Gait Recognition Using Convolutional Neural Network

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Abstract—Biometrics are the body measurements and calculations related to individuals. Biometrics validation is used as a form of identification of individual. Gait recognition system is one of the most advanced technology that people have been working on for a while now that takes center stage in the field of biometrics. Compared to the other types of existing systems of biometric recognition such as fingerprint detection, iris-scanning systems etc., Gait Recognition system ensures no human intervention. This paper focuses on recognition based on a person's gait. Every person has a distinct gait pattern that is unique to every other person. To train the model CASIA-B dataset has been used. The dataset includes 124 subjects where each sample has undergone Gait Energy Image extraction. Samples with clothing and baggage have been included which changes the silhouette of the person. Therefore, the model has been trained for a wider application where people wear different type of clothing and carry-ons. A Convolutional Neural Network consisting of 8 layers has been trained which performs well on both samples of dataset and an accuracy of 95.45% was obtained on dataset not involving layers of clothing and accuracy of 91.80% was obtained for the sample with clothing and baggage.

Keywords—gait recognition, GEI, convolutional neural network, CASIA

1 Introduction

The process of measuring and analysing the unique and special physical and behavioral characteristics of a specific person and using them to verify his or her identity is known as biometrics. Gait is one of the most distinct characteristics among human beings and hence can be used in biometrics to confirm and corroborate the identity of a person. Gait primarily means a person's way of walking. It is a pattern of steps and corresponding movement of the body that is unique to each person. Using this characteristic of the human body, one can distinguish different people. Different models can be trained using multiple types of technology available to achieve a good accuracy in recognizing different people based on their gait. The aim is to create a recognition system that accurately recognizes the person in question.

Gait recognition using video imagery approach involves study and research involving analysis of video samples of a person's walk and the trajectories of joints and angles. The motion is converted into a mathematical model and is devised and compared with various other samples to arrive at conclusions. There are other models implemented such as Deep Convolution Neural Network (CNN) which is altered and adapted for recognition with Image Augmentation (IA) technique dependent on gait features [1]. In addition, another model has been introduced uses Gait Pal and Pal Entropy (GPPE) image which has been generated and united with four proposed distances [2].

Gait recognition systems find a great deal of scope in watching for shoplifters, criminals, and maintaining security at railway stations or airports. Therefore, it has been observed that this technology has maximum use mainly in the security sector although it also finds use in other applications as well such as identifying people at malls, violent protests and public places. In the proposed work an improvised version of GEI (Gait Energy Image) based gait recognition system using neural network to obtain better results than existing recognition system has been implemented. The gait energy image is one of the most well performing method to store the gait information from a sequence. The accuracy of gait recognition greatly depends on other covariates such as the viewing angle, carrying a bag, walking speed and occlusion of clothing [3, 4]. GEI represents human motion walking sequence in a single image while retaining spatial and temporal information [5]. Scenarios such as when a person wears multiple layers of clothes such as coats or jackets or carrying bags, which affects the overall silhouette of the person, which in turn can change the gait has been taken into consideration. In addition to this, the orientation of the person with respect to the camera or the recording device has also been considered to increase the robustness.

2 Relevant work

Bari et al. [6] have proposed joint relative cosine dissimilarity and relative triangle area. Adam optimization method is used to minimize the loss. The neural network is implemented on a three-dimensional skeleton gait dataset obtained using the Microsoft Kinect Sensors. Deng et al. [7] discusses a deterministic learning and knowledge fusion-based method to make the system view-invariant thus making it a more efficient gait recognition system. The nonlinear dynamics and the width feature of the person is approximated through deterministic learning algorithm. Su et al. [8] have considered hands and limbs move as the main features. Discrete Cosine analysis is used to analyse the dynamic characteristics and shape and with that they intend to reduce the gait features. They use multi-class SVMs to distinguish the different gaits of a human. Liao et al. [9] proposes the model known as PoseGait. This model is said to take human 3D pose estimated from images by CNN as the input for gait identification. The method proposed has been evaluated on CASIA-A and CASIA-B datasets.

