2022

Human Gait Recognition Subject to Different Covariate Factors in a Multi-View Environment

Asif Asif
National University of Sciences and Technology (NUST), Islamabad, Pakistan

Mohsin I. Tiwana
National University of Sciences and Technology (NUST), Islamabad, Pakistan

Umar S. Khan
National University of Sciences and Technology (NUST), Islamabad, Pakistan

See next page for additional authors

Recommended Citation

Asif, M., Tiwana, M.I. & Khan, U.S. (2022). Human gait recognition subject to different covariate factors in a multi-view environment. *Results in Engineering*, vol. 15, pg. 100556 doi:10.1016/j.rineng.2022.100556

Authors
Asif Asif, Mohsin I. Tiwana, Umar S. Khan, Muhammad W. Ahmad, Waqar Shahid Qureshi, and Javaid Iqbal Javaid Iqbal

Results in Engineering 15 (2022) 100556

Contents lists available at ScienceDirect

Results in Engineering

journal homepage: www.sciencedirect.com/journal/results-in-engineering

Human gait recognition subject to different covariate factors in a multi-view environment

Muhammad Asif [a,b,f,*], Mohsin I. Tiwana [a,b], Umar S. Khan [a,b], Muhammad W. Ahmad [c], Waqar S. Qureshi [a,b,e], Javaid Iqbal [b,d]

[a] Department of Mechatronics Engineering, National University of Sciences and Technology (NUST), Islamabad, Pakistan
[b] National Centre of Robotics and Automation (NCRA), National University of Sciences and Technology (NUST), Islamabad, Pakistan
[c] Department of Computer and Software Engineering, National University of Sciences and Technology (NUST), Islamabad, Pakistan
[d] School of Mechanical & Manufacturing Engineering (SMME), National University of Sciences and Technology (NUST), Islamabad, Pakistan
[e] Department of Computer Science, Technological University Dublin, Ireland
[f] Department of Mechatronics Engineering, University of Engineering and Technology (UET), Taxila, Pakistan

A R T I C L E I N F O

Keywords:
CASIA-B
Classification rate
Gait energy image
Human gait recognition
SVM

A B S T R A C T

Gait recognition provides the opportunity to identify different walking styles of people without physical intervention. However, covariates such as changing clothes and carrying conditions may influence recognition accuracy. Our objective was to identify the walking patterns of people for different covariates through analyzing images from publicly available data set CASIA-B on gait. On the dataset, the proposed method was evaluated by using GEI (gait energy image) as inputs for normal walking, changing clothes, and carrying conditions in a multi-view environment. A support vector machine (SVM) and a histogram of oriented gradients (HOG) were applied to classify images of the human gait in order to meet the objectives. Observations show that, under consideration of the mean of the individual accuracies, the accuracy of recognition is in the following order: clothing > normal walk > carrying at a 90° angle. Measurement accuracy of 87.9% was achieved for the coat-wearing people and measurement accuracy of 83.33% was achieved for all the mentioned covariates. The accuracy of the clothing covariate stated as 87.9% is a useful for people especially for different season like winter.

1. Introduction

Human gait recognition system identifies individuals based on their biometric traits. A human's biometric features can be grouped into physiologic or behavioral traits. Biometric traits, such as the face [1], ears [2], iris [3], finger prints, passwords, and tokens, require highly accurate recognition and a well-controlled human interaction to be effective. In contrast, behavioral traits such as voice, signature, and gait do not require any human interaction and can be collected in a hidden and non-invasive mode with a camera system at a low resolution. In comparison with other physiological traits, one of the main advantages of gait analysis is the collection of data from a certain distance. However, gait is less powerful than physiological traits, yet it still has widespread application in surveillance for unfavorable situations. From traditional algorithms to deep learning models, a gait survey provides a detailed history of gait recognition. Traits related to deep gait can be classified into static and dynamic categories. It is helpful to provide inspiration to deep gait datasets and performance analysis [4]. An existing video of a person was used to extract silhouette data for re-identification. The generated dataset was used to compare gait recognition and person re-identification in real-life scenarios [5].

A gait analysis can be challenging due to varying factors like changing clothes, carrying conditions, walking surfaces, shoes, disabilities, injuries, and different viewpoints. The appearance changes in a person's walk might be the most influencing factor that may be caused by changing clothes. Gait, the behavioral biometric, is less robust than physiological biometrics such as fingerprint, iris, and face.

Gait in fact defines a person's walking pattern, which is unique when compared with other behavioral traits, such as speech. In response to variances, such as the view angle, carrying, changing clothes, and illumination, gait characteristics are likely to change substantially. Some earlier work describes how to model the human body & how to capture

* Corresponding author. Department of Mechatronics Engineering, National University of Sciences and Technology (NUST), Islamabad, Pakistan.
E-mail addresses: m.asif@ceme.nust.edu.pk (M. Asif), mohsintiwana@ceme.nust.edu.pk (M.I. Tiwana), u.shahbaz@ceme.nust.edu.pk (U.S. Khan), waqas@ceme.nust.edu.pk (M.W. Ahmad), waqar.shahid@ceme.nust.edu.pk (W.S. Qureshi), j.iqbal@ceme.nust.edu.pk (J. Iqbal).

https://doi.org/10.1016/j.rineng.2022.100556
Received 21 June 2022; Received in revised form 19 July 2022; Accepted 19 July 2022
Available online 3 August 2022

differences in movement patterns between subjects to improve stability of the extracted features [6–8].

With the help of a DSLR camera, strain measurements were carried out using the Ncorr 2D MATLAB program for structural element plots. Comparisons were made between the results obtained from conventional measuring devices and digital image correlations. It is helpful to classify images using stereo vision imaging and digital image correlation techniques [9,10].

