View-Invariant Person Identification by Orthogonal View Gait Signature and Fusion of Classifiers

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***Abstract*—In this paper, we proposed the use of three orthogonal views of gait signature for view-invariant person identification system. We also experimented the fusions of classifiers in order to improve the recognition performance. Two classifiers used corresponding to two LDA spaces. The first classifier used for angle classification followed by second classifier for person identification. The proposed mechanism of selective kNN (s-kNN) has boosted the recognition performance and found very effective. We got 97.07% maximum rank-1 angle classification accuracy and 93% maximum rank-1 person identification accuracy.**

***Index Terms*—Gait Bio-metrics, View-Invariant, Linear Discriminant Analysis.**

I. INTRODUCTION

BIO-METRICS is considered as one of the successful applications of pattern recognition and has been widely used in several domains, such as authentication in highly restricted areas, attendance record in office premises, citizenship identification-verification and in the field of forensics. These bio-metric systems are mostly based on modalities like fingerprint, iris and face. However, commonly used bio-metric recognition systems usually operates in constrained acquisition scenarios and under rigid protocols. This scenario motivates researchers to explore the development of *non-cooperative* systems [1]. In the bio-metrics application which requires distant data (sample) capture, it becomes almost impossible to acquire the samples, e.g. fingerprints or iris. Besides popular bio-metric modalities like fingerprint, face and iris; activity based biometrics [2] can add the value to the identification process. Especially, in the case of bio-metric applications where far distant data capture process is involved. In such scenario, gait is the useful bio-metric trait. The gait recognition is based on the activity of person, namely walking. The gait activity is the composition of motion trajectories and coordinated movements of the various body parts and mostly suffer from the co-variate conditions.

There are several advantages of the gait based person identification over the conventional bio-metrics such as:

1) Most suitable for non-cooperative and unconstrained bio-metric process.
2) Walking normally happens with subject without demanding from it and hence it's a natural sample.
3) Unlike face and iris, gait can be captured from multiple angle / views, which makes data acquisition more informative.
4) Even works well with low quality video data.
5) No fine details are required as in face, iris or fingerprint based recognition system.

Though, the gait recognition has been researched for long time, there are challenges such as:

1) In some situations like restaurants, shopping malls walking doesn't always happen.
2) In crowded places, walking can be done in restrictive manner, leading to a change in gait cycle and affecting bio-metric process negatively.
3) Particular place or situation may have predictable activity to be happened more frequently and hence can be exploited e.g. in college / department canteen, shaking hands and paying bill after taking out wallet can be more dominant activities.
4) Gait sample may not give accurate shape profiles with loose clothes.
5) Gait can be affected by various co-variate factors like speed, cloths, surface of walking, illness, drunkenness, pregnancy.
6) Viewing angle effect plays vital role in multi view system.

In the unconstrained environment and distant data capture based bio-metric system, fingerprint, iris and face recognition could not be the right choice. Comparatively gait, comprised of motion trajectories of various body parts, have a potential to get captured properly from relatively far distance. It doesn't need systematic data capture process and only camera installation is required, where subjects are not necessarily be informed, which makes the identification process protocol free.

II. LITERATURE OVERVIEW

Gait recognition have attracted researchers in recent years because of it's various advantages as discussed earlier. The gait recognition methods can be broadly categorized as model free and model based methods. In model free methods, the features for recognition are directly extracted from the spatial domain and in model based methods the features are extracted by modelling the human body by some mathematical means.

a) Model Free Approach: This approach directly extract features from the spatial domain like [3], [4], which use Procrustes shape analysis. After extracting silhouette, authors apply Procrustes shape analysis to obtain mean shape as gait signature. Whereas in [5], gait energy image obtained

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from the sequence of gait images used for recognition as it preserves the temporal information. In [6], author use fusion of multiple gait cycles for recognition. The gait cycle is estimated by calculating auto correlation. From each gait cycle, they extract gait energy image and motion silhouette image for classification and recognition. The wavelet analysis is also used in gait recognition [7], [8]. In [7], author utilize the property of radon transform and Haar wavelet transform to extract horizontal and vertical features. Another wavelet based approach [8] use time-frequency analysis of extracted gait cycle. After wavelet decomposition they calculate mean, standard deviation, skewness and kurtosis of each sub-band. A simple city block distance measure is used for classification. Methods based on image geometry transformations have also been proposed [9], which is independent of view angle. In [10], author use height and stride length as soft bio-metrics in a probabilistic framework for gait recognition.

