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Biometric gait identification based on a multilayer perceptron

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HIGHLIGHTS

- Novel biometric gait identification approach based on a multilayer layer perceptron.
- Identification of disordered and abnormal gait patterns is a fundamental problem.
- Development of an intelligent system to identify human activities.

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ABSTRACT

In this study, we propose a novel approach for biometric gait identification. We designed a multilayered back-propagation algorithm-based artificial neural network for gait pattern classification and we compared the results obtained with those produced using the *k*-means and *k*-nearest neighbor algorithms. A novel aspect of our feature extraction procedure was the use of a kernel-based principal components analysis because the captured real-time data exhibited significant nonlinearity. The gait data were classified into four classes: normal, crouch-2, crouch-3, and crouch-4. The proposed method achieved gait identification with very good activity recognition accuracy (ARA). The experimental results demonstrated that the proposed methodology could recognize different activities accurately in outdoor and indoor environments, while maintaining a high ARA. The identification of disordered or abnormal gait patterns was the fundamental aim of this study. Thus, we propose a method for the early detection of abnormal gait patterns, which can provide warnings about the potential development of diseases related to human walking. Furthermore, this gait-based biometric identification method can be utilized in the detection of gender, age, race, and for authentication purposes.

0. Introduction

The human gait is considered to be a unique biometric identification tool [1] similar to a fingerprint [2]. It can be used to identify people in various security applications and to detect walking abnormalities before permanent damage occurs. The data used for pattern classification and in the analysis of different walking styles [3] can also be employed to predict the likelihood of diseases by detecting abnormalities in the gait pattern. Furthermore, the gait is a signature of human walking that can be used for personal identification [4] purposes. However, human gait synthesis is a complex phenomenon because it involves the synchronized motion of upper and lower body parts. This synchronization develops over several months of learning (for a normal child, up to one year is required before stable walking is achieved), where different parts of the brain are involved in the learning process to establish co-ordination among the nerves and muscle, i.e., the motor system and sensory organs. The mechanism of learning is almost impossible to study based on our current knowledge of human brain functioning. Thus, it is necessary to collect data and construct biped robots in digital space to operate these robots using these data. This type of research can also obtain insights into the humanoid push recovery capacity [5] as well as capturing biometric identity features related to gender, age, and race based on human locomotion [6,7]. Many previous studies have used various machine learning techniques to capture the complex nonlinear features of gait patterns [8,9]. In addition, the identification of abrupt changes in gait patterns may also provide timely warnings to facilitate enhanced security [10–13] (e.g., in a video surveillance environment) and safety (e.g., in a life-critical environment such as a patient monitoring system). In the present study, we aimed to correlate the gait with human activity recognition. Due to its inherent uniqueness, the gait research community [14–17] is actively involved in the development of gait pattern recognition techniques using various machine learning tools [18] which may help

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Table 1
Comparison of existing approaches for gait recognition.

Ref.	Method	Advantage	Disadvantage	Uses
Bobick et al. [14]	Activity recognition using temporal templates	Real time application	More than one classifier reduces the accuracy	Indoor/outdoor both
Vega et al. [15]	Spectral analysis of human motion	Higher-order spectral	Periodic detection	Differentiates between people and vehicular objects
Vega et al. [15]	View-based motion analysis	Object models are not required	Needs to reduce the combinatorial distribution	Outdoor scenario
Wang et al. [16]	Gait recognition	Locomotion human model	Insensitive to noise	Indoor scenario
Noorit et al. [17]	Model-based action recognition	Inclusion of motion texture	Poor performance during walking	Indoor environment
Iverach-Brereton et al. [24]	Relies entirely on motion in the frontal plane to propel the robot	Gait design for an ice skating humanoid robot	Classical inverted pendulum-based walking gait when using the same skates unstable	Both ice skates and inline skates

to recognize people from a distance [19]. Thus, when CCTV cameras are used as a surveillance tool, they may fail to detect potential threats due to the time gap between identification and recognition, which could be improved by using distance-based identification technique. Similar techniques can be useful in various areas such as parking lots, crowded market places, pedestrian crossings, and banks. The overall aim of classification is to discriminate among individuals based on their locomotion characteristics [20]. In contrast to conventional biometric identification techniques such as fingerprint, iris, and face recognition [21], gait recognition is unobtrusive [22] but it is also inherently nonlinear and complex. A comparison of existing approaches for gait recognition is provided in Table 1. Humanoid robots must be able to access complex social environments, so it is necessary to develop a humanoid gait that is suited to complex terrain [23]. To facilitate the development of complex robots, Iverach-Brereton et al. proposed a complex gait design method for an ice skating humanoid robot [24]. The method proposed by Iverach-Brereton et al. is a major advance in the development of sophisticated robots for uneven terrain.

Gait data may be classified using different machine learning techniques, such as artificial neural network (ANN) [25], k-nearest neighbor (KNN) [26], and k-means [27] algorithms. Studies related to locomotion may help us to understand the problems of disabled people and to develop more sophisticated advanced humanoid robots. The different types of gait patterns include jumping, running, dancing, walking, pushing, and sitting, but not all of these gait types are cyclic. In particular, jumping is considered to be coordinated and cyclic but it is not treated as locomotion. The high-dimensional feature spaces involved in gait analysis incur high computational costs, which means that the number of dimensions should be reduced. Reducing the dimensionality also improves the classification accuracy. The methods that require the least training comprise the best machine learning algorithms. Feature reduction is also important for reducing the computational costs. Let us assume that the data have the features $X(i),\ i = 1, 2, \ldots, l$ which comprise the l-dimensional feature vector $X = [X(1), X(2), \ldots, X(l)]^T \in R^l$. The two major objectives of dimensionality reduction are reducing the computational costs and generalizing the accuracy. The benefits of reduced dimensionality include less time required for training and classification, as well as minimizing the risk of overfitting. A lower dimensionality incurs reduced training costs and it improves the high-level generalizability of classification algorithms for reduced dimensionality feature vectors. Feature selection is used to select important features that still retain sufficient information for classification. Two feature selection approaches are available: the filter method and the wrapper method. Classification based on a distance measure is employed to express how well the classes are separated from each other, i.e., using filter-based classification. By contrast, instead of selecting an appropriate subset, the wrapper methods are classifier-dependent, where this method calculates the value directly based on a feature. The wrapper method measures the correctness of the algorithm, thereby determining whether it has good accuracy. However, the wrapper method is not used widely due its high computational costs, although it performs well.

The human gait involves locomotion with the support of various body parts [19]. The overall gait comprises the following stages: lift one leg with the support of the other leg on the ground and move the body forward while swinging the lifted leg until it is in front of the body [20]. The locomotion cycle moves the whole body forward when the lifted leg makes contact with the ground. Different types of activity are associated with humanoid locomotion such as walking, running, jumping, and jogging, which are all important activities in video surveillance. In our previous study, ANN was used for activity recognition [25] based on leg movements alone. The experimental results suggested that our method could be used to recognize human activities with a high level of accuracy. Human walking involves the coordination of regular periodic motions of the upper or lower body extremities, which are responsible for the unique locomotion patterns of individuals. It is considered to be very difficult to disguise the gait from recognition by a biometric identification system. In the present study, we first selected the principal features using kernel principal components analysis (PCA) and we then classified the gait data into five different types using an ANN machine learning technique [26] based on these features, i.e., normal and four types of crouch positions, where we also compared the performance obtained with different methods. The remainder of this paper is organized as follows. Section 1 highlights the the importance of this study and its benefits. Section 2 presents the techniques used for data smoothing, data correction, and analysis based on various machine learning methods. Section 3 presents the experimental results and the different patterns determined in the subjects who we tested. Section 4 describes the performance obtained using different machine learning techniques, where we designed a confusion matrix and tested other performance parameters in the analysis. Finally, we determined that ANN obtained the best gait classification performance.

