INTELLIGENT PLAGIARISM DETECTION FROM VARIOUS STATISTICAL REPRESENTATION

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1.1 Abstarct

Gait Analysis is very important in surveillance and identification of person where facial recognition is not possible because of far camera distance. In this paper, image based person identification is addressed including cloth , multi view and cross view invariance using the CASIA-B,C dataset. The realm of object detection algorithms from computer vision have been applied to this domain which involves feature extraction techniques like Gait Energy Image(GEI) for cloth invariance, histogram of gradients(HOG) for multiview invariance and Zernike moment with random transform for cross view invariance. The features have been fed into a different machine learning classifier and achieved a state of the arts performance. The proposed model is very robust for view, cloth and speed variant. The method is evaluated on the data set CASIA Gait data set-B,C. The proposed method has achieved 99respectively for three different scenarios of invariance speed, cloth pose.

1.2 Introduction

Gait is the process in which upper and lower body act in unison. It can be loosly understood as person's way of walking. The Gait cycle has two distinct phase. One is stance and other is swing.The entire gait cycle can be divided into 8 subphases as shown in Figure 1. In stance phase, the gait cycle have initial contact, loading response, mid stance and terminal stance. In swing phase, the gait cycle have pre swing, initial swing, mid swing and terminal swing [1]. In the Gait cycle, hip, knee and ankle move is distinct way to produce Gait. We aim to differentiate and identify people based on their Gait [2].

Human gait is used to identify the person from distance and it is unobstructed biometric trait process for person identification. Gait Analysis is very important in surveillance, identification purpose, and security infrastructure system [3]. Right now we have fingerprint, face recognition for biometric recognition but none of the technique works when the subject to be identified is at a distance. Gait is the only biometric trait that can identify subject at a distance[4]. Gait analysis is done for medical purposes too where it can be used for early detection of Gait abnormalities including Parkinson disease. The gait study further can be utilized for generation of robot walking trajectories[5]. Gait is also used for planning the path of Humanoid robot[6].

Gait is considered as behavioral biometrics which has highest collectabilty [Table 1.1,1.2]. Gait suffers with low permanence at early state of learning. A learnerâĂŹs gait dynamics can change drastically within a short period of time as the learners gets accustomed to the environment being used. Once it is acquired and accustomed it is very less like to change with time[7]. Figure 1.2 shows the different subphases of one complete gait cycle. The one human gait cycle consists of two broad phases one is single support phase (SSP): when one foot will be in air and another will be on ground) and another phase is double support phase (DSP): when both foot will be place on ground) [8]. The DSP is observed very less during normal walk and quantitative it is only 10-12% one gait cycle. One healthy person can complete the one gait cycle in between 0.52 second to 1 second [9]. The one complete gait cycle cab be further divided into 7 different linear sub-phases[10].

Table 1.1: Different Physiological based Biometirc characteristics

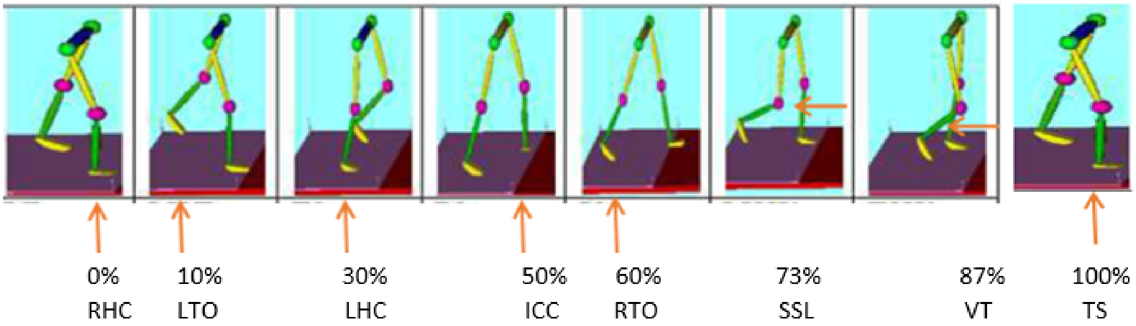
Biometric	Universality	Distinctiveness	Permanence	Collectabilty	Circumvention
Face	High	Medium	Medium	High	Low
Iris	High	High	High	Medium	Low
Palm print	High	High	Medium	Medium	Medium
Fingerprint	High	High	Medium	Medium	High
Retina	High	High	High	Low	Low