In a recent GEI based method [11], horizontal motion estimated by computing Shanon entropy of each row of GEI. Further, group Lasso learning algorithm is used to segment the motion based vector into blocks of similar motion values. The body part, which has highest average motion vector value is selected as a feature vector.

b) Model Based Approach: In this approach, the various features can be extracted by modelling human body. An initial model based attempt for gait-based recognition in a spatio-temporal (XYT) volume is done by Niyogi and Adelson [12]. A 5-stick model is used to generate gait pattern in XYT which is further used for classification. In [4], Procrustes analysis is used for static feature extraction and the dynamic features extracted by modelling the human body by truncated cone for various body parts and sphere for head. In [13], bulk motion, shape and articulated motion estimation was done by gait motion model adaptation. In [14], authors proposed a fusion based method, in which they divide silhouette into 7 parts and fit ellipse in those regions. They extract various parameters of ellipse. All these parameters of 7 regions constitute a novel feature vector. Whereas, [15] use fusion of several features for recognition like area, gravity center and orientation of each body part.

Recent development in model based gait recognition emphasizes modelling the multi-view gait sequences by using view normalization techniques. Worapan et al [16]–[19] use View Transformation Model (VTM) to normalize probe and gallery view in the same direction. The method presented in [16] is SVD based VTM approach and [17] is SVR based. The problem like data redundancy in their earlier methods is improved in [18]. Whereas, [19] uses MLP to construct VTM model for multi-view and cross-view gait recognition.

c) View-Invariant Approach: The view-invariant gait identification is relatively new research area. The most desirable property of this approach is to identify test subject walking at any arbitrary view angle. It uses either any one of two or both approaches as discussed earlier. i. e. model free or model based. In [20], a viewpoint independent method is proposed which requires single camera without calibration and prior knowledge of subject / person pose. The test subject is identified by projecting the limb motion of subject which is walking at arbitrary view angle onto the lateral / side-view plane. First, they do marker less joint estimation followed by reconstruction method for viewpoint rectification. In [21], author proposes a joint subspace learning method for view-invariant gait recognition. First, radon transform based energy images of sequences extracted and further they perform canonical correlation analysis to get representation coefficients, which they use as view-invariant features. Next, they obtain prototypes of various views by using PCA. The samples of different views represented as linear combination of these prototypes and then extract the coefficients which further used for recognition. Whereas in [22], author extracts a gait texture image which preserves gait information of a particular view angle. Further, they apply transform invariant low rank textures to project gait information of arbitrary view on to sagittal plane. In a recent paper [23], gait flow image extracted by Lukas-Kanade method as dynamic feature, head and shoulder mean shape by Procrustes shape analysis as static feature. In identification phase, they compute view angle or walking direction of test subject along with the static and dynamic features. A simple Euclidean distance classifier is used to find similarity measure between test and gallery images.

In [24], complete canonical correlation analysis is used to investigate correlation between two gait features considering normal walking sequences. They randomly select a sample for training and testing on different view angle. In [25], the authors extract width of 4 different sub regions of silhouette which then combined to construct gait signature. They considered all view angle and 3 normal walking sequences for training and each view angle taking one view at a time and 3 normal walking sequences for testing. A robust view invariant approach is proposed by [26], in which view angle is classified using entropy of the limb region of GEI and person identification is done by using multi scale shape analysis.

III. Overview of the Proposed Method

Gkalelis et. al. decomposes motion in activity as a combination of basic movement patterns, the so-called dynemes, calculated from fuzzy C-means (FCM) clustering method as described in [27]. The number of dynemes are decided from the leave-one-out cross-validation procedure, which is an extension of the method described in [28]. Their algorithm combines fuzzy vector quantization (FVQ) of [29] using posture vectors (column/row wise one-dimensional vector of binary silhouettes) and Linear Discriminant Analysis (LDA) to discover the most discriminating dynemes as well as represent and discriminate the different human movements in terms of these dynemes. This method was extended in [30], [31] and [32] for the multi-view videos. The training and testing videos were captured by multi-view cameras and dynemes were calculated from all the videos irrespective of their view angles to make the motion representation and their classification view independent.