0.1. Background

The main objective of gait analysis is to understand the problems of disabled and elderly subjects, as well as those using prosthetic legs [28]. In addition, the classifications obtained can be used to develop biologically inspired bipedal machines, which can operate in similar human environments [29]. In cluttered environments, pushing against obstacles is a very common phenomenon, so push recovery [5] is essential for allowing humanoid robots to mimic this capability, which requires intelligence. Thus, many

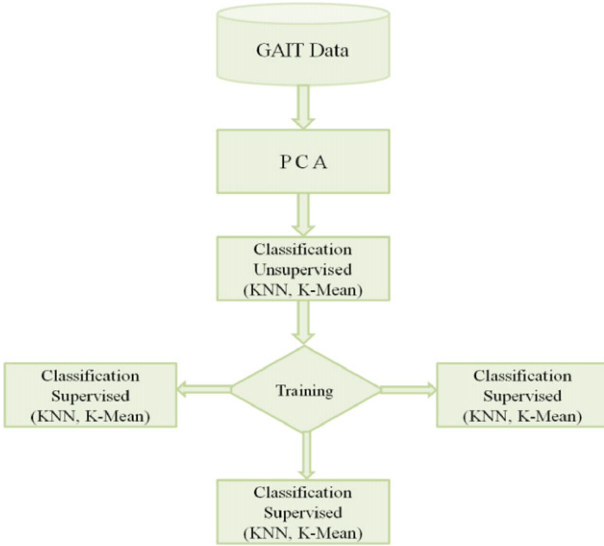

Fig. 1. Flow diagram showing gait classification using different machine learning techniques.

areas of research are aiming to develop intelligent agents for machines that emulate human behavior [30,31]. Fig. 2 shows an earlier implementation of artificial intelligence in a machine, which planned an activity before subsequent processing. Fig. 3 illustrates the coordination of the brain and body actions. Fig. 1 shows a flow diagram of gait classification using different machine learning techniques (see Fig. 4).

In general, we use three memories to allow different phases of the gait pattern to be learned [32]: the first memory component is perceptual, where it is used to perceive and store information related to an external event; the second component is the working memory (also referred to as the short-term memory); and the third is the long-term memory. The working memory stores the results temporarily. The information stored in the long-term memory as previous experience comprises an entire learning cycle of experience [33].

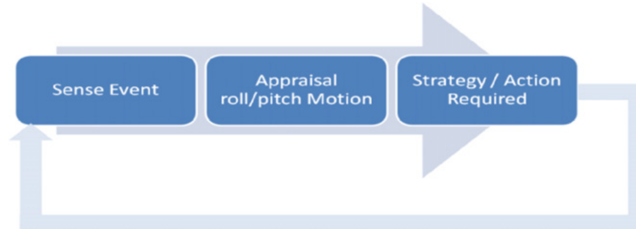

Fig. 4. Sense–Appraise–Act [32].

1. Methodology

Human tracking and activity recognition

To recognize human activities, we need to establish the features of each activity based on the parameters of a human model, as follows. Walking feature: during walking, each human body part generally moves at the same speed in the same direction. Thus, walking can be identified when the velocities of all the components exceed zero but less than a predefined threshold for walking [34,35]. It should be noted that the main difference between running and walking is that at least one of the feet will be in contact with the principal axis (ground) at any given time during walking, as shown in Fig. 5(a). Jumping feature: during jumping,

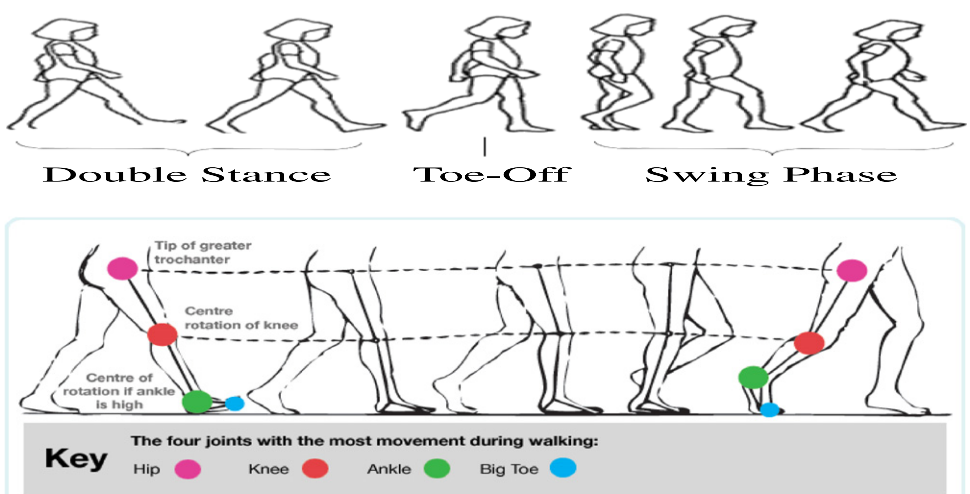

Fig. 2. Human gait sagittal plane view [6].

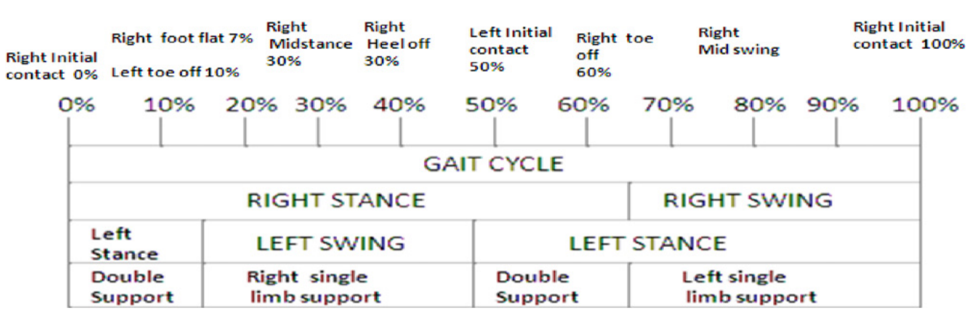

Fig. 3. Different phases in human gait patterns.

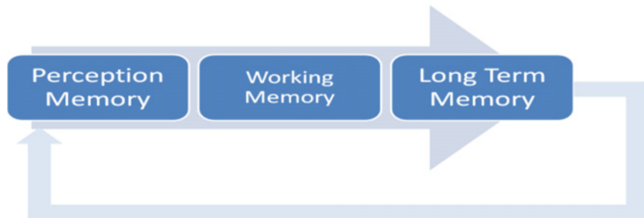

Fig. 5. Multiple types of stored human memories [33].

