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RESEARCH ARTICLE

SURVEY OF CURRENT TRENDS IN HUMAN GAIT RECOGNITION APPROACHES.

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Abstract

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Gait recognition is capable of identifying humans at a distance by inspecting their walking manners. Gait is an emerging biometric which attracts both the researchers and the industry to a greater extend in recent years. This paper presents a survey of different methods used for recognition of a person based on different activities such as walking style, carrying objects, wearing cloths, shoes etc. All recent and effective methods are explained and discussed individually and the comparative study of the methods is also reported.

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Introduction:-

Gait is one of the few biometric features that can be measured remotely without physical contact and proximal sensing, which makes it useful in surveillance applications. Such applications play a decisive role in monitoring high security areas including banks, airports, military bases and railway stations. In the real world, there are various factors, significantly affecting human gait including clothes, shoes, carrying objects, walking surfaces, walking speeds and observed views. A large number of gait recognition methods have been published recently, which can be roughly divided into two categories, model-based methods include “A new view-invariant feature for cross-view gait recognition” and appearance-based method include “Recognizing gaits across views through correlated motion co-clustering”. These methods require a preprocessing of foreground/background segmentation (FG/BG) on a gait video, in order to extract shape contours, silhouettes, skeletons, or body joints for further gait analysis. The model-based methods generally aim to model kinematics of human joints in order to measure physical gait parameters such as trajectories, limb lengths and angular speeds. The appearance-based methods typically analyze gait sequences without explicit modeling of human body structure. These methods have shown their effectiveness on human gait recognition under fixed view. However, they lack a proper methodology to address the problem of view change.

Recently, the research of gait recognition under view change falls into three categories. Methods in the first category [1]-[3] are to construct 3D gait information through a system of multiple calibrated cameras. Then, 2D gait information from any required view is reconstructed from 3D gait information. However, the methods in this category are only suitable for a fully controlled and cooperative multi camera environment such as a biometric tunnel which is costly and complicated. Methods in the second category [4]-[6] are to extract gait feature which is invariant to view change. It is difficult to seek the view-invariant gait feature because the view-dependent information is embedded complexity in gait. The different methods in this category may be developed from completely different perspectives.

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Methods in the third category [7]-[10] rely on learning mapping/projection relationship of gaits across views. The relationship obtained through training will normalize gait features from different views into shared/associated subspaces(s) before gait similarity is measured. The method for Gait Recognition considered in this paper are tested with CASIA A (normal), CASIA B database (normal), USF database (normal) and Virginia University dataset (Abnormal Cerebral Palsy).

Methods for Gait Recognition:-

2.1 View-Invariant Gait Recognition:-

A Gait recognition method “A New View-Invariant Feature for Cross-View Gait Recognition” [11] is studied. In figure 1, figure 1a and figure 1b given below rectangles represent inputs/outputs, while ellipses represent processing steps. Given a probe gait and a galley gait recorded from different views, they are individually processed through the process of view-normalization and feature extraction. Then, their similarity is measured under a common canonical view.

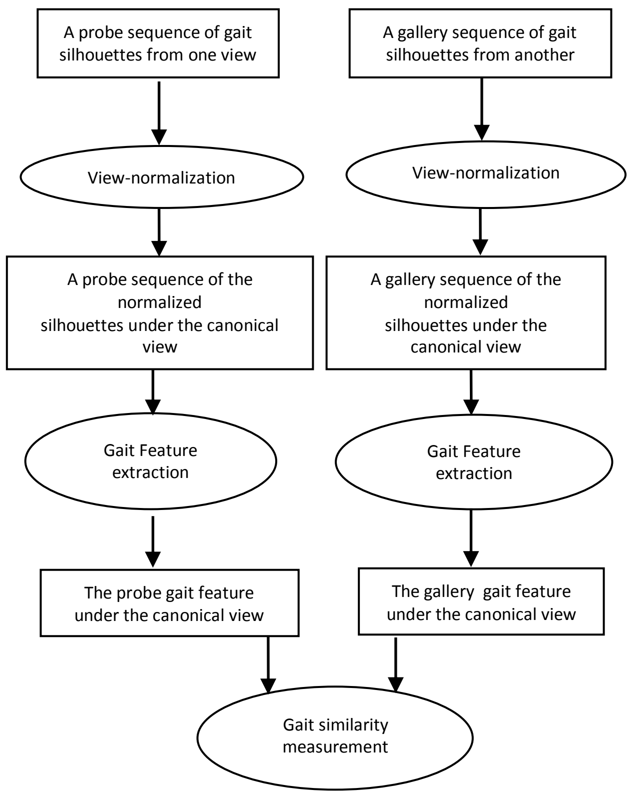

Figure 1:- Framework of view-invariant gait recognition.

