according to X -axis skewness. The specific calculation formula is as follows:

$$P = \frac{\sum_{i=1}^S (D - \bar{A})^3}{(S-1)(S-2)}. \quad (8)$$

According to the formula skewness, human jumping and squatting can be effectively distinguished. Kurtosis change curve can directly reflect the change degree of all signals at the peak of data curve, which is an important statistical feature. The specific calculation formula is as follows:

$$Q = \frac{\sum_{i=1}^S (A_i - \bar{A})^4 n_i}{S a^4}. \quad (9)$$

In the formula, n_i represents the sample interval. The formula can effectively distinguish human running from action. The correlation coefficient can measure the degree of linear correlation between variables. The specific calculation formula is as follows:

$$W_{AB} = \frac{\sum_{i=1}^S Z - Q_i}{\sqrt{\sum_{i=1}^S (A_i - \bar{A})^2} \sqrt{\sum_{i=1}^S (B_i - \bar{B})^2}} \quad (10)$$

where A and B represent the correlation coefficient variable. According to the formula and combined with the correlation coefficient in the two directions of gravity Z , the human body can effectively distinguish between going upstairs and walking.

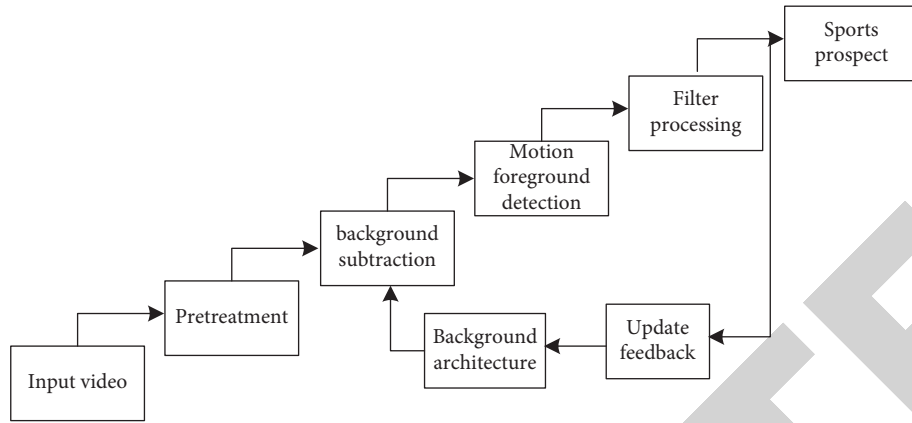


FIGURE 5: Flowchart of the gait feature background difference method.

2.3. *Realization of Gait Feature Recognition.* After the target is successfully detected, in order for further processing, the target should be formally represented; that is, the target attributes should be represented and described through relevant data structures and corresponding algorithms. From the perspective of expressing and describing the target, any attribute of the target, whether it is special or not, belongs to the category of target characteristics, is an objective part of target characteristics, is the reason why the target is different from other targets, and is also the content of target description and expression [19]. Static properties, such as shape, colour, and hierarchy, are separated from dynamic attributes, such as motion speed, motion direction, and motion mode. The extraction and representation techniques for distinct target attribute characteristics are also diverse. Perceptual layer properties such as form, contour, colour, texture, and so on are static qualities of targets [20]. The target’s representation technology is classified into three categories depending on the target’s static attribute characteristics: boundary based representation, region based representation, and transformation based representation. The closed contour of the target is used to depict the target’s boundaries. Figure 6 depicts the technical classification based on multisource sensing data, which includes boundary point aggregate representation, parameter multisource sensing data, and curve approximation data.