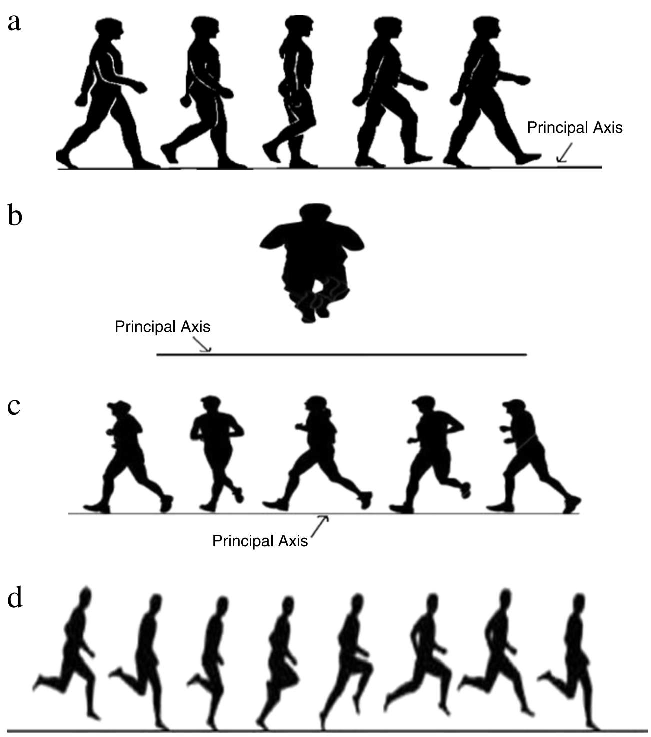

Fig. 6. Silhouette patterns for: (a) walking, (b) jumping, (c) jogging, and (d) running [34].

every human part only moves vertically and in the same direction, either up or down. Therefore, jumping can be identified when the velocities of all three components are close to or equal to zero in the horizontal direction but greater than zero in the vertical direction, as shown in Fig. 6(b). Jogging feature: The only differences between jogging and running are that the travelling speed is greater during running than the jogging, while there is also a difference in the distance ratio between the leg components relative to the ground axis, as shown in Fig. 6(c). Running feature: during running, the travelling speed is greater than jogging and the distance ratio between the leg components relative to the ground axis also differs, as shown in Fig. 6(d). Fig. 6 shows the different types of gait during different movement pattern, i.e., (a) walking, (b) jumping, (c) jogging, and (d) running. These are stable gait patterns, which humans can execute perfectly.

Multi-layer neural networks [36] comprise an input layer, a hidden layer, and an output layer. Multi-layer neural networks can

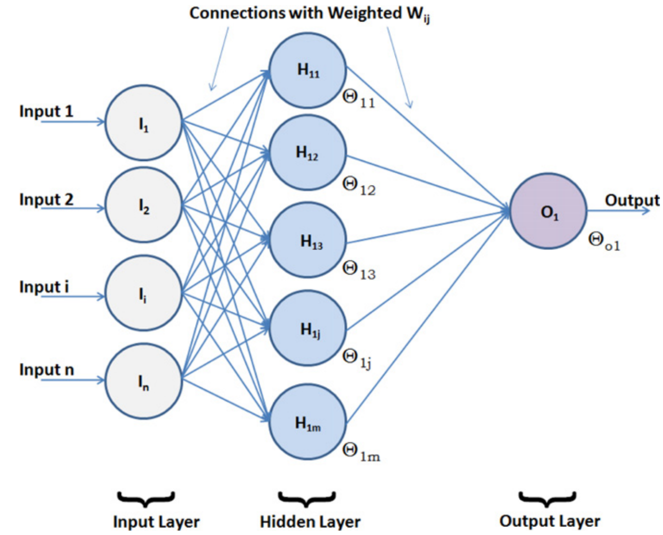

Fig. 8. Multi-layer back-propagation ANN.

have several output units, where the output units of the hidden layer function as the input units for the next layer. However, multiple layers of linear units still only produce linear functions [37]. Using a step function in a perceptron is another choice, but it is not differentiable, and thus it is not suitable for gradient descent search. The solution is a sigmoid function, which is a nonlinear, differentiable threshold function [38,39]. Fig. 6 shows a model of the multi-layer propagation ANN we employed in the present study.

Fig. 7 shows the data fusion process at the feature level, followed by dimensionality reduction using PCA, and the subsequent classification procedure with different machine learning techniques. PCA was used to select the major features. Fig. 7 shows the overall model of the neural network based on back-propagation [40].

Algorithm for human activity recognition

(1) Input is fed into the system as a feature of different gait types.
(2) Select the principal components, which are used for further processing.
(3) Reduce the dimensionality.
(4) Apply various technique for classification, i.e., ANN, KNN, and *k*-means algorithms.
(5) KNN and *k*-means are used for classification based on the similarities of features.
(6) The features depend on the following criteria: walking, jumping, jogging, and running.
(7) Compare all of the different gait types.
(8) ANN outperforms the KNN, *k*-means, and other existing methods in classification.

Fig. 8 shows templates for different gait styles: jogging, running, walking, and jumping. ANN algorithm for gait classification [41]: the algorithm starts by initializing the weights on the nodes, before calculating the output for each data point, computing the error, and propagating it back. Finally, the weights are updated and this loop runs until the error is not below a threshold.

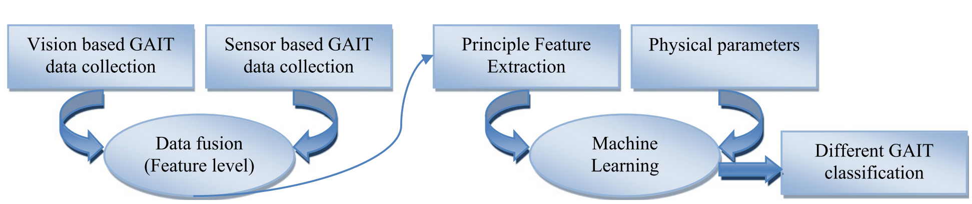

Fig. 7. Overall data fusion (feature level) and classification process.

Back-propagation ANN

Step 1 propagate the input through the network.
Step 2 propagate the errors backward through the network in a similar manner to the delta rule in gradient descent.
Step 3 sum over the errors of all the output units affected by a given hidden unit (this is because the training data only provide direct feedback for the output units).

1.1. Classification methods

The main aim of this study was to classify gait data into different categories based on training data with known categories. Thus, a new gait sample could be used to predict a new sample category. PCA was used to reduce the data dimensionality. PCA converts high-dimensional data into a lower dimensional space [42]. PCA ignores the minor variability and captures the main (principal) variability in the data using higher eigenvalues.

1.1.1. KNN

Previously, the KNN algorithm has been applied to gait categorization [43]. The aim is to determine the gait category of a given gait sample based on its nearest neighbors in the gait space, which also depend on the nearest categories of k gait samples. Thus, the k nearest neighbors can be used to classify an unknown sample based on k nearest data points rather than a single neighbor. Each time a new sample point joins the cluster, the centroids are recomputed for the cluster. Two types of learning method are suitable for this approach: a stochastic, probability-based method, e.g., a Bayesian classifier, or an eager learning approach, such as neural networks and decision trees.

Euclidean distance: this metric is used to compare real value attributes where the instance x is often referred to as a feature vector:

$a_1(x), a_2(x), \ldots, a_n(x)$.

The distance between two instances x_i and x_j is computed as:

$$d(x_i, x_j) = \sqrt{\sum_{r=1}^{n}(a_r(x_i) - a_r(x_j))^2}. \quad (1)$$

The KNN algorithm performs classification based on a similarity measure. The k-means algorithm is defined as follows.

The k-means algorithm is a method for clustering objects into k partitions based on their attributes.
It assumes that each of the k clusters has a Gaussian distribution.
It assumes that the object attributes form a vector space.
The objective is to minimize the total intra-cluster variance.

Algorithm fitness function

The k-means algorithm is used to minimize the squared error of all the data points in all of the clusters.
The squared error (E) of all the data points in the dataset is given by Eq. (2), where p is a given data point, E is the sum of the squared error for all of the elements in the dataset, and m_i is the mean of cluster C_i:

$$E = \sum_{I=1}^{K}\sum_{P\in C_i} |p - m_i|^2 . \quad (2)$$

Algorithm:

(1) Select the value of $K \in$ Prime && ODD.