Wu et al. [10] studies an approach to gait recognition using similarity learning by deep CNNs. They have tested using different network architectures, different pre-processing techniques on datasets like CASIA-B, OU-ISIR (Large Gait Dataset) and USF gait dataset. Yao et al. [11] have proposed Skeleton Gait Energy Image (SGEI) based upon the skeleton points extracted from a two-branch multi-stage CNN network. Sokolova et al. [12] have proposed a Pose based Gait recognition system. They have considered additional information of the movement of points in the areas around human joints as one of their important features and have not considered the full height of the silhouette.

Lishani et al. [13] discusses a gait identification system that selects various features for gait identification with various conditions like normal walking, with luggage and clothes for various angles. It mainly focuses on two feature extraction methods which are multi-scale local binary pattern and gabor filter bank. Singh et al. [14] have surveyed on the developments made in the field of human gait recognition. They also take us through historical research in the field of gait recognition and walks us through on how gait recognition or identification is performed. They describe features and metrics that can be used in gait recognition model and also provides information on gait databases available which are used in various gait identification system.

Tafazzoli et al. [15] explore the scope of the gait features extracted from different body parts of a human. The recognition is done with K-nearest neighbour classifier and also with the help of other scientific tools like Fourier components. Bhargavas et al. [16] propose to build an automatic biometric system to identify a person based on their Gait. They have proposed to implement the same by recognizing the subject from a video frame and using the skeleton information. Babaee et al. [17] have proposed a method using a gait recognition algorithm from an incomplete gait cycle. Wang et al [18]. have implemented a new type of gait assessment system based on the measures of gait variability imitated through the variability of shapes of the gait cycles trajectories. Chaitanya et al [19]. have mainly focused on recognition and identification of the genuine user of the smartphone and thus information theft is prevented by continuous authentication. The subject is recognized by analysing the physiological or behavioural attributes. Qiu et al [20] have proposed ensemble empirical mode decomposition method to analyse and recognize gait motions for subjects who are using an exoskeleton for motion. The intrinsic mode functions (IMF) were extracted using the original signals by EEMD which are then fed to classification algorithms to recognize. It is found that there are some similarities between IMF and the gait of a person. The experiments were conducted on 14 people. It is seen that some algorithms perform very well on the data such as logistic regression, Kmeans, Naive Bayes, decision tree, random forest methods and SVM. The subjects are made to walk on different floor materials with varying friction and see how it affects the gait. It is found that this has very little effect on the gait of a person.

Huan et al [21] makes use of acceleration sensors in smartphones and explores a way to analyze the gait of a person. Si et al [22]. have made use of remote sensing system for security area monitoring which collects signals from people walking towards the system where the data of their walking and face is extracted and is processed to recognize the person. Systems such as GRF (Ground Reaction Force) are employed which helps to find the force exerted on the floor when the person is walking and a camera is used to capture the image of face. The face detection signals and the gait signals are merged together to get better accuracy when performing the classification and it provides a more robust system. The extracted features have been used as input to GRF identification system and the face recognition was performed using SVM classifier.

Zhou et al [23]. have proposed a model based on Long Short-Term Memory (LSTM) and is combined with orthogonalization method to separate out and enhance the generalization ability of the model for different groups and follow the exoskeleton more precisely. A CNN was used to extract features related to personal information and the LSTM is used to extract features based on the gait. This is done by using cosine similarity. Elharrouss et al [24] have used a method to perform person re-identification via gait recognition which involves calculating the angle of the gait first and then this information is used to recognize the person through convolutional neural network. Then this GEI and the CNN is used to calculate the angle of the gait and recognize the person. Datasets like CASIA-B, OUMVLP and OU-ISIR have been used for testing and training purposes. This has been evaluated using Scene Background Modeling and initialization dataset.