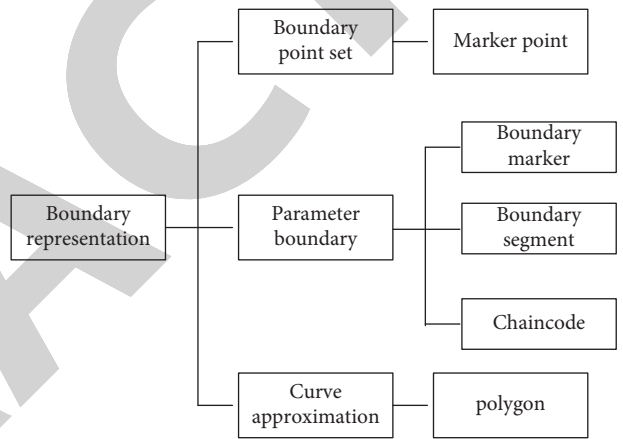


FIGURE 6: Motion gait feature segmentation based on multisource sensing information.

The target entering the video is detected and tracked, and the moving human body is segmented. Then the gait features are extracted from the moving human body by using multisource sensing information and image processing algorithms. Finally, the classifier 2 is compared with the trained and stored gait pattern library to complete the gait classification and generate the recognition results. Among them, gait feature extraction, gait training, and recognition algorithm are the main technical links of gait method design, and they are also the key research contents in the field of gait recognition. The architecture of athlete gait feature contour segmentation module is shown in Figure 7.

The basic purpose of the athlete gait feature contour segmentation module, as shown in the image, is to input a picture of a human body and output the subject’s human

body contour. It is important to note that this module will employ example segmentation to segment the human contour while creating and constructing multisource sensing information for athletes’ gait feature contour segmentation. As a result, multisource sensing information must be designed and built on instance segmentation. It is important to design and develop backbone multisource sensing information, take the backbone network as an overall unit, extract the features in the image, and offer the features to the following network throughout the particular design and building process. Gait recognition, like motion recognition, is dependent on multisource sensory information. Illumination, backdrop shift, and time span may all have an impact. The gait database is built using the database creation approach. The camera angle and distance, as well as the degree of occlusion of the individuals’ clothes, shoes, walking pace, carrying things, and road conditions, all have an impact on the gait video or picture. These considerations should be included into the database creation process. It will take a long time to compile the gait database, which will include all scenarios and combinations of all circumstances. It is difficult for the subjects to work closely together for such a lengthy period of time. Furthermore, algorithm research often requires the decomposition of a large issue into