A gait silhouette can be extracted from each frame in a video gait sequence [12]. However, some extracted silhouettes are incomplete. Mathematical morphological operations [13] are used for holes remedy and noise elimination. Since gait is a periodic action, it is analyzed within complete walking cycle(s). The method is adopted [9] to estimate gait period of each gait sequence. In the view-normalization process, Gait Texture Image (GTI) is extracted from a sequence of gait silhouettes within a complete walking cycle. It will be the input of low-rank texture optimization. Transform Invariant Low-rank Textures (TILT) is applied [14] on GTI to seek a convex optimization that enables robust recovery of low-rank textures based on domain transformation despite gross sparse errors. In this way, TILT will transform GTI from any view into a common canonical view where the low-rank textures are optimized. Another key component of TILT is sparse error matrix. It is used to eliminate errors/noises caused by corruption, occlusion, or shadow on gait image which may interfere the process of low-rank optimization. The recovered domain transformation is then re-applied to transform each corresponding gait silhouette into the canonical view. The sequence of view-normalized gait silhouettes will be further used in gait recognition procedure.

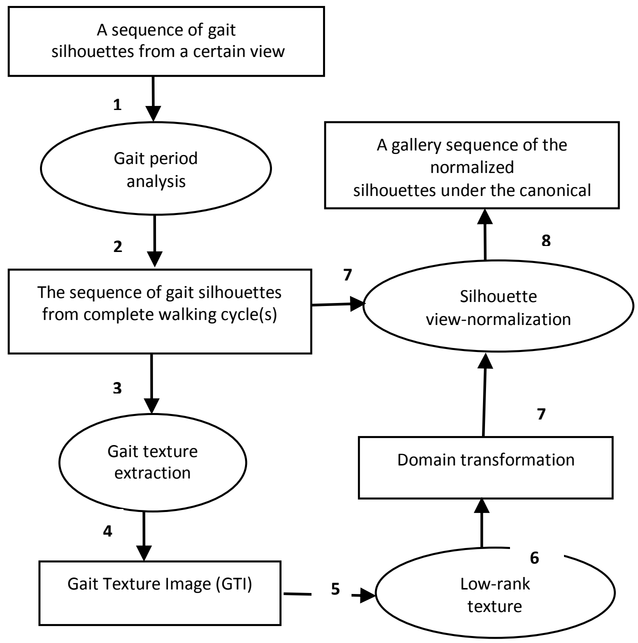

Figure 1a:- View-invariant gait recognition framework of view-normalization. The numbers present the orders of the processes.

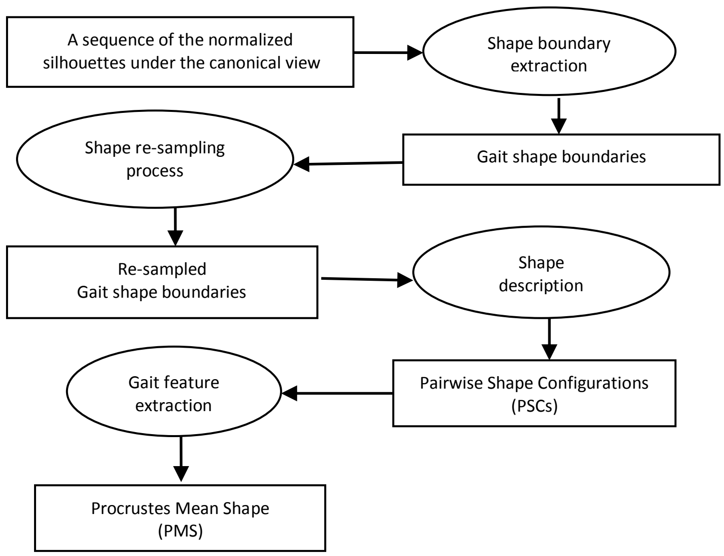

Figure 1b:- View-Invariant gait recognition of gait feature extraction.

As mentioned in the introduction above, to address the challenge remaining from the view-normalization, a scheme of Procrustes Shape Analysis (PSA) is applied [15] for gait feature extraction and similarity measurement. The preprocesses of shape boundary extraction and shape resampling are applied on each view-normalized gait silhouette to generate the resampled shape boundary which will be described using Pairwise Shape Configuration (PSC) [4]. PSC describes a shape using a first-order derivative (i.e., tangent) of the shape boundary. In PSA, Procrustes Mean Shape (PMS) is extracted from a set of PSCs in complete walking cycle(s) as a view-invariant gait feature. PMS is an average shape configuration computed from a given set of shape configurations (i.e., PSCs) by minimizing a sum of Euclidean distances between PMS and each configuration in the set. Then, the similarity between two PMSs of any two gaits from any two views is measured based on Procrustes Distance (PD) under the common canonical view.