Table 1.2: Different Behavior based Biometirc characteristics

Biometric	Universality	Distinctiveness	Permanence	Collectabilty	Circumvention
Gait	Low	Medium	Low	High	Low
Speech	High	Medium	High	Medium	Medium
Signature	High	Medium	Low	Medium	Low
Keystroke	High	Medium	Low	Medium	Low
Device Uses	Low	Medium	Low	High	Low

1.3 Literature Review

In the past various spatial and temporal feature have been used for gait based identification. A number of models have been proposed including vision, sound, pressure, and accelerometry models [11] [12]. Gait Signals can be complex which make Gait based identification tough. Two different approach have been developed for image-based gait recognition. One is Model based method which computes the model features by fitting model to the image and other is appearance based strategies [13]. Many researchers have tried to improve the accuracy is machine vision based gait identification [14]. Researcher have proposed a method in which the gait features are obtained by calculating the area of the head, arm swing and leg swing regions. This method work only in speed invariant



STANCE(60%)				SWING (40%)		
Loading Response [0-10] %	Mid Stance [10-30%]	Terminal Stance [30-50%]	Pre Swing [50-60%]	Initial Swing [60-73%]	Mid Swing [73-87%]	Terminal Swing [87-100%]
Double Support	Right Single Support		Double Support	Left Single Support		

RHC - Right heel contact , LTO - Left toe off, LHC- Left heel contact, ICC- Initial contact of the contralateral limb, RTO – Right toe off,SSL - Swimming limbs opposite to stance limb,VT- Vertical tibia, TS- Terminal swing.

Figure 1.1: Different Subphase of One Complete Human Gait Cycle

human identification problem. Several research have used Speeded Up Robust Features to depict the trajectories of the different parts of the body but this method works inly if there is only one moving object [15]. Hence it is not suited for Crowded scene. Kusakunniran [21] proposed a technique in which Space-Time Interest Points are obtained from a raw video sequence. The advantage of this method is that the time complexity occurred by pre-processing of the video is removed. Wang et al. [16] developed a temporal template called as

1.4 Proposed Methodology

The approach is based upon the notion that the boundary of the silhouettes will contain maximum information and this would hold true for any kind of gait condition including the person in a different attire, with a bag or walking at different speeds. However since the silhouettes represent a walking sequence over a particular set of frames , we need to convert them into a single frame by using GEI.

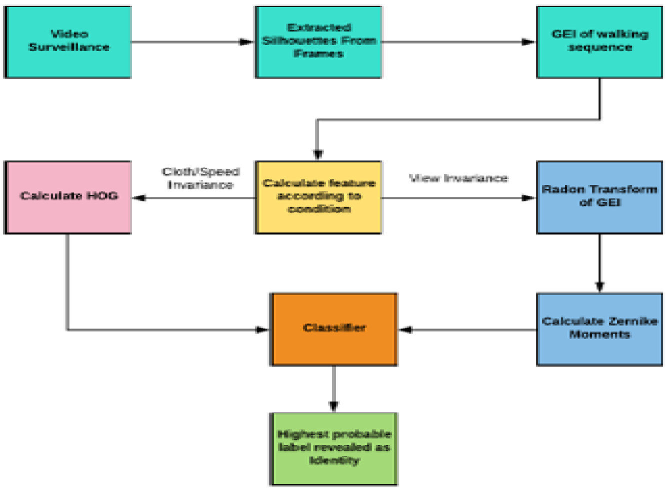


Figure 1.2: Caption

Depending upon the type of problem, we have used HOG, Gait Energy Image and Radon Transform.

1.5 Results

The model is able to identify the person with regard to different views the camera may have been placed at. Highest accuracy for multi view was obtained at 0 and 180while in cross view the model performed the best when trained at 72 and validated at 90 .

