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Journal:	*Transactions on Neural Systems & Rehabilitation Engineering*
Manuscript ID	TNSRE-2019-00079
Manuscript Type:	Paper
Date Submitted by the Author:	13-Feb-2019

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Speed, Cloth and Pose Invariant Gait recognition Based Person Identification

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***Abstract*—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 99%, 96% & 67% identification accuracy respectively for three different scenarios of invariance speed, cloth & pose.**

***Index Terms*—Biometric gait, temporal data, gait recognition, gait energy image, pose invariant, cross view invariance, multi-view invariance .**

I. Introduction

Gait is the process in which upper and lower body act in unison. It can be loosely 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 I,II]. Gait suffers with low permanence at early state of learning. A learner's 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 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 I
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 II
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

The rest of the paper is organized into 5 sections. The next section 2 presents the literature review about the gait recognition work done so far. The section 3 is presenting the our proposed view, cloth and speed invariant method. The

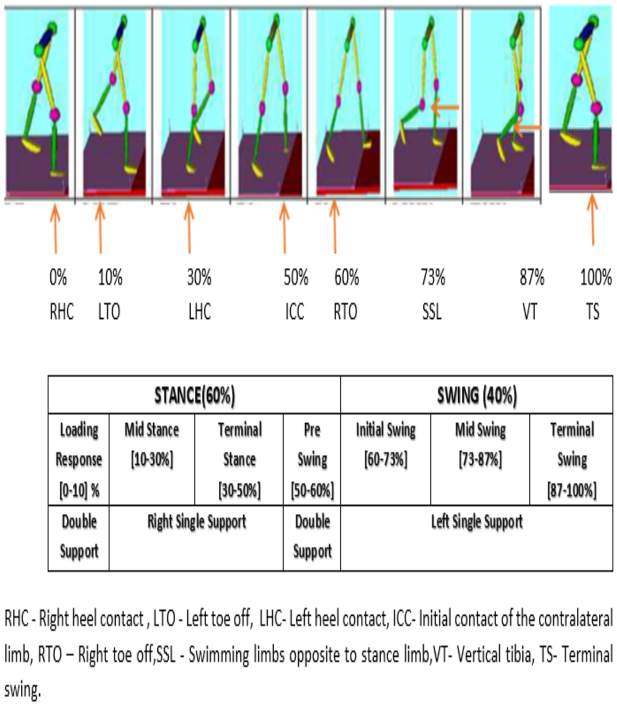

Figure 1. Different Subphase of One Complete Human Gait Cycle

section 4 is result and discussion section and presents the performance study of all the algorithm used for classification and the final section 5 presents the conclusion and future research work.

II. 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 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 Chrono Gait Image. This method requires the less computational cost to preserve the gait cycle information.

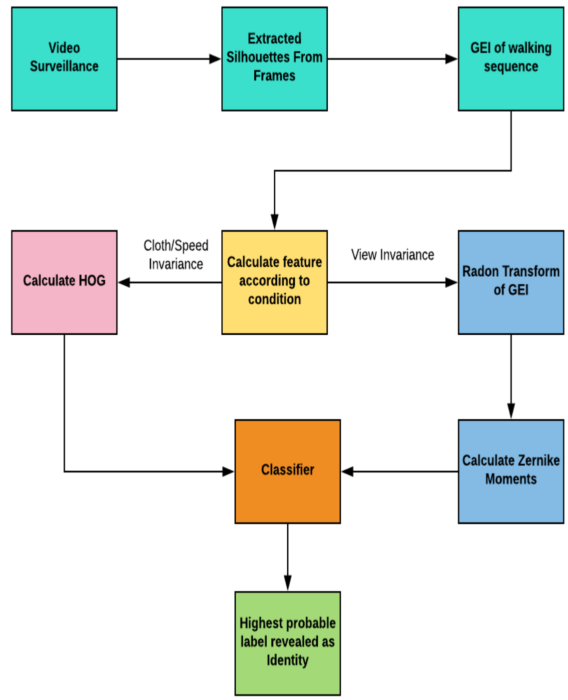

Figure 2. Process Flow Diagram

Figure 3. Gait Silhouette

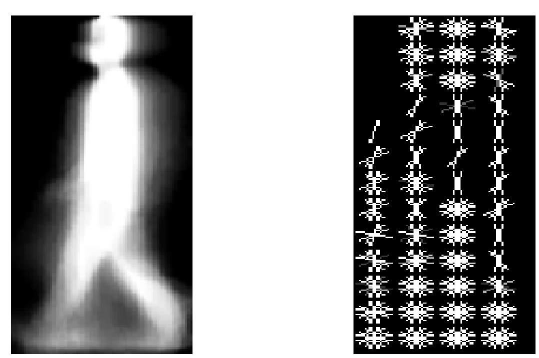

Figure 4. GEI (Left) used in obtaining HOG Features (Right)