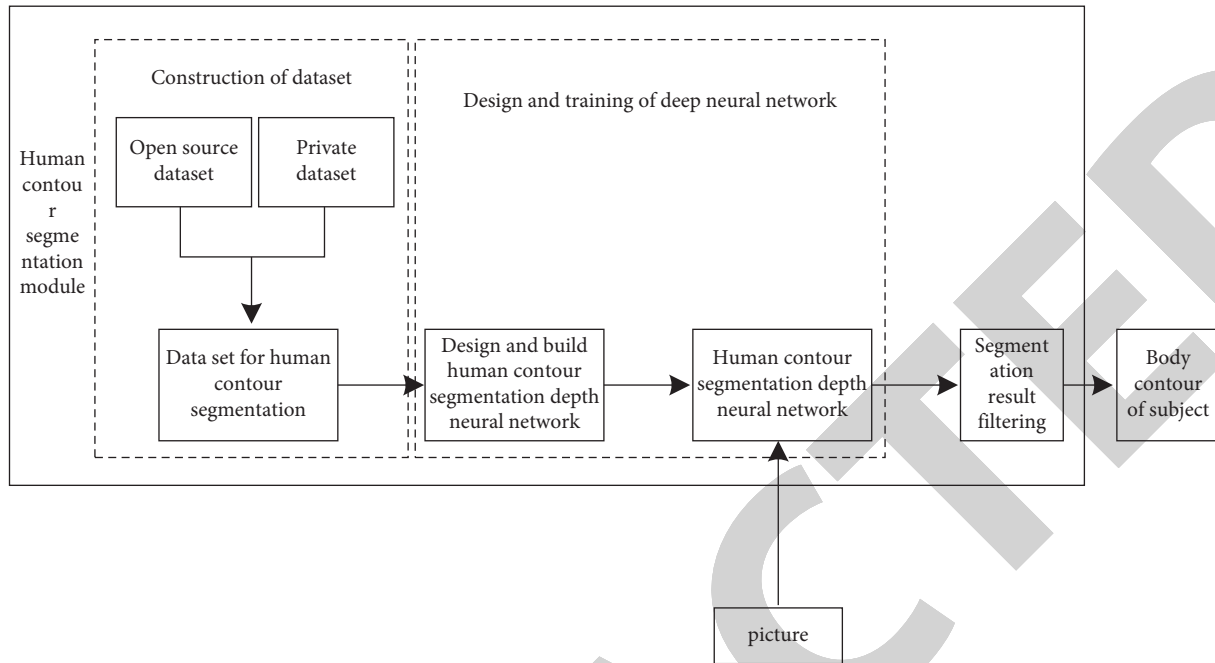


FIGURE 7: Architecture of athlete gait feature contour segmentation module.

numerous smaller problems, and the original data set contains complex problems, posing additional hurdles to algorithm research. The vision-based gait recognition technique is consistent. Gait picture sequence acquisition, image preprocessing, feature extraction, categorization, and recognition are common recognition approaches. The whole procedure is shown in Figure 8.

Gait recognition first needs to extract the moving human body image in the video and divide the video into frames to get the image of each frame. The video image can be acquired through the camera, and the scene is generally selected in the laboratory or where the scene setting is relatively simple. Image preprocessing is the process of detecting and processing gait images. In the actual operation process, there are some difficulties in the detection process due to the influence of illumination, shadow, and colour deviation. Common detection methods include background subtraction, frame difference, and optical flow. Each algorithm uses different occasions and has different characteristics. When the scene changes, the corresponding algorithm should also be adjusted with the scene changes.

3. Analysis of Experimental Results

In order to verify the effectiveness of the gait features extracted by this algorithm in gait identification, CASIA gait database is selected as the simulation data. CASIA gait database has three data sets: dataseta (small-scale database), datasetb (multiview database), and datasetc (infrared database). This paper uses dataseta as the recognition object. Dataseta contains the data of 20 people. Each person has 12 image sequences, 3 motion directions (0 degrees, 45 degrees, and 90 degrees with the image plane, respectively), and 4 image sequences in each direction. The length of each

sequence varies with the walking speed, and the number of frames in each sequence is between 37 and 127. The entire database contains 13139 images. The feature extraction part uses Python 3.5 based on opencv 3.4. Mrpsf implementation uses Java 1.8. Ubuntu 6, Cuda 7.04, and cudnn 9.2 are used to accelerate the training of multisource sensing information. In hardware, the Intel quad core i76700 processor is used to carry out the experimental work of our proposed algorithm. In addition, we use a computer equipped with Intel quad core i6700 processor and NVIDIA gtx750tigpu (2gv RAM) to train multisource sensing information for comparison. According to the process of gait recognition technology, the gait sequence diagram of the data set is extracted periodically, the skeleton is extracted by the improved ZS thinning algorithm, the joint points are located by the method based on multisource sensing information, the joint angle is calculated as the feature vector, the training set is input into SVM for feature training, and the test set is classified and recognised. Any biometric recognition method requires the feature to be stable and unique. Table 2 lists the repeatability verification results of some time-domain gait features in itcshgait gait database. The repeatability verification method adopts the intragroup correlation coefficient ICC method, which is the verification result without weighted standardization of the original GRF data.

Figure 9 shows the changes of joint angles of left and right thighs and lower legs during movement. The changes of angle characteristics in two states are recorded and displayed, which have high consistency.

Gait recognition is carried out based on the above data, and the gait recognition results of all samples by this method are recorded, as shown in Table 3.

