

# Surveillance System to Provide Secured Gait Signatures for Multi View Angles Using Deep Learning

Anubha Parashar<sup>†</sup>  
Computer Science & Engineering  
Manipal University Jaipur  
Jaipur, Rajasthan, India  
anubhaparashar1025@gmail.com

Rajveer Singh Shekhawat  
Computer Science & Engineering  
Manipal University Jaipur  
Jaipur, Rajasthan, India  
rajveer1957@yahoo.co.in

Apoorva Parashar  
Computer Science & Engineering  
Maharshi Dayanand University  
Rohtak, Haryana, India  
apoorvaparashar0000@gmail.com

## ABSTRACT

These days' security plays the greatest role in order to provide safe platforms and surveillance becomes the essential need to provide accurate results in case of security breach. Gait recognition is a biometric technique that doesn't need human intervention. Through this technique human can be uniquely identified. Gait is defined as the way human walks (human locomotion) and this can be used as biometric identity because the manner in which every person walks can uniquely categorize person. But there are many challenges like variation in viewpoints, clothing variations, carrying conditions and so on. A novel approach using deep learning is proposed to address this challenge. To address these limits, we give an idea of having multiview gait based recognition system, to provide robust system that is capable of handling one camera and subject walking on different angles from 0 to 180 degrees of view. To achieve the results 3-D CNN based model is used in order to obtain spatio temporal features. Also, computation capability of algorithm has been enhanced via. transfer learning mechanism. To carry out the experiments, OU-ISIR and CASIA-B dataset is used. Once these features are obtained, these are passed into LSTM network to obtain the long term dependencies from gait sequence. Network is trained and tested and experiment result shows the proposed technique in this paper out performs the state of art techniques.

## CCS CONCEPTS

• Security and privacy • Intrusion detection • Gait Recognition

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## KEYWORDS

Gait authentication, Human gait recognition, multi-view, convolution neural network

## 1 Introduction

Biometrics is an important technique for uniquely identify the human. There are many techniques like face recognition, iris, finger print etc. But all these either need high resolution images or need human intervention. The valuable information collected by biometric systems wide range of applications in tracking, visual surveillance and studying different fields of life like disaster management, military applications and medical. The human recognition methods being used as of now like fingerprint recognition, facial recognition and iris recognition demand subjects' cooperation, physical contact at times and a lot of images from different views. The present algorithms cannot be applied in dynamic environment or to a subject not willing to cooperate as the system will not be able to make sense out of the given information. It is crucial to develop intelligent and new recognition systems that could provide security. There is a need of developing such robust systems that could help in identification of people on the basis of their biometric behavior which includes their bodily moments and appearance [35.] These systems should be able to automatically collect and analyze the data and give out fair warnings before any incident takes place. Gait is the most efficient and effective biometric when it comes to monitoring individual subjects who are not very cooperative [36]. It is also regarded as the most satisfactory method for making surveillance system. This technique does not require the subject to touch and apparatus or go through heavy checking instead it captures their biometric while maintaining the privacy of the subject. Gait biometric collects the spatio-temporal information of the individual from a video stream and gathers information about the individual. Imitation or cheating can be done with different biometric methods but gait is operated from a distance which shows that gait is more reliable. Even though gait is most efficient biometric method, it has some limitations [37]. The gait of a person is different in various condition, like human locomotion (gait) can vary if a person is carrying bags or wearing a very heavy overcoat will differ from when that person is walking

normally without these objects [38]. There are some other external factors as well that can vary the gait [39] of an individual such as pace of walking, any injury to the individual, orientation of the camera and change in nature of ground surface [40].

## 2 Literature Review

There are lot of researchers who have been publishing a many research papers on gait identification and recognition. Recognition of gait can be categorized into two groups; that is appearance-based method [1]-[15]; and model-based methods [16]-[32].

In the appearance-based method, probe the sequences of gait is done without creating models of entire body of human outline structure and gives most of the productive results when the view is fixed.

On the other hand, the model based methods tend to create replica of a human joint in order to estimate the gait parameters such as limb length, angular speed and trajectories.

Recognizing gait with changing view is tricky. Research regarding view change can be grouped in three categories The first one [33] follows an approach of extracting a gait feature which is indifferent to change of view. An important procedure was put forth regarding this method in [34].

A markerless motion was used to depict the estimation of poses of lower limbs. The next step was to rebuild them in sagittal plane by revising the viewpoint. Using these rectified limb poses spatial displacements and angular measurements were obtained. If the view difference is large, this method and efficiently execute cross-view gait recognition but this method has certain limitations:

- 1.) We cannot apply this method for frontal view as the poses of limbs cannot be traced easily;
- 2.) for a markerless motion the estimation of limb poses is not up to mark.

The second category [8]-[10],[12], [13] is built upon projecting or mapping the connections of gaits across view. Before measuring the similarity, the relationship acquired by training normalizes gait features obtained from various views into an affiliated subspace. A simple non cooperative camera system is used in this type of gait recognition system.

Correlation between gaits of various views across camera are decided by the learning process. If we are to compare this category with the first one, we can say that the second category is more effective and secure when we provide ample training samples to the learning process. The technique proposed in this research paper falls under this category.