Gao et al [25]. have proposed an improved system which combines artificial bee colony and combination of multiple features as a way to optimize support vector machines (SVM). Features like variance, number of zero-crossing and sEMG, median frequency, fuzzy entropy features and wavelet features are extracted to use as the feature set for the SVM to work on. They have talked about the influence of different classifiers and features on the results and a new penalty coefficient is employed along with a kernel function parameter of SVM. The SVM is trained on the feature set obtained using the algorithms and it is found that the classifier performs 3.18% better than that of non-optimized SVM. Zou et al [26]. have proposed CNN for gait identification and the data is collected using Inertial sensors in smartphones. The data collected using smartphones is subjected to Gait Data Extraction and then subjected to Gait Cycle segmentation and fed to CNN for the result. They have developed an Android application to be installed on smartphones to collect data and then the data is sent to LSTM, CNN based system which performs the authentication into the application.

Sepas-Moghaddam et al [27]. have presented a survey upon the various technologies, methodologies and approaches that have been in use or can be used to perform Gait recognition. Comparison of various fields such as datasets (CASIA-A, CASIA-B), representations of Gait such as body, temporal representation and various neural network architectures and types that can be used to perform Gait recognition has been listed with the performance metrics. Ng et al [28] have proposed a Gait recognition system in which SOTON small database has been used. Multi-view Normalization and Viewpoint Normalization has been used to perform the data extraction after which five-point angular trajectories have been extracted on five main limb joints, then four classification techniques have been used such as SVM, BPANN, Fuzzy k-nearest neighbour and LDA for classification. Luo et al [29] have proposed a Gait system in which gait recognition is performed by using GEI and also AFDEI (Accumulated Frame Difference Energy Image) which considers the time frame unlike GEI. The Gait classification is performed using nearest neighbour classifier upon the AFDEI.

Kim et. al [30] have presented work related to Gait recognition system using a Microsoft Kinect Camera to capture the images and the Gait data is extracted from the Kinect device. Features of the body would be captured by Kinect camera upon which extraction would be performed to extract joint angles. Balazia et. al [31]. have proposed a gait system which learns distinctive gait features via raw MoCap data. After the collection of data all the templates are stored in the central database. Classification of an individual is done by capturing that persons walk and comparing the obtained template with any matching template that is already existing in the database. Hanqing chao et. al [32] have implemented a CNN based gait recognition system upon the CASIA-B dataset. Their algorithm called Gaitset performs Set Pooling to collect gait information.

3 Proposed system

The CASIA-B dataset was considered for the proposed work. The CNN model has been used to form the architecture of the recognition system.

3.1 Input data

Firstly, CASIA-B dataset consists of photos, which includes 124 male and female subjects with 11 different views i.e. the angle at which the subject is oriented with respect to the camera. The dataset consists of 6 normal walking samples, 2 samples carrying baggage and 2 samples with extra layer of clothing per subject. In this dataset unimpaired gait or pathological gait is not included. It also includes variations such as people with multiple layers of clothing such as coats and carrying baggage like backpacks which impacts the silhouette.

In gait representation, Gait Energy Image (GEI) is provided as the input to the CNN, which is extracted by separating out the silhouette of human and then averaged upon the sequence of the silhouettes [24]. GEI is a very prominent way in the gait representation area as they capture both the spatial and temporal information. It is also advantageous as it gives the human gait cycle in a single image. Experimentally they have proven that GEI is a robust and efficient type of gait representation [5].

$$G(x, y) = \frac{1}{N}\sum_{t=1}^{N} I(x, y, t) \tag{1}$$

Using Equation 1 the Gait Energy Image can be calculated where N specifies the total number of frames in one gait cycle, I(x, y, t) is the gait cycle image sequence, coordinate of the image is specified by x and y, t stands for total frames in a gait cycle.

GEIs contains information about dynamic walking environment and the silhouette. Before calculating and computing the GEIs, background subtraction and normalization are used to fetch the gait sequences.

Fig. 1. GEI sequence sample

A GEI sequence for a subject for various angles is given in Figure 1. Images needs to be augmented for better performance [33], therefore GEIs were then normalized using Keras ImageDataGenerator to get the grayscale value of each image as it makes all the input images have similar data distribution.