It can be seen from the table that, under different states, the recognition rate of normal walking state of this method is

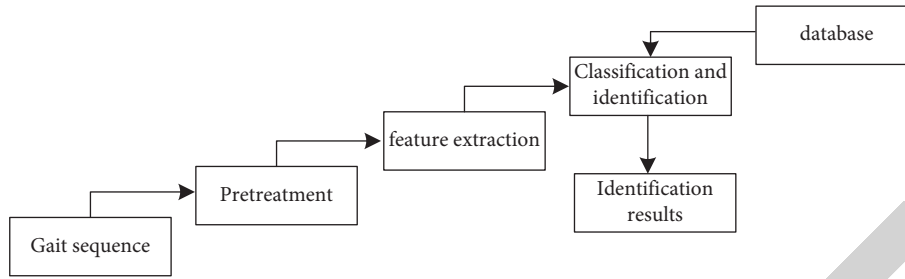


FIGURE 8: Athlete gait recognition process.

TABLE 2: Repeatability verification results of some time-domain gait features.

Characteristic parameter	Constant speed		Fast		Slow		Mixing speed	
	ICC	F-value	ICC	F-value	ICC	F-value	ICC	F-value
Q1	0.998	267.265	0.993	137.859	0.995	175.652	0.988	261.652
Q2	0.997	435.658	0.989	79.985	0.998	289.652	0.991	312.785
Q3	0.989	443.652	0.985	45.658	0.997	352.652	0.998	337.65
Q4	0.975	62.528	0.968	35.652	0.985	62.89	0.865	25.658
Q5	0.967	45.652	0.958	28.652	0.968	28.658	0.895	35.652
Q6	0.966	45.658	0.952	28.652	0.987	43.652	0.765	14.652

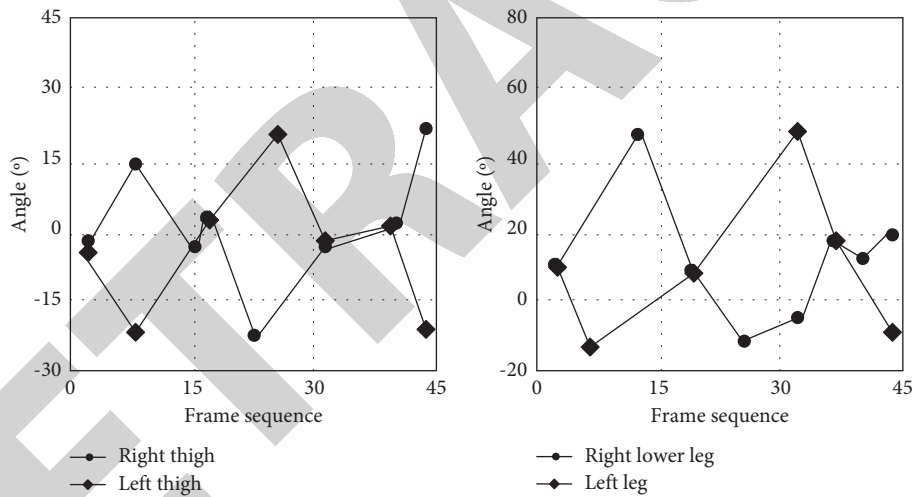


FIGURE 9: Change of joint angle during lower limb swing during movement.

TABLE 3: Gait recognition results under different motion states.

Walking state	Normal walking		Running		Jumping	
	Paper method	Traditional method	Paper method	Traditional method	Paper method	Traditional method
Correctly identify sequence	21/22	14/22	19/22	11/22	20/22	22/22
Recognition rate	96%	80%	82%	67%	91%	66%

TABLE 4: Comparison results of data mining time consumption.

Data collection volume	Traditional system (s)	Association rule based system (s)
2500	8.35	2.35
5500	125.65	15.65
8000	332.65	28.32
10500	826.52	66.79
12500	1281.99	79.95
18000	2018.98	92.05

TABLE 5: Test results of gait recognition error rate.