The View-Invariant Gait Recognition method is compared with other seven existing methods in the second category including Gait Energy Image [18], View rectification [5], Centroid Shape Configuration (CSC) + Procrustes Shape Analysis [15], Pairwise Shape Configuration + Procrustes Shape Analysis [4] + Transform Invariant Low-rank Textures + Gait Energy Image, Transform Invariant Low-rank Textures + Centroid Shape Configuration + Procrustes Shape Analysis and Transform Invariant Low-rank Textures + Pairwise Shape Configuration + Procrustes Shape Analysis. The better performance of the View-Invariant Gait Recognition is given below in Table 1.

Table 1:- Performance of View-Invariant Gait recognition (%) in the second category

Probe view (θ_p)	54^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	98	79	69	54	59
Probe view (θ_p)	72^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	79	98	97	81	57
Probe view (θ_p)	90^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	69	97	98	93	56
Probe view (θ_p)	108^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	49	82	94	97	80
Probe view (θ_p)	126^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	63	55	56	80	98

The View-Invariant Gait Recognition method is compared with other four existing methods in the third category including Fourier Transform – Singular Value Decomposition [19], Gait Energy Image – Singular Value Decomposition [9], Gait flow Image + Canonical Correlation Analysis [7] and Gait Energy Image + Support Vector Regression [8]. The better performance of the View-Invariant Gait Recognition is given below in Table 2.

Table 2:- Performance of View-Invariant Gait recognition (%) in the third category

Probe view (θ_p)	54^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	98	77	68	54	56
Probe view (θ_p)	72^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	79	98	96	81	54
Probe view (θ_p)	90^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	70	97	98	93	55
Probe view (θ_p)	108^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	47	80	95	97	78
Probe view (θ_p)	126^0				
Gallery view (θ_g)	54^0	72^0	90^0	108^0	126^0
Recognition rate (%)	58	53	55	77	98

The View-Invariant Gait Recognition method is compared with other eight existing methods in the experiment A of the USF gait database including Baseline [12], population Hidden Markov Model [20], Gait Energy Image [18], Motion Silhouette Contour Template + Static Silhouette Templates [21], Hidden Markov Model [22], Eigen feature

[23], Pose Energy Image + Linear Discriminant Analysis [24] and Compact Feature Extraction Transforms [25]. The better performance of the View-Invariant Gait Recognition is given below in Table 3.

Table 3:- Performance of View-Invariant Gait recognition (%) in the experiment A of the USF Gait Database. In Experiment A, Probe and Gallery Gaits are recorded from different cameras L and R, respectively. The camera's lines of sight are verged at approximately 30

Recognition rate (%)	85

2.2 Cross View Gait Recognition:-

A Gait recognition method "Recognizing Gaits across views through Correlated Motion Co-Clustering" [16] is studied. In figure 2 given below rectangles represent inputs/outputs, while ellipses represent processing steps. Given a training dataset containing individual gaits from two different views, our frame work contains three main steps in the training process, namely gait partitioning model using bipartite graph multipartitioning, Correlation optimization using Canonical Correlation Analysis (CCA) and view normalization using linear approximation.

The first step is to learn gait partitioning model for cross view gait recognition. A bipartite graph is used to model correlations between gaits from two different views, then apply bipartite graph multipartitioning to co-cluster gaits across the two views into multiple groups each of which contains one segment of gait from one view and another segment of gait from another view. Inside each group, it can assure that these two segments are most correlated and have most similar gait information but from different views.

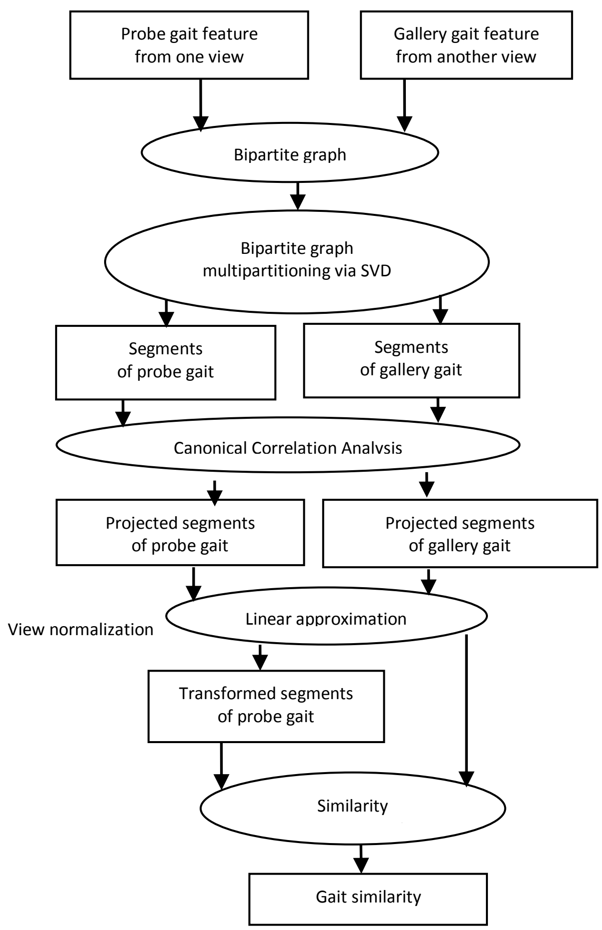

Figure 2:- Framework for cross-view gait recognition.