Many researchers around the world have contributed to the recognition of the human gait cycle by using publicly available datasets. Some of the famous publicly available datasets for recognizing the human gait cycle include CASIA-B, USF, OU-ISIR, and HuGaID, etc. Moghaddam et al. did a survey on human gait recognition methods on the basis of walking styles exploring a bunch of publicly available datasets, test protocols, state-of-the-art solutions, future directions and challenges. The authors presented a novel taxonomy with four different dimensions stated as temporal representation, body representation, feature representation & neural architecture. They presented the mostly used datasets and the results achieved using different deep learning approaches [11]. By adding a noise map layer and an adaptive resize layer, this paper [12] presents a robust CNN technique for classifying noisy images without preprocessing. A faster training process and better classification performance were achieved with the model. The authors in Ref. [13] discussed different deep learning models for human gait recognition. They also explained the prominent techniques used for gait recognition including ANN (use is 58.62%) and CNN (use is 26.315). Another research showed robust models developed using GPUs for gait recognition. The models discussed the promising recognition rate tested on 50, 75, 100, and 124 classes of CASIA-B dataset [14]. There is an issue of privacy and human rights when people use smartphone applications to trace people. The purpose of this paper [15] was to assess the suitability in terms of impact on users, employed technology, and governance methods. This techniques is also useful to trace and recognize the people.

In spite of a variety of datasets available to the authors, the CASIA-B dataset was chosen to ensure precise results. The dataset is of nominal size and variety of view angles the authors used to provide raw data on different poses & styles of human walking. A support vector machine-based state-of-the-art machine learning algorithm is used in this work to recognize different walking styles of people based on images contained in the CASIA-B gait dataset. In a proposed motion excitation module in Ref. [16], human body parts are selected as the focus of spatiotemporal features. In a dynamic environment, this model learns information between frames and intervals. Testing the model on the CASIA-B dataset yields optimized results.

Kumar et al. developed a gait recognition method based on GEI and LBP techniques for extracting features from gait representations. In this analysis, the local binary operator was used to extract the features from the entire GEI as well as the region bound by the legs. This procedure was applied to covariate factors of the gait such as changing clothes, carrying a bag, and normal walking in different normal patterns [17]. The GEI is a Spatio-temporal representation of gait images, which is calculated by averaging silhouettes over one complete gait cycle. Several contemporary studies have already used this sort of representation [18,19].

The proposed method for view-invariant gait recognition uses subspace learning. Various prototypes with different views were obtained through JSL. Then they represented each sample in the gallery setting as well as the probe set received from the different views as a linear combination of the prototypes in the respective views, and extracted coefficients to represent the features. After that, they used the nearest neighbor rule to perform recognition. By using this method, they were able to achieve a significantly high recognition rate. The correct recognition rate was enhanced from (25.5% ~ 35.5%) in view of 18 & from (68.5% ~ 81.5%) in view of 54 respectively [20].

Another work proposed a 3D convolution deep neural network for human identification with multiple gait views. This research was conducted in two stages. During the first stage, training & testing of the viewpoint angle identification were conducted on images received from the sensor model. As part of the second stage, personal identification was performed according to the given viewpoint of angle. According to the results, they performed better than the state-of-the-art models in “7” out of “11” viewpoint angles [21].

Table 1
Comparison of CASIA-B dataset for human gait recognition.

[#]	Mode	Method	CCR
[26]	Invariant gait features	Two stream GAN	63.10%
[31]	Gait identification	CNN and optical flow	64.10%
[25]	Gait biometrics	KNN with K = 5	73.60%
[29]	Flexible gait recognition	Convolution neural network	74.00%
[32]	Pose-based gait recognition	CNN	74.90%
[28]	Loss computation for gait recognition	Centre-Ranked Loss	75.03%
[27]	Effectiveness of gait features' selection	Hill climber algorithm	76.77%
[33]	Disentangled based recognition	LSTM	79.90%
[30]	Motion based gait recognition	Optical flow estimation	81.00%
[34]	Disentangled based recognition	LSTM	81.20%

Cheheb et al. investigated the use of autoencoders to recognize persons based on their gait. An architecture was proposed that models gait sequences by using gait energy images. When both testing and training samples were taken under normal conditions, both test and training results were 98.81% accurate. Subjects who carried a bag exhibited an accuracy of 75.72%, while those wearing different clothes showed an accuracy of 65.44% [22].

Min et al. proposed a convolutional neural network to learn features. They presented a simple “10” layer CNN architecture with gait energy images at the input. They had utilized Rectified Linear Unit (ReLU), Parametric Rectified Linear Unit (PReLU) & Leaky Rectified Linear Unit (LeakyReLU), and the same CNN architecture to activate the functions. Results showed proposed method achieved the recognition rate of 98.8% accuracy in less training time [23].

Isaac et al. proposed the use of posterior probability of a Bayes' classifier instead of Euclidean distance as a threshold for marking a boundary between legitimate subject and the impostor. The results showed the presented method performed better than the state-of-the-art models on the basis of Euclidean & cosine distance based thresholds when given the same features set as well as test conditions [24].

Table 1 shows the summary of different methods applied for the human gait recognition on CASIA-B datasets.

A histogram of gradient feature vector is used to develop a support vector machine based classifier for gait analysis [35]. We chose gait energy image (GEI) as input of the system with covariates such as normal walking, changing clothes, and carrying conditions. Due to its proven effectiveness, the GEI is the most commonly used method to extract the relevant feature descriptors of the human gait. GEI is dependent on Silhouettes which are extracted from gait images. As shown through a novel sketch in Fig. 1 the images were preprocessed to extract the relevant features, and then the SVM classifier was trained and validated. The output class labels are then tested to ensure they are assigned correctly. In order to calculate the classifier's accuracy, correctly classified images are compared with all images in the dataset. The accuracy of our proposed method was mainly determined by the quality of features extracted from images of the dataset.

Our original work contributes where wearing seasonal clothes significantly affects the recognition rate and is challenging for the research community. Therefore, the prime focus of authors' contribution in this work is to improve the accuracy for the factor of clothing in their machine learning model.