Fig. 10 shows a block diagram of the overall process employed by the biometric gait identification system. The process starts with feature selection, which is followed by dimensionality reduction using PCA, and the production of the feature vector. We classified gait data into different categories using three machine learning techniques in the present study to determine the most important component for identifying people (See Fig. 11.)

2. Implementation

Unsupervised Learning

The k-means algorithm is used for exact clustering, but it is highly sensitive to noise and outliers. We applied k-means to numerical data (see Figs. 12 and 13).

```
Code Step:
Input: Features F = {f1, f2, f3, ..., fn}, where F ∈ R^d
C = initial number of clusters
T = threshold for convergence
    BEGIN
     Assume vector mean [m1, m2, ..., mc]^t at t = 0, c is
     the initial number of clusters
     REPEAT /*until convergence criteria are not satisfied
     and threshold is not reached*/
       Recompute the mean vector for t = t + 1 and classify
       accordingly
       Update t = t + 1
      Calculate the Euclidean distance ||m (t) − m(t − 1)||
     < T
       Now, m(t) is the solution
    Else
     Go to repeat
    END LOOP
    UNTIL gait data are not classified/*category of gait
    classification = {normal, crouch1, crouch2, crouch3,
     crouch4}*/
    END
```

Algorithm

```
Gradient descent (I, Iterations Count)
    Initialize all weights
        For i = 1:1: Iterations Count
                do
                select a data point Dk = [i, j] from matrix D
                set learning rate α ∈ [0, 1]
                calculate outputs o(p) for each data point
                calculate error δij using back-propagation
                update all weights (in parallel)
                wij ← wij − α*Θ*ij xj(k − 1)
        end for
  update all thresholds Θij (in parallel)
  return weights w
end
```

3. Experimental results and performance

Ideally, locomotion has an exactly sinusoidal curve, i.e., oscillatory motion at the hip, two sharp peaks at the knees, and two sharp peaks at the ankle joints during normal walking, without any external perturbations. Fig. 14 shows ideal curves for the hip, knees, and ankles.

Human gait dataset:

Dataset : BUAA_IRIP and OpenSim. D
$= \{\text{Normal, Crouch2, Crouch3, Crouch4}\}, D \in R^d$.

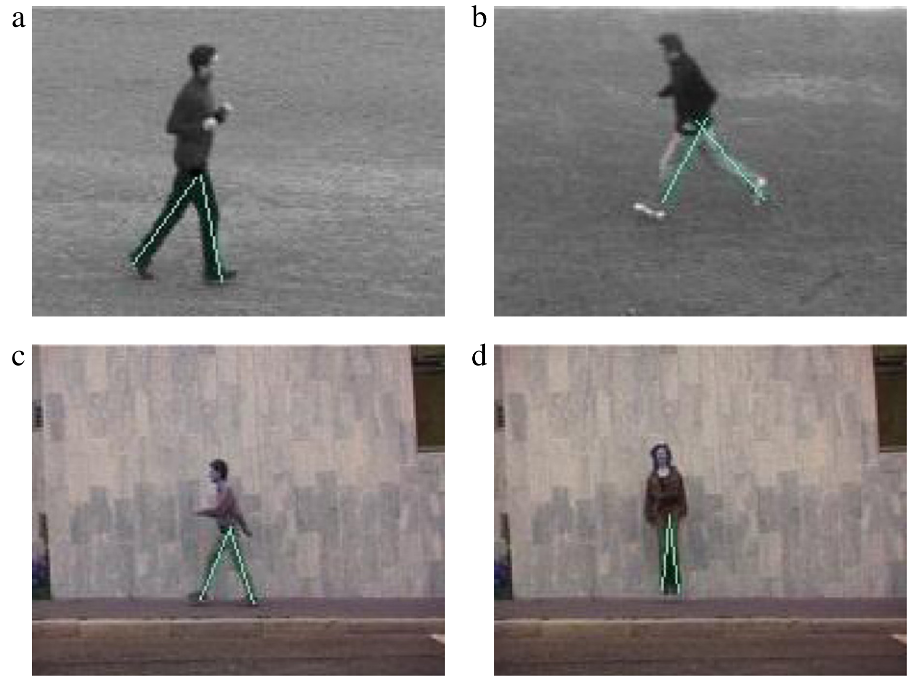

Fig. 9. Templates for human activities: (a) jogging, (b) running, (c) walking, and (d) jumping [34].

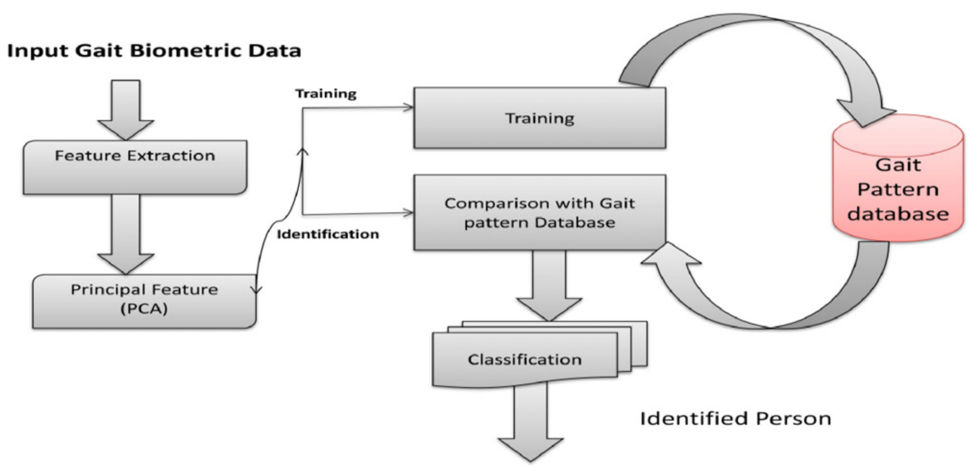

Fig. 10. Block diagram of the biometric gait identification system.

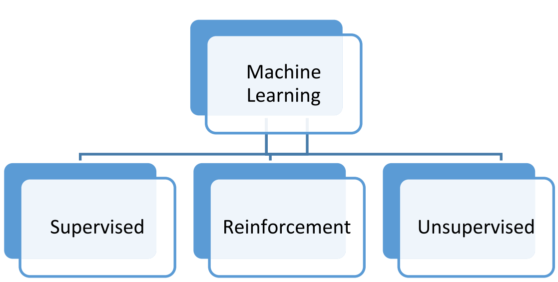

Fig. 11. Different machine learning techniques used for classification.

In this study, we tested the main approaches used for gait classification. Thus, we performed gait data classification using different machine learning techniques, i.e., KNN, ANN, and K-means [44]. The results showed that ANN obtained the best performance among the three techniques [45]. Table 6 shows the accuracy of the results. PCA was used for dimensionality reduction to select the main feature vector for k-means and KNN [46].

We used the OpenSim dataset to obtain gait data from four categories: normal, crouch2, crouch3 and crouch4. We used 30 samples from each data category for training and 20 data points for testing. The ANN was used for classification and the results obtained are shown in Table 2. $D = \{\text{normal, crouch2, crouch3, crouch4}\}$, $D \in R^d$ (see Fig. 15).

Fig. 9(a) shows the performance curves related to model training, where the mean squared error reached the threshold, i.e., the number of epochs. We set the threshold at 0.001 and reached the target in 11 epochs.

Fig. 9(b) shows the training state of our model and Fig. 9(c) shows the regression model for data fitting (see Fig. 16).