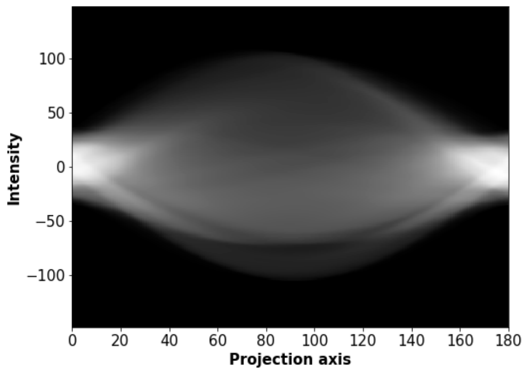

Figure 5. Radon Transformed GEI Image

III. Proposed Methodology

The approach [Figure 2] is based upon the notion that the boundary of the silhouettes [Figure 3] 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 [17].

A. GEI

Human walking is a repetitive motion which remains same upto a frequency. The order of positions of the limbs is the same in each cycle that is the legs move forward and the arms backward.This order is not important in feature extraction for gait recognition and so can be combines to form a spatio-temporal representation of a single image by using GEI [18] [19]. The greater the pixel value in the GEI, more is the frequency of occurrence of the human body.
Pre-processing steps include extracting region of interest of the silhouette image and finding out the centre of the human [20]. Although it might seem implicit in nature , the region of interest found out here is based on a novel approach which is termed as pixel approximation method Algorithm 1 which is then used to calculate the GEI.

B. HOG

HOG descriptors can be used to used to extract boundary information in a swift manner from the GEI images(Figure 4]. It is a feature descriptor technique used in image processing, mainly for object detection. The distribution [histograms) of directions of gradients are used as features here. Gradients (x and y derivatives) of an image are pivotal because the magnitude of gradients is large around edges and corners (where intensity abruptly changes).Here 9 orientations are considered with pixels per cell being (16, 16) and cells per block is (2, 2), for each image. To calculate the final feature vector for the entire image, the individual vectors of each path are flattened into a array having 1420 elements with the original image size being 210 X 70 thus representing a 90% reduction in size of feature vector. Benefits of selecting this feature is that it is compact, fast to calculate, scale and translation invariant and works appreciably for silhouette images.

Algorithm 1 ROI calcuation with centre of Image location for GEI building

Result: GEI is build on passing silhouette images of a walking sequence
Input: Image (i) with width (w) and height (h)
Output: GEI
Procedure

- Set four pointers $up \leftarrow 0$, $down \leftarrow 0$, $right \leftarrow 0$, $left \leftarrow 0$ to capture the delimiters of the silhouette in four directions.
- Increment the pointers until a white pixel is found so that the rectangular boundary is obtained
- Crop the image now by making use of the pointers

$pixelCount \leftarrow []$
for index←right−left **do**
pixelCount← $Non\,Zero\,Pixels\,In\,Cropped\,Image$
$countAll \leftarrow \sum$(pixelCount)
pixelPercent=count/countAll **foreach** count in pixelCount
countPercentSum ←0,minTheta←1,bestIndex←0
for index,val **do** in pixelPercent:
tmp← $|0.5-$countPercentSum$|$
if tmp<minTheta **then**
minTheta←tmp
bestIndex←index
end if
end for

- Centered Human is Image with new dimensions bestIndex, w-bestIndex
- Calculate mean of Centered Human for a Time frame(T) using $G(x,y)$=1/N $\sum_{t=1}^{t=N}$B(x,y,T)

HOG can not only it can capture the outlines of the different clothes and bags in the upper torso , by combining it with the Shannon Entropy (GEnI) which finds out the uncertainties of the pixel positions of the lower torso (legs),the variations in the walking speed are also captured.

C. Radon Transform and Zernike Moments

Difficulty comes with the third aspect when the subject is viewed from different angles and trained on a subset of them (multiview) or viewed at a different angle from which they are trained on (crossview) since HOG descriptors although being scale and translational invariant are not rotational invariant. To overcome this problem, the help of Radon Transform is taken from the tomography field which takes the projection of a 2-D image along a direction to give it a 1-D profile something resembling taking an X-Ray scan on the edge of the image.