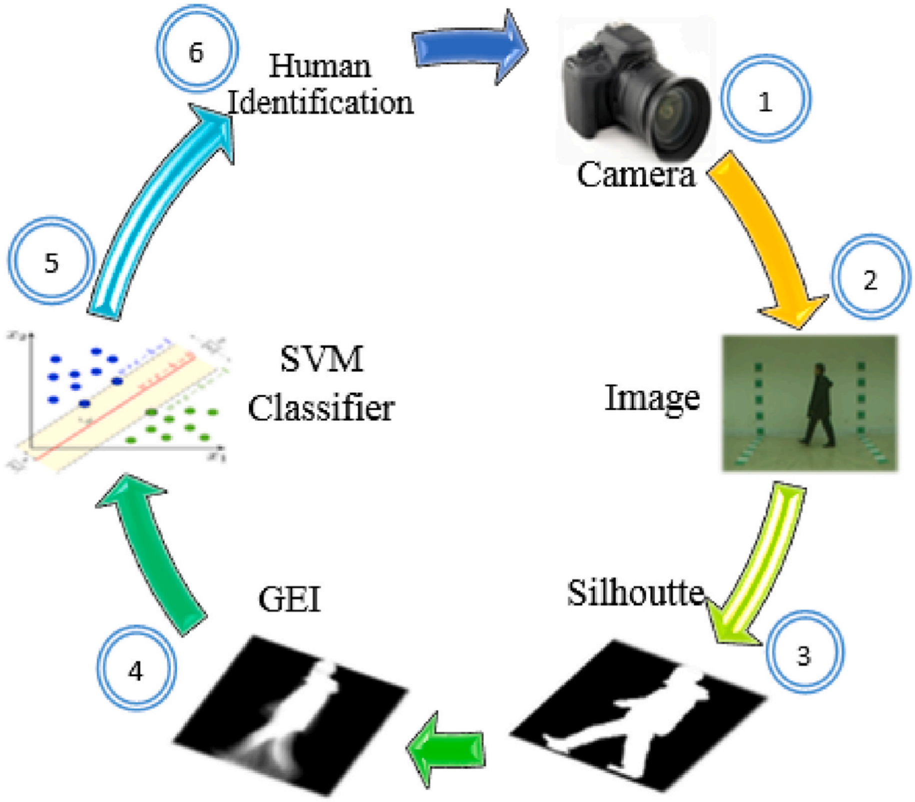


Fig. 1. This figure shows a novel depiction of the concept to take images from dataset (camera). The images are then converted to Silhouette and SVM classifier is applied to GEI to classify the correct images.

Fig. 2. Sample image of CASIA-B dataset having all the images at 11 different angles.

2. Materials and methods

The following section describes materials and methods used for gait recognition. For rigorous analysis, we selected a publicly available dataset called CASIA-B in order to determine the different walking styles of humans. It offers the marker free vision based gait acquisition equipped with the camera system. Vision based systems facilitates with the images for direct feature extraction. They are capable to provide robust features more feasible to tackle the real-time situations. In order to determine the accuracy and robustness of our proposed method, we conducted several experiments on the CASIA-B gait dataset. The method works well on gait images included in the dataset. A sample image is shown in Fig. 2 presenting subjects at different angles and gives an overview of the type and style of images [36].

Among the most commonly used datasets, CASIA-B includes images of gaits that can be used for gait recognition. A total of “124″ people walk along the straight lines against different camera angles at angles ranging from $0^\circ, 18^\circ, 36^\circ, \ldots, 180^\circ$. The total number of view angles is 11 with a resolution of 18°. Different physical scenarios, such as a normal walk, a walk while wearing a coat, and carrying a bag all pose challenges for gait recognition. We have three different covariates: cov-nm (walking normally), cov-cl (wearing coat while walking), and cov-bg (carrying a bag while walking). As a whole, each subject moved in “10″ sequences. The word sequence refers to the iteration for a walking person. Sequences were subdivided into cov-nm with “06″ sequences, cov-cl with “02″ sequences, and cov-bg with “02″ sequences. Each and every sequence was captured at all considered view angles. Therefore, this dataset contains $124 \times 10 \times 11 = 13640$ gait sequences.

Table 2
Description of covariates and view angles.

#	1	2	3	4	5	6	7	8	9	10	11
	nm	nm	nm	nm	nm	nm	bg	bg	Cl	cl	–
S	01	02	03	04	05	06	01	02	01	02	–
A	0°	18°	36°	54°	72°	90°	108°	126°	144°	162°	180°

Table 3
Description of the custom-algorithm for classification.

Our algorithm: Human Gait Analysis

1. **Input:** CASIA-B Dataset (Gait images)
2. **Output:** Correct detection of images
   Perform step 3 to 7 for each (normal, carrying bag, wearing coat)
3. **Preprocessing:** Random sampling without replacement
   - Training Data – fi(x) GEI/ i = 1 ... N
   - Validation Data – vi(x) GEI/ i = 1 ... N
   - Test Data – ti(x) GEI/ i = 1 ... N
4. **Feature extraction:**
   Perform Histograms of Oriented Gradients (HOG) for fi(x), vi(x) and ti(x)
5. **Training:**
   Train Support Vector Machine (SVM) at fi(x) HOG
6. **Validation:**
   Fine tune trained SVM model at vi(x) HOG
7. **Testing:**
   - Apply validated SVM model to perform testing for ti(x) HOG
   - Count correct prediction
   - Calculate accuracy

$$\text{For Cov} - \text{nm}: \quad 124x11x06 = 8184 \tag{1}$$

$$\text{For Cov} - \text{bg}: \quad 124x11x02 = 2728 \tag{2}$$

$$\text{For Cov} - \text{cl}: \quad 124x11x02 = 2728 \tag{3}$$

Adding the equations (1)–(3) give a total of 13,640 images. In order to accomplish our desired result, we need to understand CASIA-B in terms of the number of subjects, viewing angles, and covariates.