Number of modes	1	2	3	4	5	6	7	8	9	10	11	12	13	14	15	16	17	18	19	20
Elapsed time (s)	0.951	1.032	1.065	1.026	1.065	1.065	1.165	1.162	1.16	1.178	1.189	1.179	1.225	1.256	1.265	1.298	2.765	2.932	3.625	3.658

TABLE 6: Comparison results of test time.

Direction of motion	Traditional method (s)	Paper method (s)
Positive kick	59	36
Bend kick	67	25
Side kick	98	58
Back kick	88	45
Jump kick	85	26
Running and kicking	95	46

the highest, and the recognition rate of running state is more than 80%. It can effectively recognise the jumping gait, which shows that the gait recognition method in this paper is significantly improved compared with the traditional method, and the comprehensive recognition rate of gait under different walking states reaches 88.33%. The training biochemical index data of 50 students were grouped and divided into 5 groups. Experiments were carried out in the traditional data mining method and the data mining method based on multisource sensing information, and the time spent in data mining was recorded. The results are shown in Table 4.

It can be seen from the table that the traditional data mining methods take a long time. In the program design of the recognition module, we take the test pattern feature data, the initialization of RBF multisource sensing information weights, and the display of recognition results as the serial part and the calculation of residuals as the parallel part. In the environment of LabVIEW 2010, the recognition error is calculated for 1 to 20 groups of patterns. When the number of modes taken is different, the required calculation time is shown in Table 5.

In order to verify the time spent in the automatic detection of this method, the kick direction in motion is taken as the detection standard, mainly including positive kick, bending kick, side kick, back kick, jumping kick, and running kick. Compare the time spent by the traditional method with the time spent by the gait feature recognition method based on multisensor information, and the results are shown in Table 6.

It can be seen from the table that the time spent in using the traditional automatic detection method to detect the positive kick direction is longer than that of the designed gait feature recognition method based on multisensor information, while the time spent in detecting other kick directions is longer, which is far slower than the recognition speed of the design method in this paper.

4. Conclusion

Most gait identification algorithms are currently based on a single spatial or frequency characteristic. The combination of gait space and frequency features is suggested in this research as a gait recognition method. Gait recognition has become a research hotspot for multisource sensing information, attracting an increasing number of researchers' interest. The use of biological traits for distant identification is known as gait recognition. It may be used in a variety of sectors, including intelligent surveillance, motion analysis,

biological authentication, criminal investigation, and virtual reality. Model-based gait recognition algorithms and non-model-based gait recognition algorithms are the two types of human gait recognition algorithms currently available. However, several current approaches still have a number of flaws in terms of practical functioning. Not only does the algorithm's accuracy need to be improved, but some of the calculations are also rather complicated. The simulation results show that the algorithm in this paper not only overcomes the problem of low single feature recognition rate, but also improves the robustness of gait recognition algorithm. It is an effective and highly accurate gait recognition method.

Data Availability

The data used to support the findings of this study are included within the article.

Conflicts of Interest

The authors declare no conflicts of interest.