A projection of a two-dimensional function $f(x,y)$ is a set of line integrals. The radon function computes the line integrals from multiple sources along parallel paths, or beams, in a certain direction.[Figure] Projections can be computed along any angle theta θ.The sinogram (term used to describe the data after Radon Transform) has been computed here as θ ranging between 0 to 180 [Figure 6] with the number of values generated equal to the image width. The formula of computation is:

$R_\theta(\acute{x})$=

$$\int_{+\infty}^{-\infty} f(\acute{x}cos\theta - \acute{y}sin\theta, \acute{x}sin\theta + \acute{y}cos\theta)d\acute{y}$$

where,

$$\begin{bmatrix}\acute{x}\\ \acute{y}\end{bmatrix} = \begin{bmatrix}cos\theta & sin\theta\\ -sin\theta & cos\theta\end{bmatrix}\begin{bmatrix}x\\ y\end{bmatrix}$$

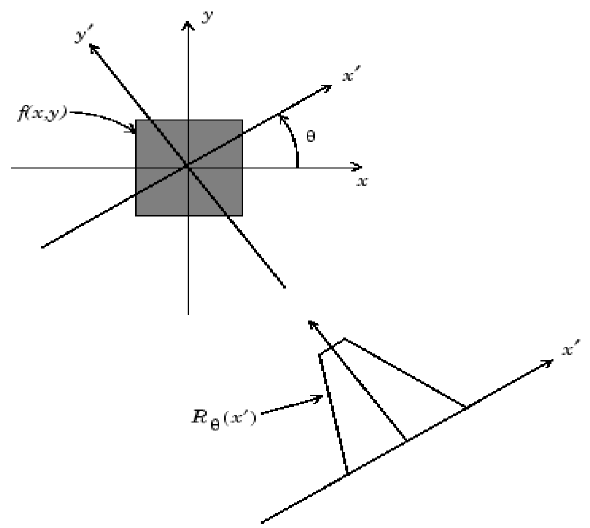

Figure 6. Random Transform

This RGEI(Radon GEI) is then used to obtain the Zernike Moments which are rotational invariant [Figure 5] unlike HOG but do not capture boundary information so well nor are substantial enough to be fed into a classifier.Complex Zernike moments are constructed using a set of complex polynomials which form a complete orthogonal basis set defined on the unit disc $(x^2+y^2) \leq 1$. They are expressed asA_{pq}Two dimensional Zernike moment:

$$A_{mn} = \frac{m+1}{\pi}\int_x\int_y f(x,y)[V_{mn}(x,y)]^* \ dx \ dy$$

. The moments were calcuated here according to the maximum radius for the Zernike polynomials being 85 pixels and degree being 8 to get 27 values for each feature vector of the image. Advantages of using Zernike Moments include simple rotation invariance ,higher accuracy for detailed shapes, Orthogonal which means it has less information redundancy and better at image reconstruction. It also gives rotational invariance unlike HOG.

D. Classifier Model

The final step is to feed the mentioned features into a classifier according to the condition for prediction of identity of individuals though their walking sequence obtained

Table III
Description of Model Parameters

Model Used	Parameters
SVM	Kernel=Linear,Penalty Parameter (C)=1 height Solver = Limited Memory Broyden–Fletcher–Goldfarb–Shanno (LBFGS),
ANN	Hidden Layers=4, Neurons=(3000,4000,4000,3000), Alpha (Regularization L2)=0.001
XGBoost	Booster=Dart

from the video frames. For investigation purposes different classifiers have been trained ranging from traditional methods like ANN (Artificial Neural Network)[Figure 7] to SVM (Standard Vector Machine) to newly discovered techniques including XgBoost which has obtained higher accuracy in recent classification challenges. Detailed description of models is given in the Table III.