We developed Table 2 to represent the pictorial view after understanding it from the developers. The number 1 to 6 represents the normal walk, the number 7 to 8 represents the carrying conditions, and the number 9 to 10 represents changing clothes. In the first row, "S" represents the total sequences against the covariates, while the second row, "A" shows all the view angles of camera system [36].

The position of the camera is fixed whereas the persons are moving. The perpendicular direction of the person during walking was taken into consideration in this work. The support vector machine (SVM) is proposed to classify different images based on view angle under different conditions. An analysis of covariate factors has been conducted in order to extract features. In the next section, we present brief information about the programming step by step starting with input as GEI (gait energy images) and progressing through feature extraction to the final step, gait recognition. An optimized algorithm was developed to ensure a reliable detection rate. Python was used to write the code of the recognition system.

In this section, the algorithm for the overall recognition system is presented in Table 3. A set of gait images representing normal walking, walking with changed clothes, and walking with carrying bags with all sequences were used as an input for the code. It shows different angles of the subject under different conditions. Each image of a different pose of the subject is repeated from step#3 of preprocessing to step#7 of testing. In preprocessing, training, validation, and testing data are split based on random samples without replacement.

A feature extraction procedure is then carried out using the histogram of oriented gradients, commonly referred to as HOG. The proposed

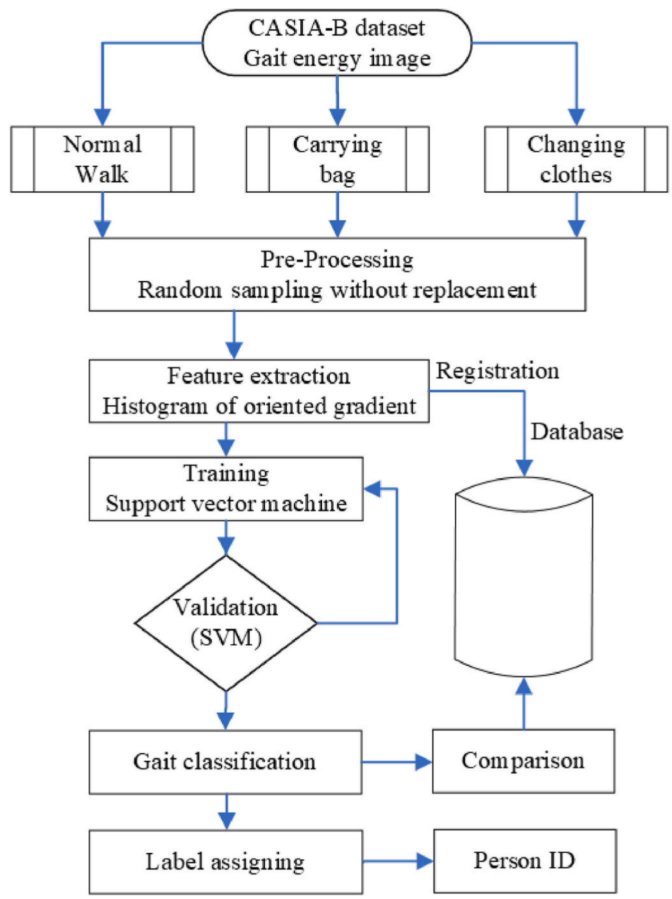


Fig. 3. Design of the algorithm for the gait recognition.

SVM classifiers are trained in the training phase. In the validation phase, training is further refined for better performance. A validated SVM model was applied during the testing phase to perform classification. Afterward, the correctly predicted images were evaluated and counted in order to calculate the accuracy.

A diagram of the proposed method is shown in Fig. 3, which is divided into five main phases: (1) pre-processing; (2) feature extraction; (3) training; (4) validation; and (5) labeling.

In order to achieve recognition results, it is vital to remember the input to the system, which is a gait energy image (GEI) representation. From the dataset, low-resolution images showing the normal walk, carrying bag, and changing clothes can be received as GEIs. The flowchart in Fig. 3 presents the steps from input to the final output of the research work, describing the overall methodology. Extracted features are stored in the database for comparison.

The GEIs are pre-processed in a way that performs random sampling without replacing the images. Then, feature extraction is performed using the histogram of oriented gradients. We select the relevant features for classification after feature extraction. During the training phase of the support vector machine (SVM) model, the incoming gait images were recognized. In the validation phase, the trained model was further trained to perform precise image recognition by fine tuning its

Fig. 4. Sample image of CASIA-B dataset at 90° view.

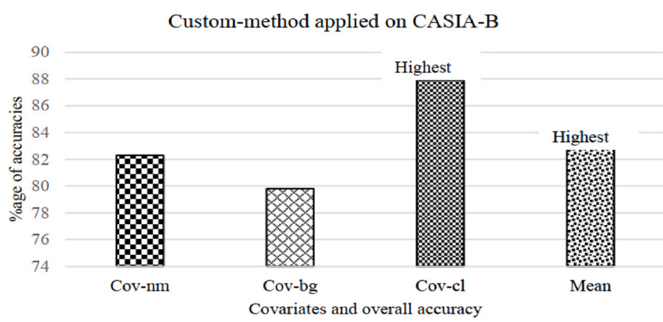


Fig. 5. It shows the individual and overall classification rates for the covariates considered. The label "Highest" shows the prominent comparable accuracies.

Table 4
Algorithms and correct classification rate at 90°.

[#]	Classifier	Cov-nm	Cov-bg	Cov-cl	Mean
[40]	SVM	94.50	60.90	58.50	71.30
[41]	SR	**99.00**	79.00	60.00	79.30
[42]	WA	93.60	**81.70**	68.80	81.40
[43]	KNN	85.36	79.90	74.74	80.00
[44]	RTN	89.00	72.00	52.00	71.00
[45]	CNN	90.50	69.20	61.00	73.60
[46]	CNN	97.58	70.16	56.45	74.73
[47]	ACDA	100.0	78.30	44.40	74.20
[48]	EnDFT	97.61	83.87	51.61	77.69
[49]	LFFR	91.90	80.30	72.30	81.50
	Our method	82.30	79.80	**87.90**	**83.33**

parameters. In the final testing phase the gait images are classified for their labels for different categories of the covariates.