Accuracy reported for cloth, speed, multi-view and cross-view gait recognition is given below.

Table 1.3: Metrics Obtained Showing Speed Invariance

Model	Accuracy	Precision	Recall	F1-Score	Support
SVM	1.00	1.00	0.99	0.99	459
ANN	1.00	0.99	1.00	0.99	459
XGBoost	0.97	0.96	0.97	0.96	459

Table 1.4: Metrics Obtained Showing Cloth Invariance

Model	View Angle	0	18	36	54	72	90	108	126	144	162	180
	Accuracy	0.95	0.94	0.95	0.96	0.94	0.94	0.91	0.92	0.94	0.93	0.96
	Precision	0.96	0.96	0.97	0.97	0.96	0.96	0.93	0.94	0.95	0.95	0.97
SVM	Recall	0.96	0.96	0.96	0.96	0.94	0.94	0.91	0.92	0.94	0.93	0.96
	F1	0.95	0.94	0.96	0.96	0.94	0.94	0.91	0.92	0.94	0.93	0.96
	Support	357	360	360	357	360	360	360	358	359	356	360
	Accuracy	0.94	0.90	0.92	0.93	0.90	0.91	0.90	0.94	0.93	0.92	0.91
	Precision	0.95	0.92	0.94	0.94	0.92	0.93	0.92	0.96	0.95	0.94	0.93
ANN	Recall	0.95	0.92	0.93	0.93	0.94	0.95	0.91	0.94	0.94	0.93	0.93
	F1	0.95	0.92	0.93	0.93	0.92	0.93	0.91	0.94	0.94	0.93	0.93
	Support	357	360	360	357	360	360	360	358	359	356	360
	Accuracy	0.83	0.85	0.93	0.93	0.84	0.90	0.85	0.88	0.89	0.90	0.89
	Precision	0.84	0.86	0.92	0.94	0.85	0.92	0.85	0.89	0.90	0.91	0.90
XGBoost	Recall	0.83	0.87	0.91	0.93	0.86	0.93	0.86	0.90	0.91	0.90	0.89
	F1	0.83	0.86	0.91	0.93	0.85	0.92	0.85	0.89	0.90	0.90	0.90
	Support	357	360	360	357	360	360	360	358	359	356	360

Table 1.5: Metrics Obtained Showing Cross View Invariance

Model	Training	Validation	Accuracy	Precision	Recall	F1 Score	Support
	90	108	0.67	0.68	0.66	0.67	120
SVM	72	90	0.77	0.78	0.77	0.76	119
	162	180	0.67	0.69	0.68	0.68	120
	90	108	0.70	0.69	0.71	0.70	120
ANN	72	90	0.76	0.76	0.76	0.76	120
	162	180	0.66	0.66	0.64	0.65	119
	90	108	0.66	0.67	0.68	0.67	120
XGBoost	72	90	0.70	0.72	0.73	0.72	120
	162	180	0.70	0.71	0.72	0.72	119

1.6 Conclusion and Future Work

In this paper high accuracy is achieved with normal gait and cloth invariant gait. The accuracy associated with cross view invariant gait needs to be improved. The gait recognition based person identification becomes challenging in real time due to cloth, different view angle and posture of human. The challenge involves in extracting the correct gait features of different person which is invariant for all conditions. We have adopted technique which is invariant gait extraction. Most of the model used to consider gait from sagittal plane not from other Transverse and Coronal plane moment. Our algorithm is robust and work for all the view and mapped into single view image.

Table 1.6: Comparison with State of the Art models

	Methods	Accuracy
	WBP[21]	91.66
Speed	FDI +2DLDA[22]	89.0
	Proposed Method	99
	GEI+part-based[23]	85.2
Cloth	Golden ratio Segmentation [24]	93.14
	Proposed Method	96
	Stacked Autoencoder[25] (MultiView)	97.58
	Proposed Method	79.00
View	Stacked Autoencoder[25] (CrossView)	63.90
	Proposed Method	67.00

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