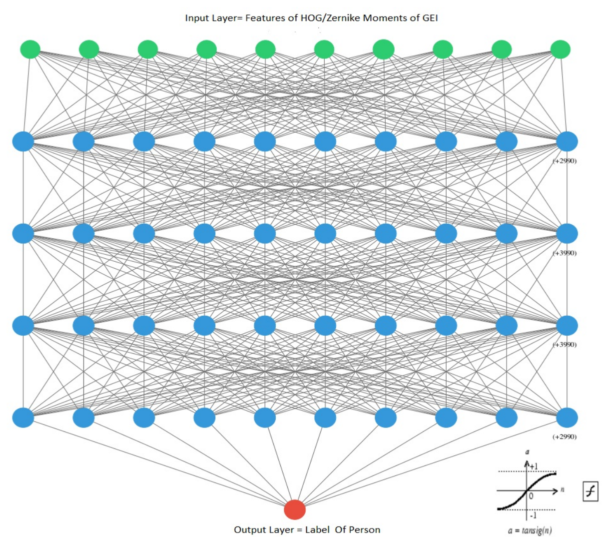

Figure 7. Structure of Neural Network (Plotted in graphviz) + denotes additional neurons not shown

IV. Result & Discussion

A. About the Database

Casia-B Database

CASIA gait database contains the human walking pattern of 124 subject. It has been made open-source by Centre for Biometric and Security Research, CASIA. For each subject, video is captured from 11 different angle. Also each subject is captured in 3 different variation namely normal walking, walking with bag, and walking with different clothing conditions.

Casia-C Database

CASIA-C contains 153 subject and consider 4 variations namely normal walking, slow walking, fast walking and walking with a bag. It was captured via Infrared camera and has been been maded Open-source by Centre for Biometric and Security Research, CASIA.

From a machine learning domain, these datasets represent a multi class classification task with balanced classes since for each class there is only one GEI created from the frames. Thus results are given in macro average format which gives equal importance to all classes which is applicable here because it is balanced in nature.

B. Speed Invariance

Experimental Condition

CASIA-C dataset was used for this instance and the training set consisted of 2 normal walking sequences(fn) , 1 fast walking sequence(fq) ,1 slow walking(fs) sequence. Validation set consisted of 1 nomral walking sequence (nm), 1 fast walking sequence (fq) and 1 slow walking sequence(fs).The accuracy obtained by the three classifiers has been shown in the Figure.

Discussion

Our model is able to identify the person despite the speed the person is walking. This feature is useful particularly in surveillance fields when security measures have to be taken to stop crimes like robberies so that while fleeing the person is identified. Highest accuracy of 99% has been achieved by SVM in this regard [Table IV, Figure 10].

C. Cloth Invariance

Experimental Condition

CASIA-B dataset was used for this instance and the training set consisted of 5 normal sequences (nm) , 1 sequence with bag (bg) and 1 sequence with cloth (cl). Validation was with 1 normal sequence (nm), 1 sequence with bag (bg) and 1 sequence with cloth (cl). The accuracy obtained by the three classifiers has been shown in the Figure. View angle was kept constant here that is each sequence both in the training and validation set was of the same view angle.

Discussion

Our model is able to identify the person in spite of what the person is wearing.[Figure 8] He or she can have a bag or a coat but can still be recognized when the camera is set a certain view angle. Above 90 % accuracy has been achieved with respect to every view angle with SVM performing better in almost all the cases [Table 8, Figure 11].

D. Pose Invariance

Experimental Condition

CASIA-B dataset was used for this instance and the two different experiments to test cross view and multi view invariance were carried out. For cross view, the training features were obtained at a particular angle and validated for another angle as shown in Table . For multi view , the training features were obtained at each of the view angles together. Validation was then done for each angle separately. 5 normal sequences (nm) was used in training sample and 1 normal sequence was used in the test sample.

Discussion

Our model is able to identify the person with regard to different views the camera may have been placed at [Figure 9]. Highest accuracy for multi view was obtained at 0°and 180°[Table VI , Figure 12] while in cross view the model performed the best when trained at 72°and validated at 90°[Table VII, Figure 13].

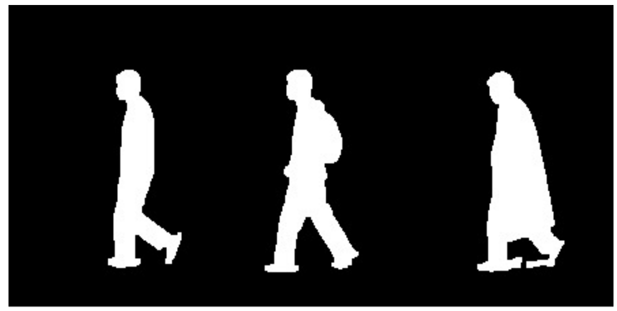

Figure 8. Different clothing conditions of subjects with or without bag

Figure 9. Poses captured of subjects from different angles

Table IV
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 V
METRICS OBTAINED SHOWING CLOTH INVARIANCE