In terms of functionality, the method proves to be effective for human gait recognition. Matovski et al. [37] demonstrated that the factor of changing clothes significantly affects the performance of gait recognition. Hence, improving gait recognition requires eliminating the recognition issues caused by cloth variations. GEI is an easy-to-represent and easy-to-calculate feature representation method that stands out among the available methods. It is the best compromise between computational cost & recognition performance [38].

3. Results and discussion

It is a common observation of practical life that people wear different clothes in summer and winter depending on the weather. Especially in the winter, it is imperative that humans wear a coat or jacket. Because of the styles and different colors of clothes in different seasons, it significantly affects the recognition rate and challenging for the research community. Therefore, we conducted the experiments at an abruptly changed angle of 90° between the camera axis and the walking subject especially for covariate factor for clothing. The effects of differences were observed in the body composition caused by normal walking, changing clothes, and carrying conditions. We focused all the images of the dataset to compute the accurate recognition rate at our level best. Here is the brief information about the images.

Fig. 3 illustrates the three prime scenarios for the images captured and stored in the dataset. It is evident from Fig. 4 that the person during the normal walk on the leftmost, the person wearing the coat in the middle, and the person while carrying the bag on the rightmost side. It is one of the images which are available in the CASIA-B dataset and is shown here to illustrate the changing environmental conditions.

It is famous for generating greyscale images from normalized images and is subject to very few errors. In order to recognize gait, the covariates must be present. As a result of different walking conditions in front of the camera system, the covariates differ from one another [39].

Results obtained for the custom method are shown in Fig. 5 for the different covariates. It shows the accuracy of recognition is in the ascending order as: clothing > normal walk > carrying at a 90° angle. A measurement accuracy of 87.9% was achieved for the coat-wearing people and an overall measurement accuracy of 83.33% was achieved for the mentioned covariates. Both the accuracies are labelled as "Highest" in Fig. 5 clearly showing that our method applied proved best for the people wearing coats and also leads to an overall highest accuracy.

In Table 4, the classification rates for three covariate factors are compared using various state-of-the-art classification algorithms of machine learning. According to the 4th column, the rate of correctly classifying while carrying bag is lower than the conditions for normal walk and changing clothes. Table 4 shows that we were able to achieve very good results compared with various classical methods for the people wearing coats.

Our HOG based SVM classifier with a comparison of classification accuracies has been shown in Fig. 6. The graph shows the accuracies with normal, wearing a coat, and carrying bag. The mean of all three accuracies is also shown to observe the overall performance of the classifiers applied.

It shows the accuracies at the right most with different bars showing the highest accuracy of recognition of the proposed method for humans wearing different clothes. The analysis however, shows the lowest recognition rate for the normal walk but meanwhile the highest recognition rate while wearing different clothes as well as the highest overall accuracy.

The majority of classifiers show a good recognition rate during the normal walk, however they show a lower recognition rate during the activities of changing clothes and carrying bags. Some of the classifiers were reached a good overall recognition rate with a good recognition rate for a normal walk and with carrying bags, but recognition less rate for changing clothes. Our feature selection approach considers conditions while wearing the different clothes as observed in images of the persons when recognizing the gait.

This work should be made useful by making the algorithms as time

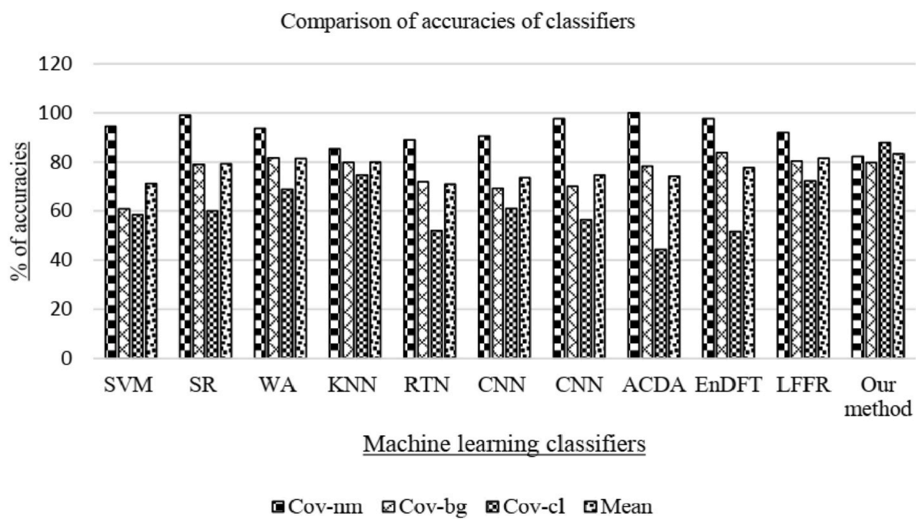


Fig. 6. Comparison of the accuracies by applying different machine learning algorithms by researchers on CASIA-B dataset is shown. The right most position shows our proposed method which shows highest among all the accuracies found for changing clothes as well as the overall accuracy.

Table 5
Abbreviations and Acronyms used in this Manuscript.

#	Abbreviation	Stands for
1.	ACDA	Adaptive Component and Discriminant Analysis
2.	CDA	Canonical Discriminant Analysis
3.	CNN	Convolutional Neural Network
4.	CASIA	Chinese Academy of Sciences & Institute of Automation
5.	EnDFT	Frequency-Domain Gait Entropy
6.	DPLC	Discriminative Projection with List-wise Constraints
7.	GEI	Gait Energy Image
8.	GAN	Generative Adversarial Network
9.	HOG	Histogram of Oriented Gradient
10.	JSL	Joint Subspace Learning
11.	KNN	Number (K) of Nearest Neighbors
12	LFFR	Local Features Flow Regulation
13.	RTN	Resistive Triplet Network
14.	LSTM	Long short term memory
15.	SC	Semantic Classification
16.	SR	Sparse Representation
17.	SVM	Support Vector Machine
18.	WA	Wrapper Algorithm

efficient as possible for prosthetic wearers. When it is capable to overcome the early and late stances of the human gait cycle, it will avoid the deviations in the gait [50]. In real-time scenarios, it may be possible to determine the different phases of the human gait cycle based on the methodology implemented for the dataset. We may calculate the mean normalized curves for human walking in dynamic equilibrium equipped with a sensing unit. The idea described in Ref. [51] successfully computed the forces and acceleration for the computation of dynamic equilibrium.