### 1.1 Dataset

#### 1.1.1 CASIA B

CASIA B consist of multi-view gait database. In this dataset there exist 124 subjects and has 11 views. In order to provide variations in covariate condition, dataset consist of three variants: clothing, view angle, and carrying bag in figure 1.

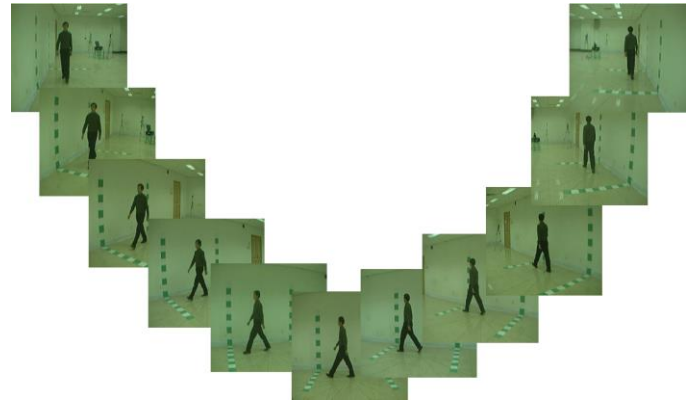


Figure 1: Multi-View dataset

#### 1.1.2 OU ISIR Database

Dataset consist of gallery for training and probe for testing sequences per subject. Each subject is divided in 5 angles, 55 degrees, 65 degrees, 75 degrees, 85 degrees, and inclusion of all four angles in figure 2.

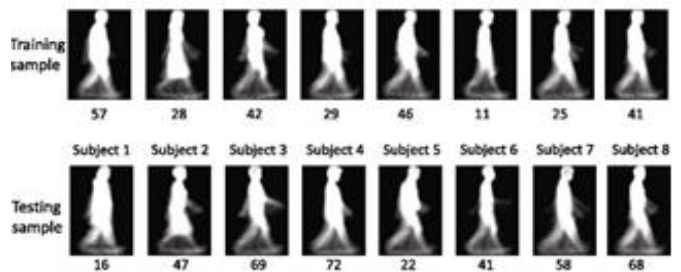


Figure 2: OU-ISIR dataset

### 1.2 Proposed Model

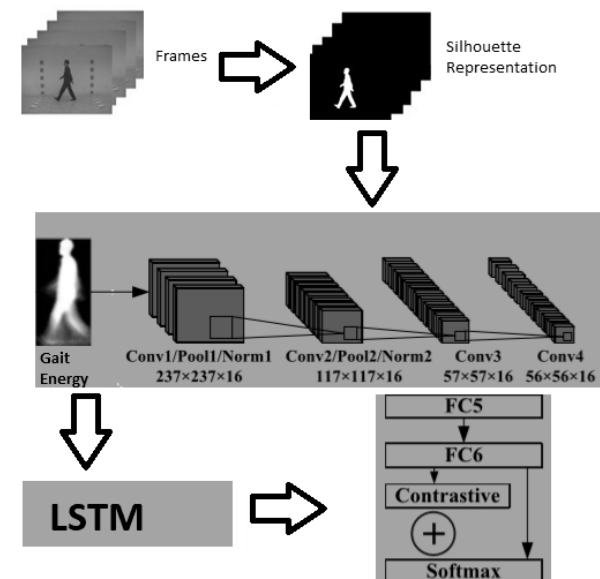


Figure 3: Proposed framework

From figure 3, the proposed methodology can be seen, it is divided into five steps. First the videos are converted into frames then in second step the background is subtracted. In third step the gait energy image is created by take the average of frames by given formula:

$$G(a, b) = 1/N \sum_{c=1}^N B(a, b, c)$$

here a, b are x and y coordinates of an image, N are the total number of frames in one gait cycle, c represents the time frame with respect to frame.

In the fourth step 3-D CNN model is given to extract the spatial and temporal features. In the fifth step these features are sent to LSTM layer in order to remember the features in all iterations. Finally, fully connected layer is formed to and softmax activation function is used to get the final prediction.

3 Dimensional Convolution Neural Network layer size is 237x237x16. In the proposed network, Gait energy images are compared with local regions, after this linear-projection technique is applied in order to calculate the variance between similar pairs of GEIs.

#### 4 Performance and Discussion

In order to check the performance of the system different angles are taken in order to see the accuracy in CASIA B dataset to see in the presence of various covariates. Figure 4 shows the performance of CASIA- B dataset in Normal state. Figure 5 shows performance of CASIA- B under Clothing state. Figure 6 shows performance of CASIA- B while carrying Baggage.

Table 1 shows the match curve of all the cumulative accuracies given in figure 4, 5, 6. Second experiment was performed on OUISIR dataset in order observe variation in view angles of different covariates.

Corresponding results have been summarized in Table one and 2 shows that the results have outperformed from the state of art.