The second step is to maximize the correlation between gaits from different views. In each group mentioned above, we apply CCA to project the corresponding segments from the two views into two subspaces where their linear correlation is maximized. Such subspaces are called CCA subspaces. The final step is to learn a linear approximation model to linearly transform the corresponding segments of gaits from the two CCA subspaces into the same CCA subspace.

In the testing phase, probe and gallery gaits are co-clustered into segments using the relevant (i.e., regarding their views) trained gait partitioning model. Then, the correlation optimization model (i.e., CCA projection matrices) and the linear approximation model which have been obtained in the training process, are applied on the gait segments to project them onto a common CCA subspace where the similarity measurement can be carried out properly.

The Cross-View Gait Recognition method is compared with other six existing methods including Baseline [12], View rectification [5], Gait Energy Image – Canonical Correlation Analysis [7], Gait Energy Image – Singular Value Decomposition [9], Gait Energy Image – Support Vector Regression [8] and Fourier Transform – Singular Value Decomposition [19]. The better performance of the Cross-View Gait Recognition is given below in Table 4.

Table 4:- Performance of Cross-View Gait Recognition (%)

Probe view (θ_p)	0^0									
Gallery view (θ_g)	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0
Recognition rate (%)	85	47	26	25	28	25	27	37	68	95
Probe view (θ_p)	54^0									
Gallery view (θ_g)	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0
Recognition rate (%)	24	65	97	95	63	53	48	34	23	22
Probe view (θ_p)	90^0									
Gallery view (θ_g)	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0
Recognition rate (%)	18	24	41	66	96	95	68	41	21	13
Probe view (θ_p)	126^0									
Gallery view (θ_g)	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0
Recognition rate (%)	25	29	35	49	60	78	98	98	75	22

The Multi-View To One-View Gait Recognition method is compared with other three existing methods including: Gait Energy Image – Singular Value Decomposition [9], Gait Energy Image – Support Vector Regression [8] and Fourier Transform – Singular Value Decomposition [19]. The better performance of the Cross-View Gait Recognition is given below in Table 5.

Table 5:- Performance of Multi-View to One–View Gait Recognition (%)

Scenario	Two-view to one-view	Cross-view	Cross-view
Gallery view (θ_g)	54^0		
Probe view (θ_p)	36^0, 72^0	36^0	72^0
Recognition rate (%)	99	92	92
Gallery view (θ_g)	54^0		
Probe view (θ_p)	18^0, 90^0	18^0	90^0
Recognition rate (%)	83	53	66
Gallery view (θ_g)	54^0		
Probe view (θ_p)	0^0,108^0	0^0	108^0
Recognition rate (%)	57	26	44
Gallery view (θ_g)	126^0		
Probe view (θ_p)	108^0,144^0	108^0	144^0
Recognition rate (%)	57	26	44
Gallery view(θ_g)	126^0		
Probe view(θ_p)	90^0,162^0	90^0	162^0
Recognition rate (%)	90	68	59
Gallery view(θ_g)	126^0		
Probe view(θ_p)	72^0,180^0	72^0	180^0
Recognition rate (%)	60	47	34

The Cross-View Gait Recognition method is compared with other eight existing methods in the experiment A of the USF gait database including Gait Energy Image [18], Motion Silhouette Contour Template + Static Silhouette

Templates [21], Population Hidden Markov Model [20], Pose Energy Image + Linear Discriminant Analysis [24], University of South Florida [12], Hidden Markov Model [22] and Compact Feature Extraction Transforms [25]. The better performance of the View-Invariant Gait Recognition is given below in Table 6.

Table 6:- Performance of Cross-View Gait Recognition (%) in Clustered Outdoor Environment using the experiment A of the USF Gait Database

Recognition rate (%)	89

The Cross-View Gait Recognition method is compared with other three existing methods including Gait Energy Image – Canonical Correlation Analysis [7], Gait Energy Image – Support Vector Regression [8] and Gait Energy Image – Singular Value Decomposition [9]. The better performance of the Cross-View Authentication is given below in Table 7.