4. Abbreviations and acronyms

Abbreviations and acronyms used throughout this manuscript are summarized in Table 5. These are defined in the manuscript where appeared first time.

5. Conclusions and suggestions

It is still challenging to recognize gaits in real-time environments if the conditions are ever-changing. However, machine learning approaches are enabling researchers in recognizing gaits more efficiently. In this work, we have presented a system for recognizing the human gait using the support vector machine and a histogram of oriented gradients. A good recognition rate is achieved with the proposed method based on experimental results. Specifically, the method proved to be robust to variations such as changing clothes' conditions.

People wear seasonal clothes in summer and winter and in the winter, it is imperative that humans wear a coat or jacket. It significantly affects the recognition rate and is challenging for the research community. Therefore, we conducted the experiments at an abruptly changed angle of 90° between the camera axis and the walking subject. The prime focus of authors in this work is the factor of clothing in their machine learning model. Observations depict that the recognition rate after considering the overall mean of the individual accuracies is in the descending order as clothing > normal walk > carrying. Accuracies for wearing the coat, normal walk, and carrying a bag are found to be 87.90%, 82.30%, and 79.80% respectively. The overall accuracy achieved through the proposed method is 83.33%. In future work may include for the benefits of researchers and clinicians by identifying the swing and stance phases for the complete gait cycle, which will be useful for identifying the human gait. It is recommended to co-relate this work with lower limb prostheses, so that the dataset may be useful for prosthetic community.

Credit author statement

All the authors have equally contributed to this research work.

Declaration of competing interest

The authors declare that they have no known competing financial interests or personal relationships that could have appeared to influence the work reported in this paper.

Acknowledgement

The authors wish to acknowledge the support provided by NCRA (National Centre of Robotics and Automation) under RDDL (Robot Design and Development Lab) of College of Electrical and Mechanical Engineering, NUST Islamabad Pakistan. This work is funded by the Higher Education Commission of Pakistan under grants titled "Establishment of National Centre of Robotics and Automation (DF-1009-31)".

References

[1] A. Sepas-Moghaddam, F. Pereira, P. Correia, Face recognition: a novel multi-level taxonomy based survey, IET Biom. 9 (2) (March 2020) 1–12.