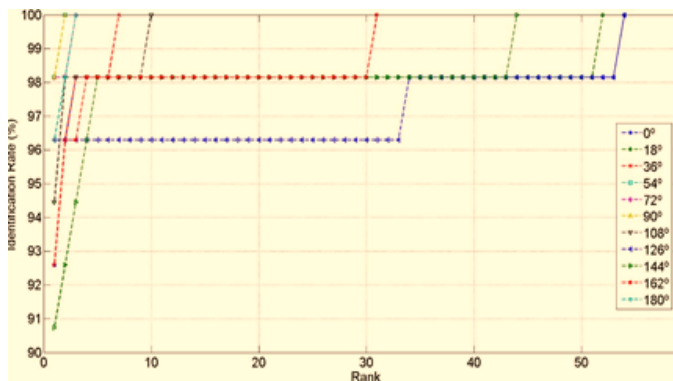


Figure 4: Performance of CASIA- B Normal state

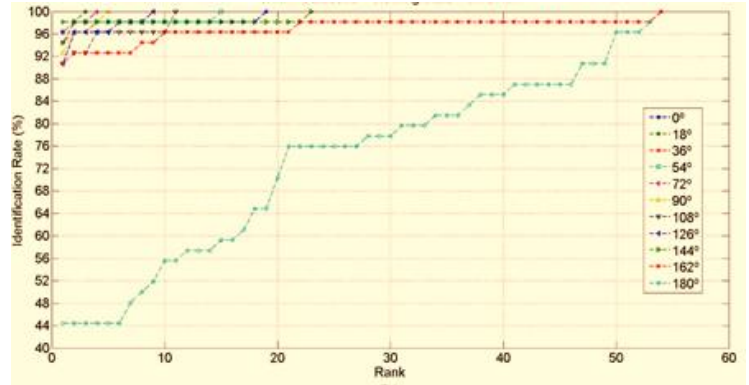


Figure 5: Performance of CASIA- B Clothing state

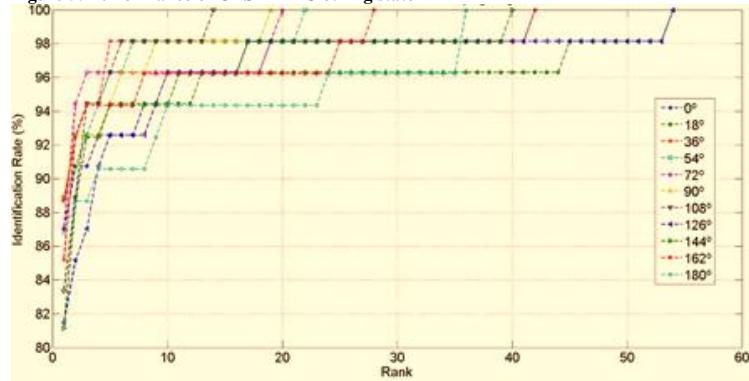


Figure 6: Performance of CASIA- B Carrying Bag state

#### 4 Results

Recognition of human gait while carrying a bag falls under 80–90%. In overcoat clothing recognition rate is 46–100%. For normal gait is in 95–100%.

Table 1: Accuracy of CASIA B

Angle in degrees	With Bag Our Results	Overcoat		Our Results	Normal	
		Deng. Et al.	Glorot Et al.,		Rank 1	Our Results
0	<b>87.64</b>	92.49	96.59	<b>98.35</b>	93.59	<b>98.14</b>
18	<b>88.49</b>	94.74	98.35	<b>90.30</b>	95.44	<b>98.14</b>
36	<b>85.49</b>	98.75	94.34	<b>98.44</b>	94.29	<b>98.14</b>
54	<b>88.69</b>	96.50	96.39	<b>98.35</b>	94.14	<b>98.04</b>
72	<b>87.44</b>	96.40	96.69	<b>99.09</b>	95.14	<b>98.05</b>
90	<b>88.59</b>	94.44	92.59	<b>99.08</b>	96.14	<b>97.05</b>
108	<b>83.63</b>	96.30	90.34	<b>95.29</b>	96.44	<b>97.14</b>
124	<b>81.58</b>	92.39	90.64	<b>95.30</b>	97.29	<b>97.29</b>
144	<b>81.63</b>	94.34	94.64	<b>94.15</b>	97.74	<b>96.14</b>
162	<b>88.78</b>	94.34	90.64	<b>94.59</b>	97.59	<b>95.14</b>
180	<b>86.49</b>	90.37	44.24	<b>46.44</b>	95.29	<b>98.04</b>

**Table 2: Accuracy of OU-ISIR**

Approaches	55°	65°	75°	85°	Overall
Shiraga et al.,2016	94.60	95.20	96.20	94.40	94.62
<b>Our Approach</b>	<b>98.80</b>	<b>99.60</b>	<b>98.70</b>	<b>99.70</b>	<b>99.30</b>

## 5 Conclusion

Experimental result shows the proposed approach is more robust and efficient than previous state of art. Further, it has produced better results than the previous model-free approaches. The major contributions of this research can be summarized as below:

1. Provides efficient multi variant model.
2. Proposed methodology gives better result than the existing methods (that is with bag, Overcoat, Normal).
3. As the results are good in all the angles this system can actually be used for real surveillance for providing security.

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