Table 7:- The Performance (%) of Cross-View Gait Authentication method θp denotes Probe view. θg denotes Gallery view

	Θ_g										
θ_p	0^0	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0
0	91	79	41	26	27	27	26	37	34	65	86
54	22	59	91	92	89	57	45	41	27	18	16
90	11	21	37	56	86	93	89	61	42	23	11
126	24	25	31	41	58	72	88	91	84	68	17

2.3 Recognizing Gaits on Spatio-Temporal Feature Domain:-

A Gait recognition method “Recognizing Gaits on Spatio-Temporal Feature Domain” to extracts and recognizes gait feature from a raw video sequence on a spatio-temporal feature domain without any pre-processing on the video [17] is studied. In figure 3 given below rectangles represent inputs/outputs, while ellipses represent processing steps.

Given a Probe gait and a Gallery gait dataset, gait recognition is to find the best matched identity of the probe gait against the other gaits in the gallery dataset. First, Spatio-Temporal Interest Points (STIPs) are detected from a gait video individually. STIPs provide compact and abstract representations of patterns in each gait video, which are local structures in spatio-temporal domain where image values have significant local variations in both space and time. These variations are linked to significant movements of human gait patterns in a video. Therefore, STIP is an interest point of a dominant walking pattern, which is used to represent characteristics of each individual gait.

Second, Histogram of Image Gradient (HOG) and Histogram of Optical flow (HOF) are used to compute a descriptor of each STIP. They are applied on a 3D video patch (i.e. width * height * time) in a neighborhood of each detected STIP. A concatenation of HOG and HOF features are then used as a STIP descriptor. It will describe walking patterns around the interest point in space and time.

Third, Bag-of-Words (BoW) is used to extract a gait feature by applying on the detected STIP descriptors in each gait video. Then the simple but widely adopted Euclidean distance is used to measure the dissimilarity between any two gait features, and Nearest Neighbor is used as a classification method. It can be seen that, this method is also does not rely on any foreground/background segmentation. This method is more robust to partial occlusions caused by many real-world factors such as carrying a bag and varying a cloth type.

The Gait Recognition method on Spatio – Temporal Feature Domain is compared with baseline [26] method in the Experiment set A. The better performance of the Gait Recognition method on Spatio – Temporal Feature Domain is given below in Table 8.

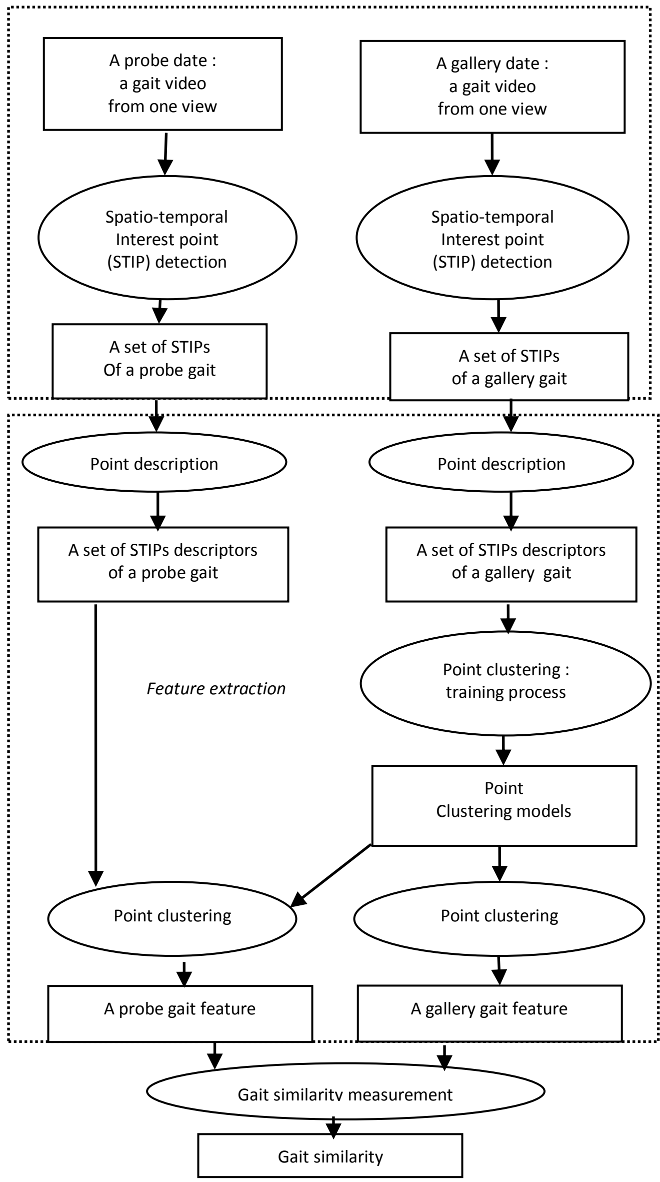

Figure 3:- Framework of gait recognition on a spatio-temporal feature domain.