Performance measure Fig. 17 shows the accuracy (percentage) of gait classification using k-means where $k = 1$. We calculated the error, i.e., the total misclassification rate, using Eq. (3):

$$\text{Error (Total misclassification rate)} = \text{total misclassified/total sample test}. \quad (3)$$

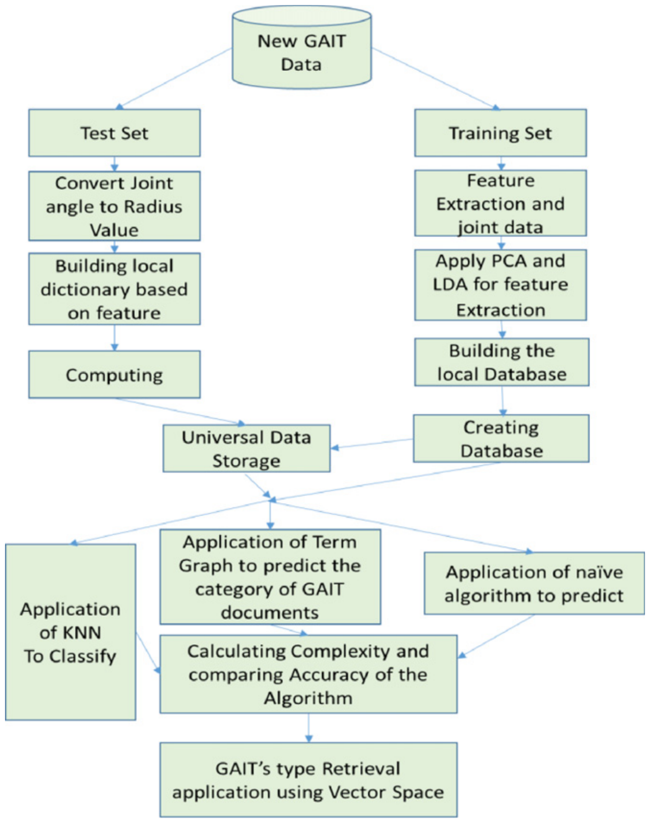

Fig. 12. Gait classification process.

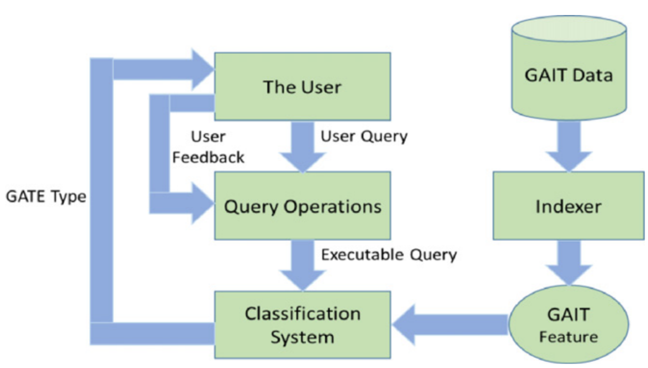

Fig. 13. Gait classification system.

Table 2
Gait data for subject 1 with normal walking.

Right hip	Left knee	Left ankle	Left hip	Left knee	Left ankle
37.5	−3.97	−2.14	−4.5	−13.86	10
37.2	−7	−3.7	−4.2	−16.97	8.5
36.9	−10.52	−4.8	−2.6	−20.96	6
36.2	−14.12	−4.8	0.1	−26	0
35.7	−17.38	−3.7	2.1	−32.03	−5
34.8	−19.84	−2.14	4.1	−38.74	−9
33.5	−21.27	−1	6.8	−45.6	−12.7
30.7	−21.67	0.6	10.2	−52.05	−13.5
27.4	−21.22	1.8	14	−57.54	−12.7
25.3	−20.2	2.8	18.5	−61.66	−10
23	−18.86	3.9	22	−64.12	−7.1
21	−17.35	4.5	25	−64.86	−4.1
18	−15.73	5.2	27.8	−63.95	−2.1
16	−14.08	5.7	30.22	−61.59	0
13.8	−12.5	5.9	33	−57.97	1.3
12.4	−11.09	6.2	35	−53.27	2.2
10.8	−9.91	6.8	36.4	−47.58	2.8
8.8	−8.97	7.5	37.8	−40.94	3.1
6.9	−8.28	8.2	38.3	−33.46	2.8
5	−7.86	8.9	38.2	−25.38	2.3
3	−7.72	9.8	37.8	−17.27	1.5
1.2	−7.94	10.5	37.5	−9.94	0.5
0	−8.6	11.2	37.2	−4.31	0.2
−2.4	−9.76	11.5	36.8	−1.12	0
−4.2	−11.5	10.9	37.2	−0.54	0
−4.5	−13.86	10	37.5	−3.97	−2.14
−4.2	−16.97	8.5	37.2	−7	−3.7
−2.6	−20.96	6	36.9	−10.52	−4.8
0.1	−26	0	36.2	−14.12	−4.8
2.1	−32.03	−5	35.7	−17.38	−3.7
4.1	−38.74	−9	34.8	−19.84	−2.14
6.8	−45.6	−12.7	33.5	−21.27	−1
10.2	−52.05	−13.5	30.7	−21.67	0.6
14	−57.54	−12.7	27.4	−21.22	1.8
18.5	−61.66	−10	25.3	−20.2	2.8
22	−64.12	−7.1	23	−18.86	3.9
25	−64.86	−4.1	21	−17.35	4.5
27.8	−63.95	−2.1	18	−15.73	5.2
30.22	−61.59	0	16	−14.08	5.7
33	−57.97	1.3	13.8	−12.5	5.9
35	−53.27	2.2	12.4	−11.09	6.2
36.4	−47.58	2.8	10.8	−9.91	6.8
37.8	−40.94	3.1	8.8	−8.97	7.5
38.3	−33.46	2.8	6.9	−8.28	8.2
38.2	−25.38	2.3	5	−7.86	8.9
37.8	−17.27	1.5	3	−7.72	9.8
37.5	−9.94	0.5	1.2	−7.94	10.5
37.2	−4.31	0.2	0	−8.6	11.2
36.8	−1.12	0	−2.4	−9.76	11.5
37.2	−0.54	0	−4.2	−11.5	10.9
37.5	−2.21	0	−4.5	−13.86	10

Fig. 18 shows the accuracy of gait classification using KNN for different majority values of k. Fig. 19 shows the classification of normal gait patterns using KNN with different majority votes.

The graph shows that normal data obtained a better classification rate. The gradient descent-based ANN was used for classification. The table shows that the ANN-based classification technique outperformed the other classification techniques that we tested. The ANN-based model propagated the input through the network and propagated the errors backward through the network in a similar manner to the delta rule in gradient descent. Finally, the data were summed over the errors of all the output units affected by a given hidden unit (this is because the training data only provide direct feedback for the output, where this information can used in surveillance and to identify the possibility of future disease). Overall, the data were classified into four gait categories using the ANN: normal, crouch2, crouch3, and crouch4. The results shown in figure demonstrate that ANN performed better than the other machine learning techniques. The flow diagram shows that a user-based query could be submitted to recognize and identify a human gait pattern by indexing the gait data in the database. In the next step, the feature extracted by the system was matched with those available in the database to obtain the human gait classification.

Performance matrix

The main performance indicator used for classification by biometric identification systems is the receiver operating characteristic (ROC), which plots the true acceptance rate (TAR) versus the false acceptance rate (FAR)/The ROC curve compares the number of false instances classified as positive among all of the classified cases.

False Rejection Rate (FRR)—The probability of the biometric system failing to identifying a true positive result. The FRR is a statistical metric used to assess the performance of a biometric system during verification tasks.

True Rejection Rate (TRR)—A metric used for biometric performance assessments in a verification task. The percentage of times a system correctly rejects a false result.