Model	View Angle	0	18	36	54	72	90	108	126	144	162	180
SVM	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
	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
ANN	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
	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
XGBoost	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
	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 VII
METRICS OBTAINED SHOWING CROSS VIEW INVARIANCE

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

Table VI
METRICS OBTAINED SHOWING MULTI VIEW INVARIANCE

Model	View Angle	0	18	36	54	72	90	108	126	144	162	180
	Accuracy	1.00	0.99	0.77	0.67	0.65	0.70	0.75	0.74	0.70	0.99	1.00
	Precision	0.96	0.96	0.77	0.67	0.66	0.69	0.76	0.75	0.71	0.98	0.99
SVM	Recall	0.96	0.96	0.76	0.68	0.67	0.70	0.77	0.76	0.72	0.99	0.98
	F1	0.96	0.96	0.77	0.67	0.66	0.69	0.75	0.75	0.70	0.98	0.98
	Support	117	120	120	120	120	120	120	118	120	118	120
	Accuracy	0.90	0.96	0.79	0.68	0.70	0.76	0.80	0.66	0.68	0.96	0.99
	Precision	0.89	0.95	0.78	0.69	0.71	0.75	0.81	0.67	0.69	0.95	0.98
ANN	Recall	0.88	0.94	0.79	0.68	0.72	0.76	0.82	0.68	0.70	0.96	0.99
	F1	0.98	0.94	0.78	0.68	0.71	0.75	0.81	0.68	0.70	0.95	0.98
	Support	117	120	120	120	120	120	120	118	120	118	120
	Accuracy	0.88	0.85	0.70	0.75	0.76	0.70	0.75	0.76	0.74	0.70	0.67
	Precision	0.85	0.86	0.71	0.73	0.72	0.72	0.77	0.78	0.76	0.71	0.68
XGBoost	Recall	0.83	0.87	0.71	0.73	0.74	0.73	0.76	0.80	0.77	0.72	0.69
	F1	0.83	0.86	0.71	0.73	0.72	0.72	0.75	0.79	0.76	0.71	0.68
	Support	117	120	120	120	120	120	120	118	120	118	120

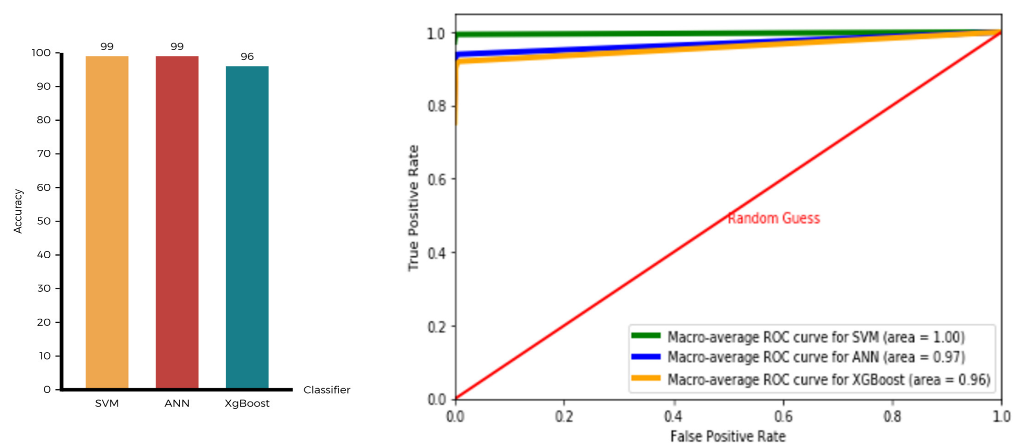

Figure 10. Comparison of accuracy with AUC curve when subject moves with different speeds