Table 8:- Performance of Gait Recognition (%) on Spatio -Temporal Feature Domain on the Experiment Set A

(Gallery,Probe)	Recognition rate (%)
(0^0,180^0)	36.7
(0^0,0^0)	91.1
(0^0,18^0)	39.5
(18^0,0^0)	23.9
(18^0,18^0)	91.0
(18^0,36^0)	39.7
(36^0,18^0)	38.8
(36^0,36^0)	92.3
(36^0,54^0)	43.4
(54^0,36^0)	39.5
(54^0,54^0)	95.3
(54^0,72^0)	34.9

$(72^0,54^0)$	42.3
$(72^0,72^0)$	95.7
$(72^0,90^0)$	84.0
$(90^0,72^0)$	86.3
$(90^0,90^0)$	95.4
$(90^0,108^0)$	83.3
$(108^0,90^0)$	86.4
$(108^0,108^0)$	94.1
$(108^0,126^0)$	52.0
$(126^0,108^0)$	50.3
$(126^0,126^0)$	95.2
$(126^0,144^0)$	37.8
$(144^0,126^0)$	42.6
$(144^0,144^0)$	94.8
$(144^0,162^0)$	8.2
$(162^0,144^0)$	7.5
$(162^0,162^0)$	94.2
$(162^0,180^0)$	6.6
$(180^0,162^0)$	46.9
$(180^0,180^0)$	94.1
$(180^0,0^0)$	48.0
Average	61.0

The Gait Recognition method on Spatio – Temporal Feature Domain is compared with baseline [26] method in the Experiment set B. The better performance of the Gait Recognition method on Spatio – Temporal Feature Domain is given below in Table 9.

Table 9:- Performance of Gait Recognition (%) on Spatio - Temporal Feature Domain on the Experiment Set B

(Gallery,Probe)	Recognition rate (%)
$(0^0,180^0)$	2.4
$(0^0,0^0)$	26.2
$(0^0,18^0)$	5.6
$(18^0,0^0)$	6.5
$(18^0,18^0)$	29.0
$(18^0,36^0)$	15.7
$(36^0,18^0)$	8.1
$(36^0,36^0)$	34.3
$(36^0,54^0)$	16.9
$(54^0,36^0)$	13.3
$(54^0,54^0)$	36.7
$(54^0,72^0)$	13.3
$(72^0,54^0)$	14.9
$(72^0,72^0)$	42.7
$(72^0,90^0)$	26.2
$(90^0,72^0)$	33.1
$(90^0,90^0)$	52.0
$(90^0,108^0)$	21.4
$(108^0,90^0)$	32.7
$(108^0,108^0)$	39.1
$(108^0,126^0)$	18.5
$(126^0,108^0)$	21.8
$(126^0,126^0)$	39.9
$(126^0,144^0)$	15.3

$(144^0,126^0)$	19.8
$(144^0,144^0)$	33.5
$(144^0,162^0)$	2.4
$(162^0,144^0)$	5.0
$(162^0,162^0)$	31.5
$(162^0,180^0)$	7.5
$(180^0,162^0)$	11.2
$(180^0,180^0)$	23.0
$(180^0,0^0)$	8.1
Average	21.4

The Gait Recognition method on Spatio – Temporal Feature Domain is compared with baseline [26] method in the Experiment set C. The better performance of the Gait Recognition method on Spatio – Temporal Feature Domain is given below in Table 10.

Table 10:- Performance of Gait Recognition (%) on Spatio - Temporal Feature Domain on the Experiment Set C

(Gallery,Probe)	Recognition rate (%)
$(0^0,180^0)$	24.3
$(0^0,0^0)$	79.4
$(0^0,18^0)$	18.4
$(18^0,0^0)$	15.1
$(18^0,18^0)$	73.8
$(18^0,36^0)$	39.9
$(36^0,18^0)$	22.6
$(36^0,36^0)$	77.0
$(36^0,54^0)$	24.2
$(54^0,36^0)$	19.8
$(54^0,54^0)$	71.8
$(54^0,72^0)$	22.2
$(72^0,54^0)$	16.5
$(72^0,72^0)$	73.0
$(72^0,90^0)$	39.5
$(90^0,72^0)$	49.6
$(90^0,90^0)$	60.9
$(90^0,108^0)$	33.1
$(108^0,90^0)$	42.7
$(108^0,108^0)$	71.0
$(108^0,126^0)$	26.2
$(126^0,108^0)$	11.5
$(126^0,126^0)$	75.4
$(126^0,144^0)$	21.0
$(144^0,126^0)$	33.9
$(144^0,144^0)$	76.2
$(144,162^0)$	2.8
$(162^0,144^0)$	5.6
$(162^0,162^0)$	71.8
$(162^0,180^0)$	10.5
$(180^0,162^0)$	19.7
$(180^0,180^0)$	71.4
$(180^0,0^0)$	34.7
Average	41.4