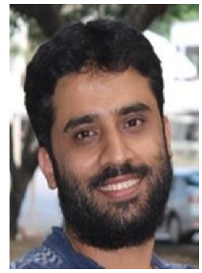
[2] Z. Emersic, V. Struc, P. Peer, Ear recognition: more than a survey, Neurocomputing 255 (September 2017) 26–39.
[3] K. Nguyen, C. Fookes, R. Jillela, S. Sridharan, A. Ross, Long range iris recognition: a survey, Pattern Recogn. 72 (1) (December 2017) 123–143.
[4] C. Shen, S. Yu, J. Wang, G.Q. Huang, L. Wang, A Comprehensive Survey on Deep Gait Recognition: Algorithms, Datasets and Challenges, 28 Jun 2022, pp. 1–20, arXiv preprint arXiv: 2206.13732.
[5] S. Zhang, Y. Wang, T. Chai, A. Li, A.K. Jain, RealGait: Gait Recognition for Person Re-identification, 13 Jan 2022, pp. 1–16, arXiv preprint arXiv:2201.04806.
[6] M.S. Nixon, J.N. Carter, J.M. Nash, P.S. Huang, D. Cunado, S.V. Stevenage, Automatic Gait Recognition," Motion Analysis and Tracking (Ref. No. 1999/103), IEE Colloquium, 1999, pp. 3/1–3/6.
[7] R. Tanawongsuwan, A. Bobick, Gait recognition from time-normalized joint-angle trajectories in the walking plane, in: Proceedings of the IEEE Computer Society Conference on Computer Vision and Pattern Recognition, 2001. II-II.
[8] L. Wang, H. Ning, T. Tan, W. Hu, Fusion of static and dynamic body biometrics for gait recognition, IEEE Trans. Circ. Syst. Video Technol. 14 (2) (2004) 149–158.
[9] L.S. Kumar, H.B. Aravind, N. Hossiney, Digital image correlation (DIC) for measuring strain in brick masonry specimen using Ncorr open source 2D MATLAB program, Results in Engineering 4 (Dec. 2019) 1–4.
[10] A. Abdulqader, D.C. Rizos, Advantages of using digital image correlation techniques in uniaxial compression tests, Results in Engineering 6 (Jun. 2020) 1–5.
[11] A.S. Moghaddam, A. Etemad, Deep Gait Recognition: A Survey". IEEE Transactions on Pattern Analysis and Machine Intelligence, 2022, pp. 1–20.
[12] M. Momeny, A.M. Latif, M.A. Sarram, R. Sheikhpour, Y.D. Zhang, A noise robust convolutional neural network for image classification, Results in Engineering 10 (Jun. 2021) 1–12.
[13] V. Kukreja, D. Kumar, A. Kaur, Deep learning in human gait recognition: an overview, in: International Conference on Advance Computing and Innovative Technologies in Engineering (ICACITE) Mar 4, 2021, pp. 9–13.
[14] K. Apostolidis, P. Amanatidis, G. Papakostas, Performance evaluation of convolutional neural networks for gait recognition, in: 24th Pan-Hellenic Conference on Informatics, Nov 20, 2020, pp. 61–63.
[15] R. Vinuesa, A. Theodorou, M. Battaglini, V. Dignum, A socio-technical framework for digital contact tracing, Results in Engineering 8 (Dec. 2020) 1–4.
[16] Y. Zhang, Z. Wang, S. Zhuang, H. Wang, Motion Gait: Gait Recognition via Motion Excitation, 22 Jan 2022, pp. 1–13, arXiv preprint arXiv:2206.11080.
[17] H.P.M. Kumar, H.S. Nagendraswamy, LBP for gait recognition: a symbolic approach based on GEI plus RBL of GEI, in: International Conference on Electronics and Communication Systems (ICECS'2014), 2014, pp. 1–5.
[18] D. Tao, X. Li, X. Wu, and S. J. Maybank, "General tensor discriminant analysis and gabor features for gait recognition," IEEE Trans. Pattern Anal. Mach. Intell., vol. 29, no. 10, pp. 1700–1715..
[19] D. Xu, S. Yan, D. Tao, L. Zhang, X. Li, H.J. Zhang, Human gait recognition with matrix representation, IEEE Trans. Circ. Syst. Video Technol. 16 (7) (2006) 896–903.
[20] N. Liu, J. Liu, Y.P. Tan, Joint subspace learning for view-invariant gait recognition, IEEE Signal Process. Lett. 18 (7) (2011) 431–434.
[21] D. Thapar, A. Nigam, VGR-net: a view invariant gait recognition network, in: *IEEE 4th International Conference On Identity, Security, and Behavior Analysis*, 2018, pp. 1–8.
[22] I. Cheheb, N. Al-Maadeed, S. Al-Madeed, A. Bouridane, Investigating the use of autoencoders for gait-based person recognition, in: NASA/ESA Conference on Adaptive Hardware and Systems (AHS), 2018, pp. 148–151.
[23] P.P. Min, S. Sayeed, T.S. Ong, Gait recognition using deep convolutional features, in: International Conference on Information and Communication Technology (ICoICT), 2019, pp. 1–5.
[24] E.R.H.P. Isaac, S. Elias, S. Rajagopalan, K.S. Easwarakumar, Template-based gait authentication through Bayesian thresholding, IEEE/CAA Journal of Automatica Sinica 6 (1) (2019) 209–219.
[25] M. Goffredo, I. Bouchrika, J.N. Carter, M.S. Nixon, Self-calibrating view-invariant gait biometrics, IEEE Trans. on Systems, Man, and Cybernetics 40 (4) (2010) 997–2010.
[26] Y. Wang, C. Song, Y. Huang, Z. Wang, L. Wang, Learning view invariant gait features with two-stream GAN, Neurocomputing 339 (Apr. 2019) 245–254.
[27] T.W. Yeoh, F. Daolio, H.E. Aguirre, K. Tanaka, On the effectiveness of feature selection methods for gait classification under different covariate factors, Appl. Soft Comput. 61 (Dec. 2017) 42–57.
[28] J. Su, Y. Zhao, X. Li, 'Deep metric learning based on center-ranked loss for gait recognition, in: Proc. IEEE Int. Conf. Acoust., Speech Signal Process. (ICASSP), May 2020, pp. 4077–4081.
[29] G. Huang, Z. Lu, C. Pun, L. Cheng, Flexible Gait Recognition Based on Flow Regulation of Local Features between Key Frames, IEEE Access, May 2020, pp. 75381–75392.
[30] Z. Mahfouf, H.F. Merouani, I. Bouchrika, N. Harrati, Investigating the use of motion-based features from optical flow for gait recognition, Elsevier Journal of Neurocomputing 283 (Mar. 2018) 140–149.
[31] A.R. Hawas, H.A.E.I. Khobby, M.A. Elnabi, F.E.A. El-Samie, Gait identification by convolutional neural networks and optical flow, Multimed. Tool. Appl. 78 (18) (Jun. 2019) 25873–25888.
[32] A. Sokolova, A. Konushin, Pose-based deep gait recognition, IET Biom. 8 (2) (February 2019) 134–143.
[33] Z. Zhang, L. Tran, X. Yin, Y. Atoum, X. Liu, J. Wan, N. Wang, Gait recognition via disentangled representation learning, in: Computer Vision and Pattern Recognition, Long Beach, CA, USA, June 2019.
[34] Z. Zhang, L. Tran, F. Liu, X. Liu, On learning disentangled representations for gait recognition, IEEE Trans. Pattern Anal. Mach. Intell. 44 (1) (January 2022) 1–16.
[35] P. Nithyakani, M.F. Ukrit, Person identification using histogram of gradient and support vector machine on GEI, in: Data Intelligence and Cognitive Informatics, Springer, Singapore, 2021, pp. 471–478.
[36] CASIA-B dataset, Center for Biometrics and Security Research. Accessed: Dec. 11, 2021. [Online]. Available: http://www.cbsr.ia.ac.cn/users/szheng/.
[37] D.S. Matovski, M.S. Nixon, S. Mahmoodi, J.N. Carter, The effect of time on gait recognition performance, IEEE Trans. Inf. Forensics Secur. 7 (2) (2012) 543–552.
[38] Y. Dupuis, X. Savatier, P. Vasseur, Feature subset selection applied to model-free gait recognition, Image Vis Comput. 31 (8) (Aug. 2013) 580–591.
[39] J. Han, B. Bhanu, Individual recognition using gait energy image, IEEE Trans. Pattern Anal. Mach. Intell. 28 (2) (Feb. 2006) 316–322.
[40] W. Kusakunniran, Attribute-based learning for gait recognition using spatio-temporal interest points, Elsevier Journal of Image and Visio Computing 32 (12) (2014) 1117–1126, Dec.
[41] I. Rida, S.A. Almaadeed, A. Bouridane, Unsupervised feature selection method for improved human gait recognition, in: 23rd European Signal Processing Conference (EUSIPCO), 2015, pp. 1128–1132.
[42] I. Rida, S.A. Almaadeed, A. Bouridane, Gait recognition based on modified phase-only correlation, Journal of Signal, Image and Video Processing (Mar. 2015) 463–470.
[43] A.O. Lishani, L. Boubchir, E. Khalifa, A. Bouridane, Human gait recognition based on Haralick features, Journal of Signal, Image and Video Processing 11 (2017) 1123–1130, Feb.
[44] S. Tong, Y. Fu, H. Ling, Cross-view gait recognition based on a restrictive triplet network, Elsevier Journal of Pattern Recognition Letters 125 (Jul. 2019) 212–219.
[45] Y. Wu, J. Hou, Y. Su, C. Wu, M. Huang, Z. Zhu, Gait recognition based on feedback weight capsule network, in: *IEEE 4th Information Technology, Networking, Electronic And Automation Control* Conference (ITNEC 2020), 2020, pp. 155–160.
[46] R. Liao, S. Yu, W. An, Y. Huang, A model-based gait recognition method with body pose and human prior knowledge, Elsevier Journal of Pattern Recognition 98 (Feb. 2020) 1–11.
[47] K. Bashir, T. Xiang, S. Gong, Gait recognition without subject cooperation, Elsevier Journal of Pattern Recognition Letters 31 (13) (Oct. 2010) 2052–2060.
[48] M. Rokanujjaman, M.S. Islam, M.A. Hossain, M.R. Islam, Y. Makihara, Y. Yagi, Effective part-based gait identification using frequency-domain gait entropy features, Multimed. Tool. Appl. 74 (9) (2015) 3099–3120.
[49] G. Huang, Z. Lu, C. Pun, L. Cheng, 'Flexible gait recognition based on flow regulation of local features between key frames, IEEE Access 8 (May 2020) 75381–75392.
[50] M. Asif, M.I. Tiwana, U.S. Khan, W.S. Qureshi, J. Iqbal, N. Rashid, N. Naseer, Advancements, trends and future prospects of lower limb prosthesis, IEEE Access 9 (Jun. 2021) 85956–85977.
[51] M. Asif, M.A. Tayyab, M.H. Shahid, M.N. Zafar, K.H. Bhatti, S.A. Murtaza, M. I. Tiwana, Computation of human body equilibrium for leg based on gait cycle, in: 4th IEEE International Conference on Robotics and Automation in Industry (ICRAI), Oct, 2021, pp. 1–6.