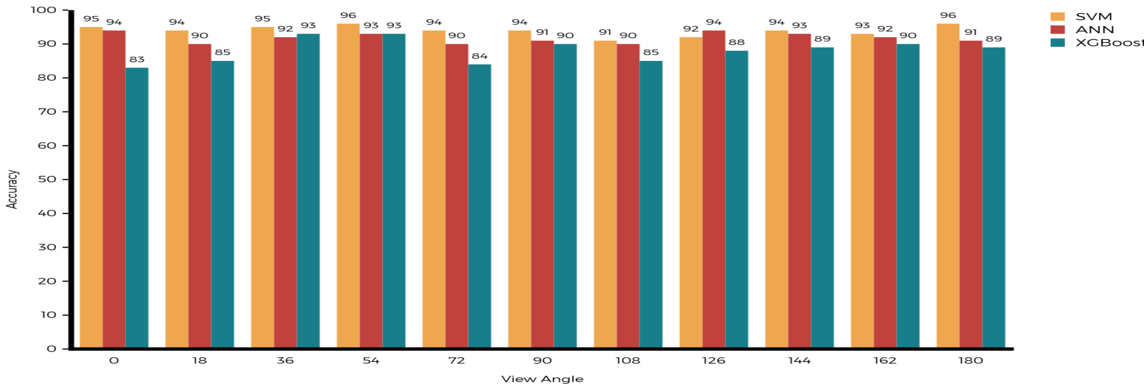

Figure 11. Comparison of accuracy when view angle is kept same and clothing conditions changed

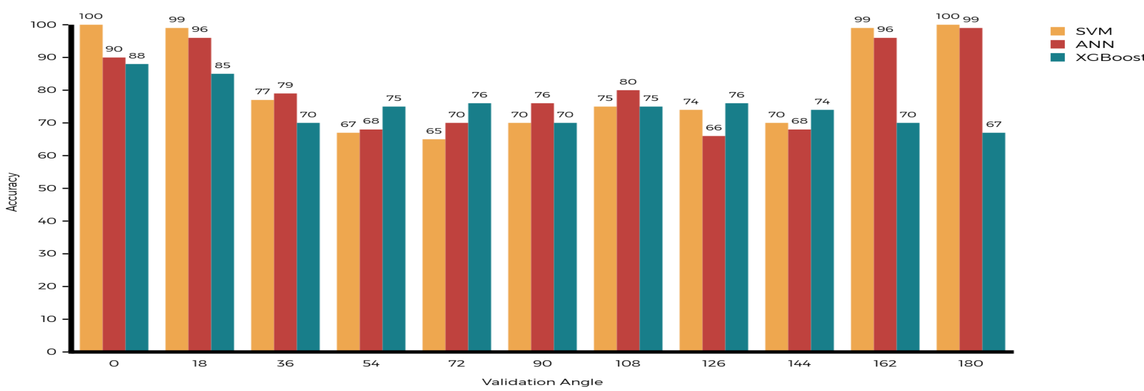

Figure 12. Comparison of accuracy when subject is trained at 0-180 angle and validated at each angle

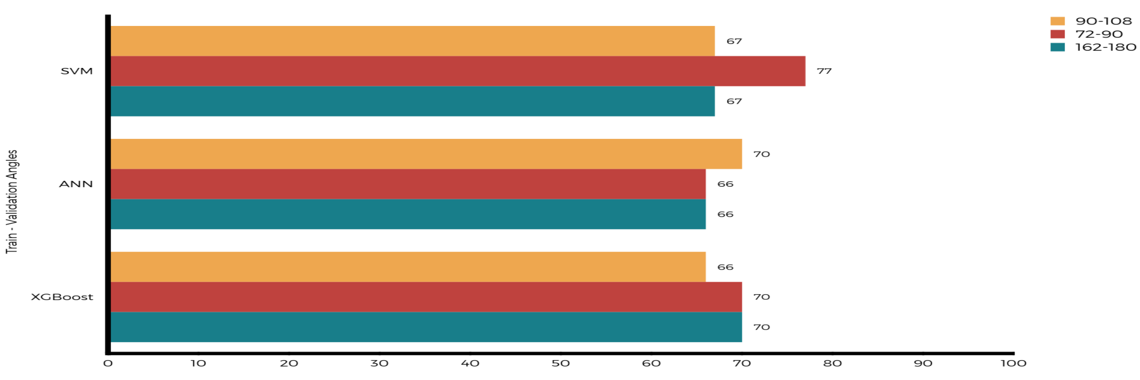

Figure 13. Comparison of accuracy when subject is trained at a specific angle and validated at a different angle

V. Comparison with Existing Approaches

A true comparison for each of the criteria with existing approaches is difficult since almost all approaches have different experimental conditions and have worked on a subset of the criteria which has been presented here. It has been ensured that the datasets used in the comparison are same with CASIA-B used in Cloth invariant and View invariant and CASIA-C used in Speed invariant detection.The accuracy values showed in the Table VIII represent the average accuracy values carried over the different experiment conditions so that uniformity is maintained. We observe that out method almost outperforms each of them except for view invariance where deep learning based methods [25] have the advantage but this approach loses in terms of longer training time and more data required for such instances.

Table VIII
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

VI. Conclusion & 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.

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