The Gait Recognition method on Spatio – Temporal Feature Domain is compared with fifteen existing methods including : Gait Energy Image + Two Dimensional Locality Preserving Projection [27], Enchanced Gait Energy Image + Two Dimensional Locality Preserving Projection [27], The baseline method [26], Gait Energy Image +

Component and Discriminant Analysis [28], Right Fore + Feature Subset Selection [29], Right Fore + Subset Selection + Component and Discriminant Analysis [29], Right Fore + Subset Selection + Multiple Discriminant Analysis [29], M_j + ACDA [30], Left Fore + AVG [31], Left Fore + Dynamic Time Warping [31], Left Fore + oHidden Markov Model [31], Left Fore + iHidden Markov Model [31], Gait Enery Image + Principal Component Analysis + Linear Discriminant Analysis[32], Gait Pal and Pal Entropy [33] and Gait Entropy Image. The better performance of the Gait Recognition method on Spatio – Temporal Feature Domain is given below in Table 11.

Table 11:- Performance of Gait Recognition (%) on Spatio -Temporal Feature Domain under changes of Clothing and Carrying Condition

Probe - Gallery	nm-nm	bg-bg	cl-cl	bg-nm	cl-nm	bg-cl	Average
Recognition rate (%)	95.4	73.0	70.6	60.9	52.0	29.8	63.6

2.4 Gait Recognition System using Modified Independent Component Analysis:-

A Gait recognition method Modified Independent Component Analysis (MICA) is studied. The MICA method based Gait Recognition System consists of three main phases i) Human detection and tracking ii) Feature extraction and iii) Feature selection and Training or Recognition using MICA. Initially, the moving objects (human) are segmented and tracked in each frame of the given video sequence (tracking). The second phase extracts the binary silhouette from each frame and maps the 2D silhouette image into a 1D normalized distance signal (feature extraction). The shape changes during the movement are transformed into a sequence of 1D signal, deriving the temporal changes of gait pattern. On these 1D signals, MICA is performed to compute the salient independent components of gait features during the training phase. Based on the similarity between the reference patterns and the test sample in the parametric eigenspace, the gait recognition is achieved. The algorithm of MICA is detailed in the figure 4 given below.

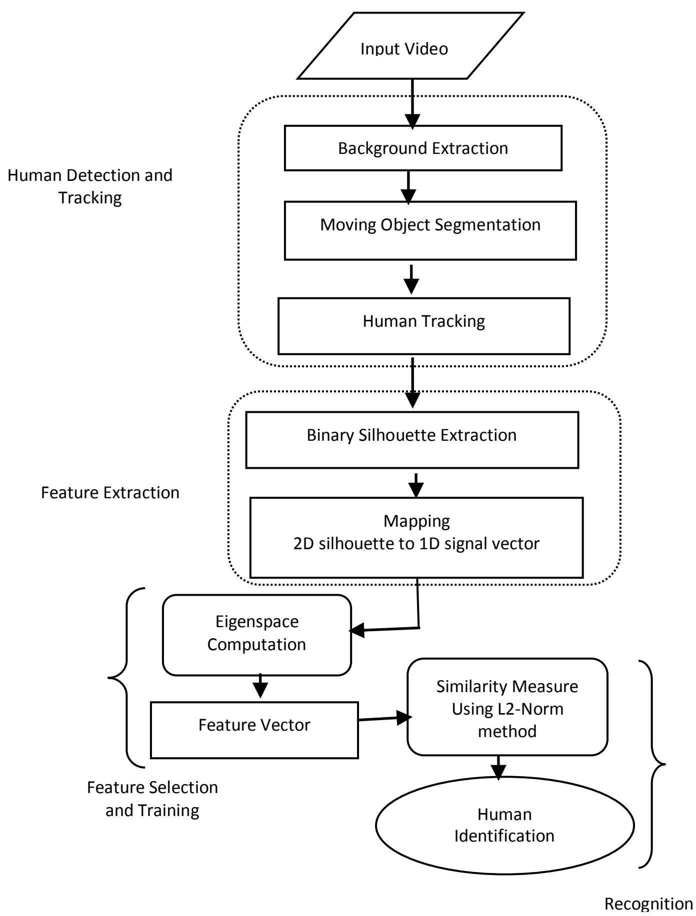

Figure 4:- Block diagram of Gait Recognition System using MICA.

A Gait recognition method "On the Analysis and Application of Gait Recognition System" is compared with other two existing methods including Principal Component Analysis and Independent Component Analysis. The better performance of the Gait Recognition system method MICA is given below in Table 12.