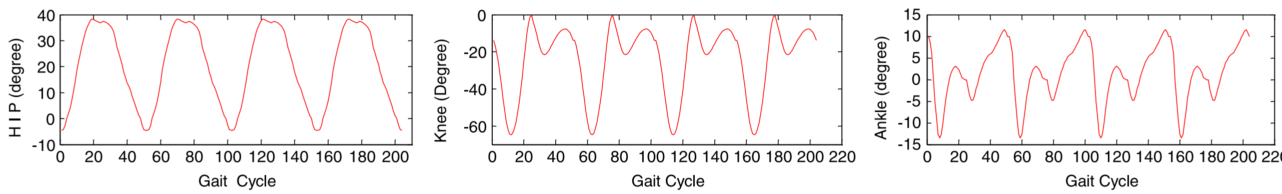

Fig. 14. Ideal curves during normal walking: (a) hip, (b) knee, and (c) ankle.

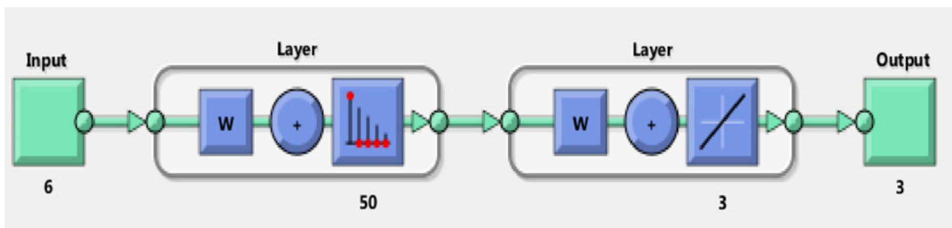

Fig. 15. Multi-layer back propagation ANN.

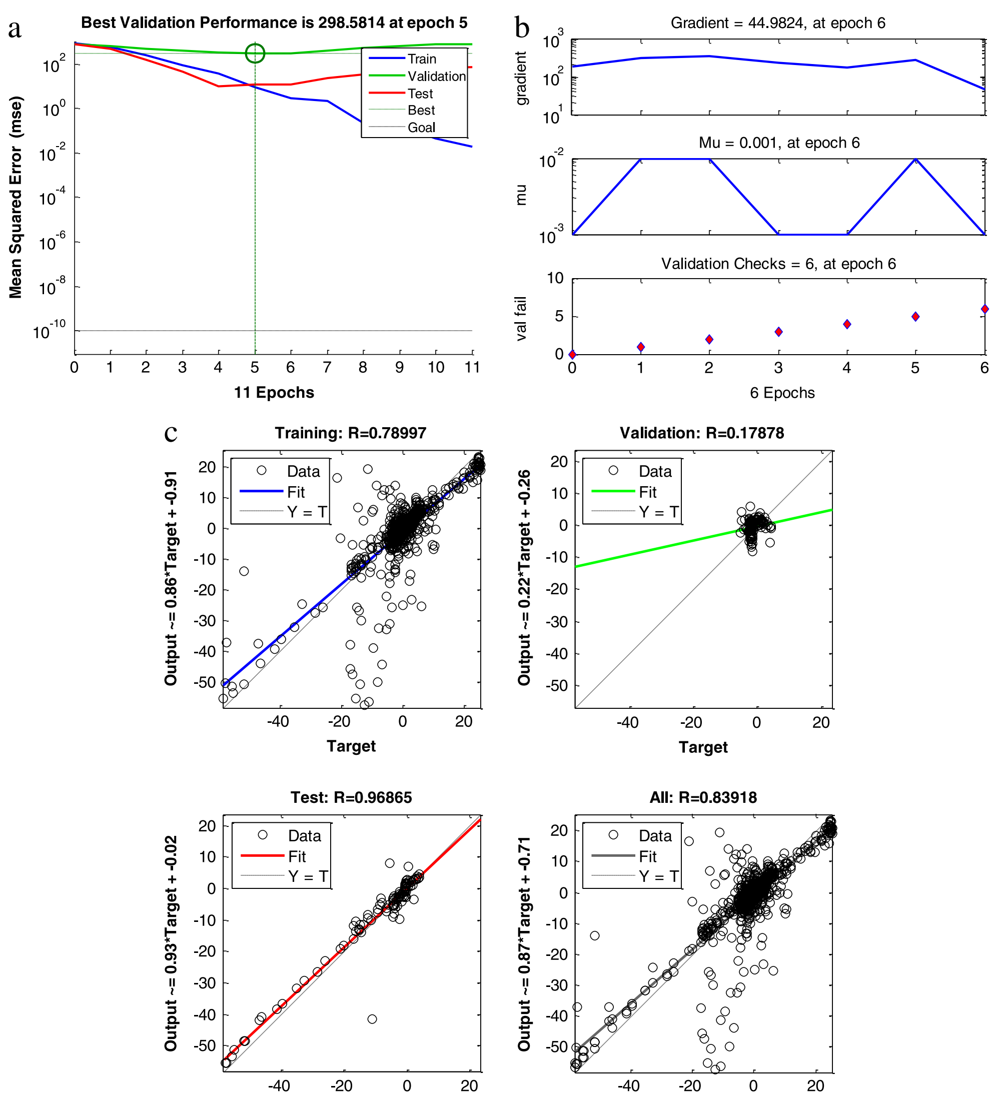

Fig. 16. (a) Performance curve mean squared error, (b) training state, and (c) regression.

Table 3
Confusion matrix for k-means {data size: 30 training samples and 20 testing samples}.

	Normal	Crouch2	Crouch3	Crouch4	TAR
Normal	17	0	2	1	$17/20 = 0.85$
Crouch2	0	17	3	0	$17/20 = 0.85$
Crouch3	1	2	15	2	$15/20 = 0.75$
Crouch4	0	1	0	19	$19/20 = 0.95$
FAR	$1/18 = 0.055$	$3/20 = 0.15$	$5/20 = 0.25$	$3/22 = 0.13$	

Table 4
Confusion matrix for KNN ($k = 1$) {data size: 30 training samples and 20 testing samples}.

	Normal	Crouch2	Crouch3	Crouch4	TAR
Normal	19	1	0	0	$19/20 = 0.95$
Crouch2	0	17	3	0	$17/20 = 0.85$
Crouch3	1	2	17	0	$17/20 = 0.85$
Crouch4	0	1	0	19	$19/20 = 0.95$
FAR	$1/20 = 0.05$	$4/21 = 0.19$	$3/20 = 0.15$	0	

Table 5
Confusion matrix for ANN {data size: 30 training samples and 20 testing samples}.

	Normal	Crouch2	Crouch3	Crouch4	TAR
Normal	20	0	0	0	$20/20 = 1$
Crouch2	1	19	0	0	$19/20 = 0.95$
Crouch3	1	1	18	0	$18/20 = 0.90$
Crouch4	2	0	1	17	$17/20 = 0.85$
FAR	$4/24 = 0.166$	$1/20 = 0.05$	$1/19 = 0.52$	0	

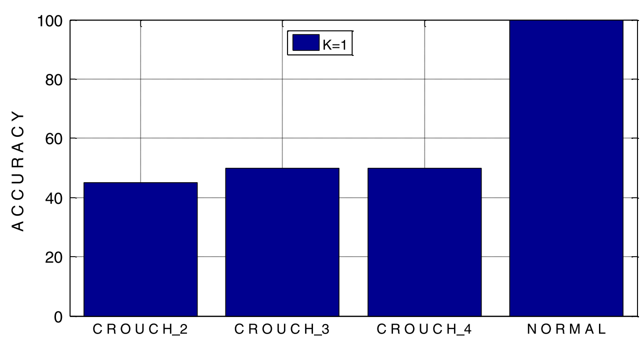

Fig. 17. Classification accuracy for different gait patterns using k-means.