References

- [1] S. Liu, D. Liu, K. Muhammad, and W. Ding, "Effective template update mechanism in visual tracking with background clutter," *Neurocomputing*, vol. 458, pp. 615–625, 2021.
- [2] S. Liu, S. Wang, X. Liu et al., "Human memory update strategy: a multi-layer template update mechanism for remote visual monitoring," *IEEE Transactions on Multimedia*, vol. 23, pp. 2188–2198, 2021.
- [3] L. Shuai, H. Tenghui, and D. Jianhua, "A survey of CRF algorithm based knowledge extraction of elementary mathematics in Chinese," *Mobile Networks and Applications*, vol. 18, no. 5, pp. 48–55, 2021.
- [4] K. Lingxin and M. Yajun, "Big data adaptive migration and fusion simulation based on fuzzy matrix," *Computer simulation*, vol. 37, no. 3, p. 4, 2020.
- [5] B. Yha, B. Tl, C. Cl, F. Hfde, G. Sjh, and B. Bw, "Dynamic maintenance of rough approximations in multi-source hybrid information systems," *Information Sciences*, vol. 530, no. 7, pp. 108–127, 2020.
- [6] D. Khatamsaz, A. Molkeri, R. Couperthwaite et al., "Efficiently exploiting process-structure-property relationships in material design by multi-information source fusion," *Acta Materialia*, vol. 206, no. 4, Article ID 116619, 2021.
- [7] T. J. B. Sizeland, A. M. Fearon, D. M. Perriman et al., "People after gluteal tendon repair have gait characteristics which are similar to those of a healthy cohort," *Clinical Biomechanics*, vol. 80, no. 4, Article ID 105176, 2020.
- [8] L. Zhornyak and M. R. Emami, "Gait optimization for quadruped rovers," *Robotica*, vol. 38, no. 7, pp. 1263–1287, 2020.
- [9] A. Gouelle, S. Norman, B. Sharot, S. Salabarría, and M. Corti, "Gauging gait disorders with a method inspired by motor control theories: a pilot study in friedreich's ataxia," *Sensors*, vol. 21, no. 4, Article ID 1144, 2021.
- [10] D. M. Desmet, A. D. Westbrook, and M. D. Grabiner, "Treadmill-belt width, but not feedback from the lower visual field, influences the noise characteristics of step width time series," *Journal of Biomechanics*, vol. 109, no. 1–2, Article ID 109943, 2020.

- [11] X. Wang, Q. Meng, H. Lan, Z. Zhewen, C. Chen, and H. Yu, "Neural network predictive control of swing phase for a variable-damping knee prosthesis with novel hydraulic valve," *IEEE Access*, vol. 8, no. 4, pp. 201622–201634, 2020.
- [12] Y. Akiyama, R. Kushida, S. Okamoto, and Y. Yamada, "Characteristics of recovery motion resulting from side contact with a physical assistant robot worn during gait," *IEEE Transactions on Human-Machine Systems*, vol. 50, pp. 518–528, 2020.
- [13] F. A. Storm, A. Cesareo, G. Reni, and E. Biffi, "Wearable inertial sensors to assess gait during the 6-minute walk test: a systematic review," *Sensors*, vol. 20, no. 9, Article ID 2660, 2020.
- [14] A. Sachan, W. W. E. Cheok, and Y. S. Choo, "Feature recognition and strength estimation of chain links by 3D inspections," *Ocean Engineering*, vol. 225, no. 1, Article ID 108785, 2021.
- [15] A. Gz, B. Fp, C. Hs, C. Qs, A. Gx, and A. Yz, "Cost-sensitive joint feature and dictionary learning for face recognition-ScienceDirect," *Neurocomputing*, vol. 391, no. 3, pp. 177–188, 2020.
- [16] M. Gomathy, "Optimal feature selection for speech emotion recognition using enhanced cat swarm optimization algorithm," *International Journal of Speech Technology*, vol. 24, no. 1, pp. 155–163, 2021.
- [17] P. Gupta, "MERASTC: micro-expression recognition using effective feature encodings and 2D convolutional neural network," *IEEE Transactions on Affective Computing*, vol. 41, no. 99, p. 1, 2021.
- [18] N. Alswaidan and M. E. B. Menai, "Hybrid feature model for emotion recognition in Arabic text," *IEEE Access*, vol. 8, no. 99, pp. 37843–37854, 2020.
- [19] S. D. Pande and M. S. R. Chetty, "Linear bezier curve geometrical feature descriptor for image recognition," *Recent Advances in Computer Science and Communications*, vol. 13, no. 5, pp. 930–941, 2020.
- [20] M. Woniak, "Advanced computational intelligence for Object detection, feature extraction and recognition in smart sensor environments," *Sensors*, vol. 21, no. 1, p. 45, 2020.