The training dataset consisted of 4 samples of normal walking sequence and 1 with baggage and 1 with extra layers of clothing for all the views. The test data consisted of 2 samples of normal walking sequence and 1 carrying baggage and 1 with extra layers of clothing. After train-test split of the dataset, 7657 images were used for the training dataset and 4945 were used for the test dataset belonging to 124 classes.

3.2 CNN

Convolutional neural network has played a crucial role in the advancement of deep learning and image recognition. CNN has proven to be a very efficient way to create classification models [34] and has many advantages over other image recognition methods. It was developed by taking inspiration from the visual cortex of the brain. CNN often requires very little image pre-processing compared to all the different algorithms.

Activation function in neural networks help in introducing non-linearity into the model. It is often required in problems involving non-linear solution. ReLu function was decided to be used as the activation function for the CNN. Equation 2 gives the ReLu function.

$$f(x) = \begin{cases} 0, & x < 0 \\ x, & x \geq 0 \end{cases} \tag{2}$$

The ReLU is a mathematical function that will output the maximum of input directly if it is positive or else it will output zero. An output is equivalent to zero when the input value is negative, as shown in equation 2. Additionally, L2 regularization was used which penalizes the loss function on the squared magnitude of sum of all weights of a neural network. Regularization is often used to avoid overfitting and complexity of the model. The magnitude of penalization depends on the hyperparameters specified. In the proposed work regularization rate of 0.0005 was used for the model.

Optimizers are algorithms that change the attributes such as weights and bias to minimize the loss function using a specified learning rate. Adam Optimizer was ideal because it has the best parts of RMSprop algorithm and deals very well with noisy problems. Learning rate of 0.001 was found to be best for the model to converge.

3.3 Architecture

The training images were sent to the CNN to perform the next steps of pre-processing using its convolutional layers and the CNN model was trained on the created input dataset.

The proposed work has a CNN with 8-layer architecture with 3 convolutional layers, 3 pooling layers, 1 fully connected layer and finally a softmax layer as shown in Figure 2. The convolutional layers help to find patterns in the data. The pooling layers decrease the number of features so that the model can learn more efficiently. In the past, CNN has delivered good results in the field of image recognition.

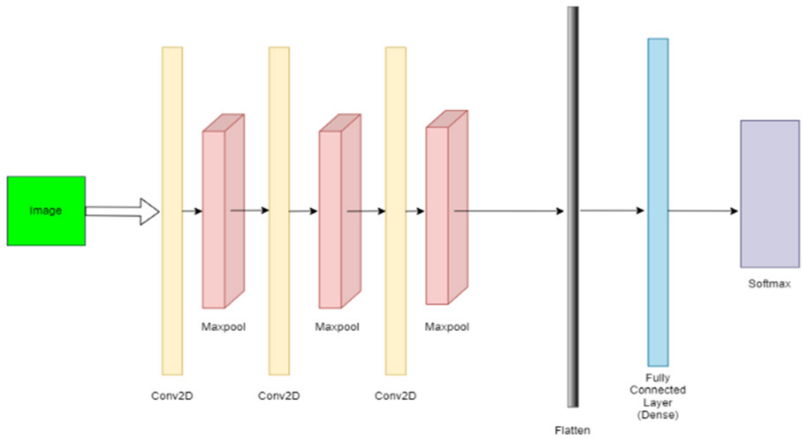

Fig. 2. CNN model architecture

The training data was injected into the first convolutional layer (Conv2D) which has learnable filters that filter the data for necessary features. The output of the convolutional layer (feature map) was passed into maxpool layer which calculates the largest value patch in each feature map. Similarly, this process goes on between every convolutional layer and maxpool layer. After the last maxpool layer, the output was fed to a dense layer which flattens the output and sends it to the fully connected layer from where it is sent to softmax layer which squishes the output into one of the range of labels that was displayed to the user. After the model was trained, it was tested using the test set to obtain the accuracy of the model. Finally, the trained CNN model was be able to classify people in the dataset based on their gait.

Pseudocode:
START
Step 1: *Input data* ← split (train data and test data)
Step 2: Normalize the *Input data* ← rescale and convert to grayscale
Step 3: Build the neural network
Step 4: Train the network with ReLu activation and Adam optimizer
Step 5: Test the network with test dataset
END

4 Results and discussion

Table 1 gives a comparison on the accuracy obtained by the proposed work and other researchers using CASIA-B data set.