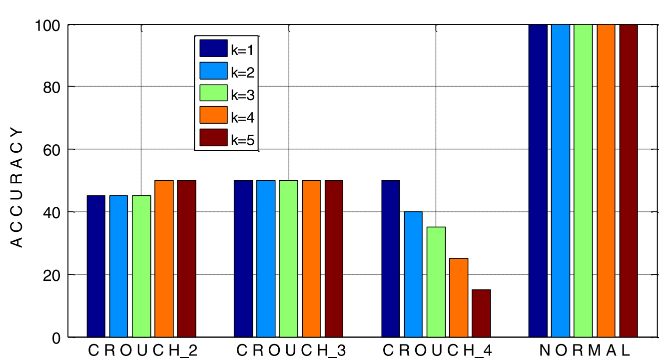

Fig. 18. Accuracy curve of gait classification using KNN.

TAR—A count of the true results verified correctly by a system.

FAR–The false acceptance rate of a system.

In biometric research, the FAR is sometimes defined such that the "impostor" makes zero effort to obtain a match:

TAR = 1 − FRR.

Thus, we can employ, FAR, TRR, TAR, and FRR as matrix terms to verify the performance of a biometric system. In the present study, we determined the verification results in terms of the TAR, FAR,

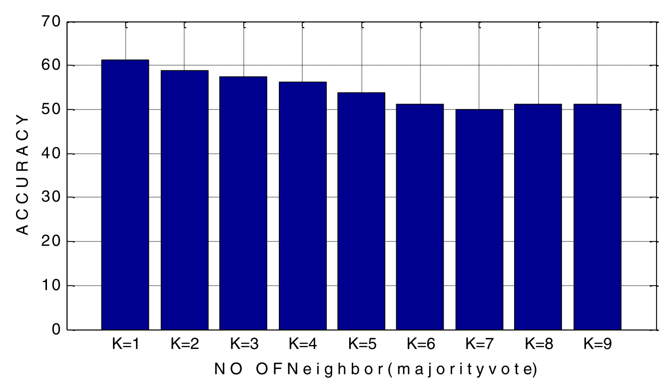

Fig. 19. Normal classification of humanoid gait patterns using different majority counts.

and ROC (see Tables 3–5 and Fig. 20).

$$\text{FRR} = 1 - \text{TAR}$$

$$\text{ROC} = \text{TAR vs. FAR}$$

$$\text{TAR} = \frac{\left(\frac{17}{20} + \frac{17}{20} + \frac{15}{20} + \frac{19}{20}\right)}{4} \times 100 = 85\%$$

$$\text{FRR} = 1 - \text{TAR}$$

$$\text{FAR} = \frac{\left(\frac{1}{18} + \frac{3}{20} + \frac{5}{20} + \frac{3}{22}\right)}{4} \times 100 = 14.79\%$$

$$\text{TAR} = \frac{\left(\frac{19}{20} + \frac{17}{20} + \frac{17}{20} + \frac{19}{20}\right)}{4} \times 100 = 90\%$$

$$\text{FRR} = 1 - \text{TAR}$$

$$\text{FAR} = \frac{\left(\frac{1}{20} + \frac{4}{21} + \frac{3}{20}\right)}{4} \times 100 = 39.04\%$$

$$\text{TAR} = \frac{\left(\frac{20}{20} + \frac{19}{20} + \frac{18}{20} + \frac{17}{20}\right)}{4} \times 100 = 92.5\%$$

$$\text{FRR} = 1 - \text{TAR}$$

$$\text{FAR} = \frac{\left(\frac{4}{24} + \frac{1}{20} + \frac{1}{19}\right)}{4} \times 100 = 6.73\%.$$

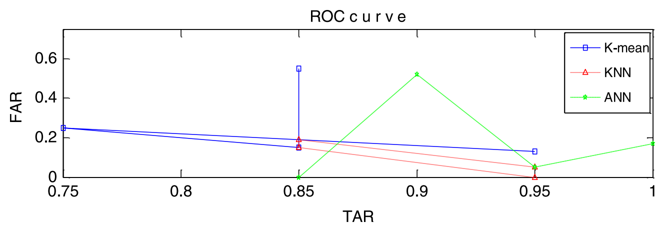

Fig. 20. ROC curve.

Table 6
Percentage accuracy of different gait data classifications.

Method	K-mean	KNN ($k = 1, 2, 3, 4, 5$)	ANN
Normal gait	74.68	100, 100, 100, 100, 100	100
Crouch2 gait	51.43	50, 50, 50, 55, 55	60
Crouch3 gait	33.19	50, 50, 50, 50, 50	50
Crouch4 gait	81.80	50, 40, 35, 25, 15	55

Table 6 shows the accuracy of the results obtained, which demonstrate that ANN obtained the best performance, except for crouch 4, which is a more complex gait; thus, exact feature selection and classification using k-means performed better.

4. Conclusion

In this study, we proposed a new gait identification method. Using the proposed methodology, the gait identification accuracy was improved by employing more accurate spatiotemporal modeling. Extensive simulations demonstrated that this is a highly robust feature extraction technique. The classification rate and activity reorganization activity were improved substantially using the new method. The main aim of our research is the identification of abnormalities, disorders, and potential diseases in the early stages. Our experimental results demonstrated that the proposed method could accurately recognize different activities in indoor and outdoor scenarios, while maintaining a high recognition rate. The proposed classification method could classify gait patterns effectively into four different classes: normal, crouch-2, crouch-3, and crouch-4. We compared the results with those obtained using the KNN and k-means algorithms, which demonstrated that our classifier outperformed these existing classifiers.