Table 12:- Performance of Gait Recognition system MICA

Data set	False Acceptance Rate (%)	False Rejection Rate (%)
Angle view	MICA	MICA
0o , Left	1.2769	2.8986
0o , Left	1.6571	2.3930
45o , Left	2.0124	1.9124
45o , Left	1.8139	1.4234
90o , Left	1.0235	1.5615
90o , Left	2.8766	2.906

A Gait recognition method MICA is compared with other five existing algorithms including: Silhouette Template matching Based [35], Self-Similarity Based [36], Baseline based [37], Silhouette Analysis-Based Recognition [38] and Model Based approach [39]. The better performance of the Gait Recognition system method on MICA is given below in Table 13

Table 13:- Performance of Gait Recognition system MICA

Algorithm	Top 5%	Top 10%
MICA	98.97	100

2.5 Gait Recognition System using Extreme Learning Machine:-

A Gait recognition method Extreme Learning Machine (ELM) is studied. The execution of Gait classifier using ELM is as follows. First, the salient gait features are extracted with suitable pre-processing. The extracted features are subjected to ranking and normalization using Principal Component Analysis and t-test methodologies prior to classification. The ELM is utilized as gait classifier considering its high accuracy rate with reduced computational complexity and time. The salient features of ELM classifier are prevailing the limitation of over fitting of samples during training phase and the problem of local minima as the case with many Artificial Neural Network (ANN) based learning methods, learning with minimal hidden nodes using a simple and compact network structure, converging faster with less training time. The ELM works well with greater accuracy in classification and detection of abnormal gait. The algorithm of ELM is detailed in figure 5 given below.

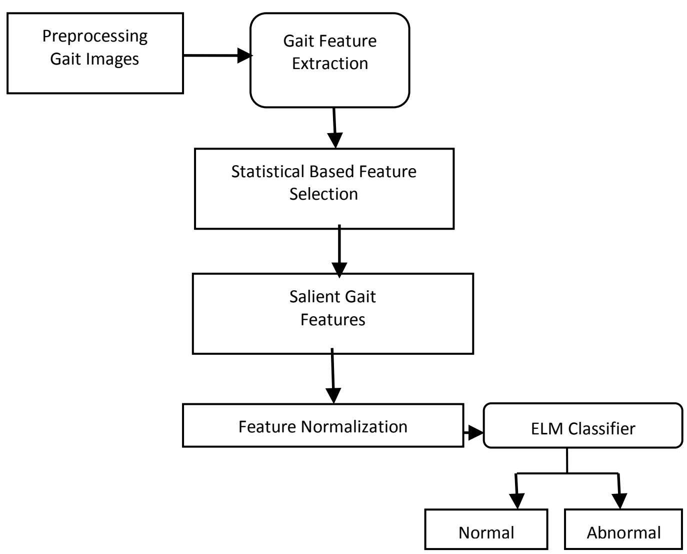

Figure 5:- Block Diagram for Gait Classification using ELM.

A Gait recognition method ELM is compared with Support Vector Machine. The better performance of the Gait Recognition system method ELM is given below in Table 14.

Table 14:- Performance of Gait Recognition system ELM with Various Normalization Technique

Algorithm		Recognition rate (%)
ELM	Std	97.56
	PCA	97.49
	T-test	99.03

A Gait recognition method ELM is compared with Support Vector Machine. The better performance of the Gait Recognition system method on ELM is given below in Table 15.

Table 15:- Performance of Gait Recognition system ELM with Total Training Time

Algorithm	Time (in sec)
ELM	125

Conclusion:-

In this paper we analyzed five advance methods for human gait recognition. They are View-Invariant Gait Recognition method, Cross View Gait Recognition method, Recognizing Gaits on Spatio-Temporal Domain method, Gait Recognition System using Modified Independent Component Analysis method and Gait Recognition System using Extreme Learning Machine method. The View-Invariant Gait Recognition method produces the recognition rate of 98%. It extracts (preprocessing) gait silhouette from each frame in video gait sequence. The angles of probe view and gallery view are same or different. It considers only normal walking cycle. The Cross View Gait Recognition method produces the recognition rate of 91%. The Gait Energy Image is constructed (preprocessing) by sequence of aligned gait images in a window of complete walking cycle(s). The angles of probe view and Gallery view are different. The Gait Recognition System using Modified Independent Component Analysis method produces the recognition rate of 98.97%. It extracts foreground human subject (preprocessing) from the original image frames. It considers only normal walking cycle. The angles are only 0^o, $45^o$and 90^o in probe view and gallery view. The Gait Recognition System using Extreme Learning Machine method produces the recognition rate of 97.56%.

There is a gait feature extraction process from the video of the walking subject. It considers both normal and abnormal gait sequences with subject age, leg length, cadence (steps), stride length. The Recognizing Gaits on Spatio-Temporal Domain method produces the recognition rate of 63.6%. It constructs a new gait feature directly from a raw video without a preprocessing of foreground-background segmentation. The angle of probe view and gallery view are same or different caused by carrying bag and clothing.

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