Muhammad Asif received his B.Sc. degree in mechatronics engineering from University of Engineering and Technology (UET) Taxila, Pakistan, in 2009, and M.Sc. degree in mechatronics and control engineering from University of Engineering and Technology (UET) Lahore, Pakistan, in 2015. Currently he is lecturer at University of Engineering and Technology Taxila. He is pursuing his PhD in mechatronics engineering from National University of Sciences and Technology (NUST), Islamabad, Pakistan. His research interests are in sensors, machine learning, biomedical instrumentation, & lower limb prosthesis.

Mohsin Islam Tiwana (Member IEEE) received the B.E. degree in mechatronics engineering from the National University of Sciences and Technology (NUST), Pakistan, in 2007, and Ph.D. degree in biomedical engineering from University of New South Wales (UNSW), Sydney, Australia. He received the Rectors Gold Medal for the B.E. degree. For his pioneering work on artificial limb design, he was given the Presidential Award. He received the Global Innovation Award for the Ph.D. degree, in 2012, and the prestigious Technology Transformer of the year award by CRDF Global, USA, in 2013.

Umar Shahbaz Khan (Member IEEE) did his bachelors in mechatronics engineering from National University of Sciences and Technology, Pakistan. He did his PhD in electrical and electronics engineering from University of Liverpool, UK. Currently he is working as a faculty at the department of mechatronics engineering, National University of Sciences and Technology and his research interests include embedded systems, robotics and automation. He was the head of mechatronics engineering department from 2015 to 2020. Currently he is the director of the National Centre of Robotics and Automation which is a consortium of labs established in thirteen universities of Pakistan.

Muhammad Waqas Ahmad is PhD candidate in software engineering at department of computer and software engineering, College of Electrical and Mechanical Engineering, National University of Sciences and Technology (NUST) Islamabad, Pakistan. He has also received Masters of Science in Computer Software Engineering MS (CSE) from NUST. He has more than 15 year's industry experience of computer programming, software design and development, software testing and quality assurance, hardware interfacing and controls. He is currently doing research on (automated) software and system failure prediction, detection and classification for mission critical autonomous flights. His research interest include applying machine learning and data science for software and system testing and quality assurance.



Waqar Shahid Qureshi is a computer vision consultant and an electrical engineer by training with over 16 years of experience, of research and development, in industry and academia. He completed his doctor of engineering in 2015 with focus on computer vision applied to agriculture. His expertise includes mostly in applied research in computer vision, image processing, and machine learning for robotics, precision agriculture, 3D scanning and video surveillance applications using different imaging sensors. He is co-inventor of a 3D scanning mechanism being used in da Vinci Color that is the world's first FFF full-color 3D printer by XYZPrinting Inc. Currently, he is working as a faculty member at the department of mechatronics engineering, NUST College of Electrical and Mechanical Engineering since 2016. He is Co-PI at Robots Design and Development Lab, National Centre for Robotics and Automation. He won HEC-technology development fund grant named Pak Zar Zameen that evolved to a startup in precision agriculture services and incubated at Telenor Velocity program and hosted at NUST Incubation centre.

Javaid Iqbal (Member IEEE) received the bachelor's and master's degrees in mechanical engineering from the College of Electrical and Mechanical Engineering (CE & ME), National University of Science and Technology (NUST), Islamabad, and the PhD degree from the University of New South Wales, Australia. He has been the Dean of the Faculty of Engineering (CE & ME), NUST. Currently, he is performing his duties as Principal at SMME (School of Mechanical and Manufacturing Engineering) NUST, Islamabad. His research interests include industrial simulation, machine learning, mechanical systems, and mobile robots among others.