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References

[1] A. Kale, A. Sundaresan, A.N. Rajagopalan, N.P. Cuntoor, A.K. Roy-Chowdhury, V. Kruger, R. Chellappa, Identification of humans using gait, IEEE Trans. Image Process. 13 (9) (2004) 1163–1173.
[2] Daniel Zapico Palacio, Victor Hugo Medina García, Oscar Sanjuán Martínez, Rubén González, Crespo: Generating digital fingerprints using artificial neural networks, IC-AI, 2008, pp. 907–912.
[3] Sajid Iqbal, Xizhe Zang, Yanhe Zhu, Jie Zhao, Bifurcations and chaos in passive dynamic walking: a review, Robot. Auton. Syst. 62 (6) (2014) 889–909.
[4] L. Wang, T. Tan, H. Ning, W. Hu, Silhouette analysis-based gait recognition for human identification, IEEE Trans. Pattern Anal. Mach. Intell. 25 (12) (2003) 1505–1518.
[5] V.B. Semwal, A. Bhushan, G.C. Nandi, Study of humanoid push recovery based on experiments, in: 2013 International Conference on Control, Automation, Robotics and Embedded Systems, CARE, 16–18 December, 2013, pp. 1–6.
[6] M. Hu, Y. Wang, Z. Zhang, D. Zhang, Gait-based gender classification using mixed conditional random field, IEEE Trans. Syst. Man Cybern. B 41 (5) (2011) 1429–1439.
[7] G. Huang, Y. Wang, Gender classification based on fusion of multi-view gait sequences, in: Computer Vision–ACCV 2007, Springer, 2007, pp. 462–471.
[8] L. Wang, T. Tan, W. Hu, H. Ning, Automatic gait recognition based on statistical shape analysis, IEEE Trans. Image Process. 12 (9) (2003) 1120–1131.
[9] C. Wang, J. Zhang, L. Wang, J. Pu, X. Yuan, Human identification using temporal information preserving gait template, IEEE Trans. Pattern Anal. Mach. Intell. 4 (11) (2012) 2164–2176.
[10] Joachim Steigenberger, Carsten Behn, Gait generation considering dynamics for artificial segmented worms, Robot. Auton. Syst. 59 (7–8) (2011) 555–562.
[11] V.B. Semwal, Shiv A. Katiyar, P. Chakraborty, G.C. Nandi, Biped model based on human gait pattern parameters for sagittal plane movement control, in: 2013 International Conference on, Automation, Robotics and Embedded Systems, CARE, 16–18 December, 2013, pp. 1–5.
[12] Liang Wang, Huazhong Ning, Tieniu Tan, Weiming Hu, Fusion of static and dynamic body biometrics for gait recognition, IEEE Trans. Circuits Syst. Video Technol. 14 (2) (2004) 149–158.
[13] Brenna D. Argall, et al., A survey of robot learning from demonstration, Robot. Auton. Syst. 57 (5) (2009) 469–483.
[14] A.F. Bobick, J.W. Davis, The recognition of human movement using temporal templates, IEEE Trans. Pattern Anal. Mach. Intell. 23 (3) (2001) 257–267.
[15] I.R. Vega, S. Sarkar, Statistical motion model based on the change of feature relationships: human gait-based recognition, IEEE Trans. Pattern Anal. Mach. Intell. 25 (10) (2003) 1323–1328.
[16] L. Wang, H. Ning, T. Tan, W. Hu, Fusion of static and dynamic body biometrics for gait recognition, IEEE Trans. Circuits Syst. Video Technol. 14 (2) (2004) 149–158.
[17] N. Noorit, N. Suvonvorn, M. Karnchanadecha, Model-based human action recognition, in: Second International Conference on Digital Image Processing, International Society for Optics and Photonics, 2010, pp. 75460P–75460P.
[18] M. Ekinci, Human identification using gait, Turkish J. Electron. Eng. 14 (2) (2006) 267–291.
[19] M. Hobon, N. Lakbakbi Elyaaqoubi, G. Abba, Quasi optimal sagittal gait of a biped robot with a new structure of knee joint, Robot. Auton. Syst. 62 (4) (2014) 436–445.
[20] L. Chen, Y. Wang, Y. Wang, D. Zhang, Gender recognition from gait using radon transform and relevant component analysis, in: Emerging Intelligent Computing Technology and Applications, Springer, 2009, pp. 92–101.
[21] M.S. Bartlett, J.R. Movellan, T.J. Sejnowski, Face recognition by independent component analysis, IEEE Trans. Neural Netw. 13 (6) (2002) 1450–1464.
[22] S.T. Venkataraman, A simple legged locomotion gait model, Robot. Auton. Syst. 22 (1) (1997) 75–85.
[23] Brian R. Duffy, Anthropomorphism and the social robot, Robot. Auton. Syst. 42 (3–4) (2003) 177–190.
[24] Chris Iverach-Brereton, Jacky Baltes, John Anderson, Andrew Winton, Diana Carrier, Gait design for an ice skating humanoid robot, Robot. Auton. Syst. 62 (3) (2014) 306–318.
[25] F. Sepulveda, D.M. Wells, C.L. Vaughan, A neural network representation of electromyography and joint dynamics in human gait, J. Biomech. 26 (2) (1993) 101–109.
[26] J.M. Keller, M.R. Gray, J.A. Givens, A fuzzy k-nearest neighbor algorithm, IEEE Trans. Syst. Man Cybern. (4) (1985) 580–585.
[27] S.Z. Selim, M.A. Ismail, K-means-type algorithms: a generalized convergence theorem and characterization of local optimality, IEEE Trans. Pattern Anal. Mach. Intell. (1) (1984) 81–87.
[28] Terrence Fong, Illah Nourbakhsh, Kerstin Dautenhahn, A survey of socially interactive robots, Robot. Auton. Syst. 42 (3) (2003) 143–166.
[29] F. Asano, M. Yamakita, N. Kamamichi, Zhi-Wei Luo, A novel gait generation for biped walking robots based on mechanical energy constraint, IEEE Trans. Robot. Autom. 20 (3) (2004) 565–573.
[30] S. Lawrence, C.L. Giles, A.C. Tsoi, A.D. Back, Face recognition: a convolutional neural-network approach, IEEE Trans. Neural Netw. 8 (1) (1997) 98–113.
[31] M. Hoffmann, K. Štěpánová, M. Reinstein, The effect of motor action and different sensory modalities on terrain classification in a quadruped robot running with multiple gaits, Robot. Auton. Syst. (2014) Available online 24 July.
[32] Xavier Perrin, Ricardo Chavarriaga, Francis Colas, Roland Siegwart, José del R. Millán, Brain-coupled interaction for semi-autonomous navigation of an assistive robot, Robot. Auton. Syst. 58 (12) (2010) 1246–1255.
[33] Cristina P. Santos, Vítor Matos, Gait transition and modulation in a quadruped robot: A brainstem-like modulation approach, Robot. Auton. Syst. 59 (9) (2011) 620–634.
[34] Jay Prakash Gupta, et al., Human activity recognition using gait pattern, Int. J. Comput. Vis. Image Process. 3 (3) (2013) 31–53.
[35] Shahid Hussain, Sheng Q. Xie, Prashant K. Jamwal, Control of a robotic orthosis for gait rehabilitation, Robot. Auton. Syst. 61 (9) (2013) 911–919.
[36] Su-Bin Joo, Seung Eel Oh, Taeyong Sim, Hyunggun Kim, Chang Hyun Choi, Hyeran Koo, Joung Hwan Mun, Prediction of gait speed from plantar pressure using artificial neural networks, Expert Syst. Appl. 41 (16) (2014) 7398–7405.
[37] Heesung Lee, Heejin Lee, Euntai Kim, A new gait recognition system based on hierarchical fair competition-based parallel genetic algorithm and selective neural network ensemble, Int. J. Control Autom. Syst. 12 (1) (2014) 202–207.
[38] Wallace M. Bessa, Max S. Dutra, Edwin Kreuzer, An adaptive fuzzy sliding mode controller for remotely operated underwater vehicles, Robot. Auton. Syst. 58 (1) (2010) 16–26.
[39] Christophe Sabourin, Weiwei Yu, Kurosh Madani, Gait pattern based on CMAC neural network for robotic applications, Neural Process. Lett. 38 (2) (2013) 261–279.

[40] J.G. Barton, A. Lees, An application of neural networks for distinguishing gait patterns on the basis of hip-knee joint angle diagrams, Gait Posture 5 (1) (1997) 28–33.
[41] Pedro Silva, Cristina P. Santos, Vítor Matos, Lino Costa, Automatic generation of biped locomotion controllers using genetic programming, Robot. Auton. Syst. (2014) Available online 5 June.
[42] Sarah V. Stevenage, Mark S. Nixon, Kate Vince, Visual analysis of gait as a cue to identity, Appl. Cogn. Psychol. 13 (6) (1999) 513–526.
[43] Vijay Bhaskar Semwal, Pavan Chakraborty, G.C. Nandi, Less computationally intensive fuzzy logic (type-1)-based controller for humanoid push recovery, Robot. Auton. Syst. (2014) Available online 16 September.
[44] P.S. Huang, C.J. Harris, Mark S. Nixon, Human gait recognition in canonical space using temporal templates, IEE Proc. Vis. Image Signal Process. 146 (2) (1999) 93–100.
[45] David Cunado, Mark S. Nixon, John N. Carter, Using gait as a biometric, via phase-weighted magnitude spectra, in: Audio-and Video-Based Biometric Person Authentication, Springer, Berlin, Heidelberg, 1997.
[46] Mark S. Nixon, Tieniu Tan, Rama Chellappa, Human Identification Based on Gait, Vol. 4, Springer, 2010.

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