Table 1. Results in different conditions for CASIA dataset

Method	Normal (Without Clothes and Bag)	Normal (With Clothes and Bag)
WideResNet [32]	100.0%	89.4%
VGG + blocks [12]	94.5%	65.1%
Gait with CNN [proposed]	95.45%	91.8%

In Table 1, it is observed from comparing the results obtained by a model that is using WideResNet [32] which presents an accuracy of 100% without clothes and bag and 89.4% with clothes and bag. The other model that is using VGG+Blocks [12], L1 which presents an accuracy of 94.5% without clothes and bag and 65.1% with clothes and bag. The proposed gait recognition system using CNN performs well in both cases with accuracies of 95.45% and 91.8% respectively and hence with accuracy of above 90% in both cases.

Table 2. Comparison of average recognition rates for 90º angle on the CASIA dataset

Method	90 Degree View %
WideResNet (PCA 230) [32]	68.8%
Gait with CNN, [proposed]	96.37%

In Table 2, it can be observed that the results obtained by a model using WideResNet (PCA 230) [32], for a 90-degree view of the subject was 68.8% when compared with the proposed model which gives an accuracy of 96.37% for the same view.

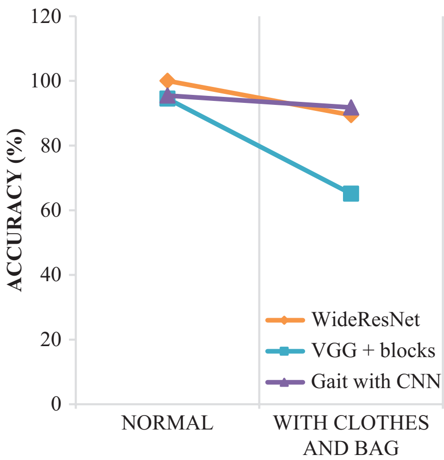

Fig. 3. Comparison of deviation in accuracies for normal and with clothes and bag

As observed in Figure 3, the proposed model which is represented by the line ending with triangles which can be seen as having minimum deviation between the accuracies of both the datasets (normal and with clothes and bag), when compared with diamond and square lines which represent the accuracies of [32] and [12] respectively. Therefore, it can be said that the proposed model has better accuracy for a dataset containing a wide range of variations compared to other models that include clothing and baggage and thus is more robust.

Methods such as "evaluate" (averages successful labels for the test data) in Keras library was used to test the model and obtain the accuracy, loss and other performance metrics. The model which was tested using 248 single-view (90°) images obtained an accuracy of 96.37% using the evaluate function. Later the same model was tested on multi-view images which did not include clothing and baggage scenarios for which accuracy of 95.45% was achieved. The model achieved an accuracy of 91.8% with clothing and baggage which had the complete CASIA B dataset. The predictions were compared with the true labels of the test dataset to plot the confusion matrix. The confusion matrix will help to see how well the model is performing on the whole dataset. After analyzing the results from testing it could be determined that using 0° and 180° angle images did not contribute to the model accuracy instead it reduced the total accuracy of the model as the difference between GEIs for these angles was minimal.

5 Conclusion

The proposed work builds a model to recognize a person based upon their gait, which can be implemented further in real-time applications. Gait Recognition can be beneficial to identify a person from a distance without his/her knowledge, which would prove to be advantageous for security surveillance or during a pandemic. The model was trained on CASIA-B dataset in normal walking condition, and it covered 11 different angles. Using a CNN of 8 layers the model was able to achieve acceptable results for both single-view and multi-view data. For single-view dataset, the model was able to achieve an accuracy of 95.45% using ReLU as the activation function. In addition, an accuracy of 91.8% was obtained for multi-view dataset including clothing and baggage scenarios with ReLU activation function. Training for multi-view data is beneficial since all the angles of gait are covered unlike the case of single view, where the model has to be trained for all the angles each time separately depending on the angle.

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