Since, FCM or CM based clustering gives vector quantization of the posture vector description, it is possible that discriminative information may loss. This can be overcome using sparse coding of posture vectors as done in [33]. Hence, in this experiment, we use sparse coding of posture vector. The objective criterion and optimization of sparse coding were formulated as given in [34] and [35]. The results with mean and max pooling of feature representation from the sparse codebook were studied and found that, mean pooling based representation is most suitable. This approach compared with the large margin nearest neighbor (LMNN) [36] and found superior to it.

In this work, we use CASIA multi-view gait databases B [40] which consists of 124 subjects. Each subject is depicted in 10 instances (video sequences) with various co-variates like; normal/slow walking ($nm-01$ to $nm-06$), with bag ($bg-01$, $bg-02$), with coat ($cl-01$, $cl-02$). The instances are captured at 11 different viewing angles (0^o, ..., 180^o). Thus, the database consists of $124 \times 10 \times 11 = 13,640$ gait instances (video sequences). In this experiment, we use 6 instances i.e. normal and slow walking sequences.

We have experimented gait recognition using LDA with different number of training (K) and testing (S) sample's set (instances/sequences). The performance in form of recognition accuracy is shown in the Table I. Figure 1 shows it's graphical plot. It can be inferred that the reduction in the number of training samples generates over-fitting issue in the classifier and hence degrades the performance. Another hypothesis generated here by experimentation is that, performance with particular angle gait sequence is dependent on whether that angle samples are included in the training or not. In unconstrained environment, where subject is expected to walk in any direction yielding gait sequence in any angle, the issue of inclusion of particular angle becomes vital with two constraints. First, having the the number of all angle or regular discrete angles in the range of 0 to 180 degree in training can load the system resources like memory and computational power. Secondly, it can be unmanageable to capture gait sequences from subjects in all possible angle views. The performance across the possible angles with different set angles in training is shown in the Table II and Figure 2 shows it's plot. It is observed that, non-inclusion of particular angle-view gait sequences in training gives abrupt degradation by more than 90% fall in rank-1 accuracy. More recently there are some attempts as reported in [37], [38], [39] and [2], where classifier is trained with the set of instances which includes all the view angle sequences from each subject.

IV. Proposed Methodology

The main complexity of the activity based recognition lies in three components, namely, 1) Dynemes Calculation, 2) Feature Extraction and 3) Classification. Our proposed approach use three orthogonal views in multi-view capture and sparse coding of posture vectors. The dynemes were used to calculate its histogram using distance measure and its fuzzification as described in [2]. The training features can be obtained by projecting training instances on the LDA subspace to maximize the discrimination in inter-class samples and minimize the intra-class variance. However, in doing so, kNN training instances with different gait-angles or view angles can give the enough variation in their features to overlap

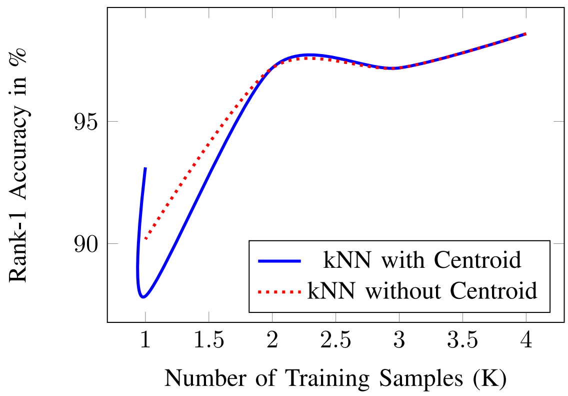

Fig. 1. Plot of Performance with different values of Training Samples -K (CASIA B)

with space of other classes. To overcome this problem, we proposed to have two kNN classifiers corresponding to the two LDA subspaces in series. The first LDA subspace is to have projection from gait samples for discriminating them in different view-angle classes irrespective of the subject identity. The view angle is obtained from the first LDA subspace using kNN classifier trained by same training samples as used in dynemes calculation. The second LDA subspace, obtained with subjects classes irrespective of their view-angles (gait-angles), is then used to project gait samples for testing and training. The histogram features extraction and two LDA subspace construction are shown in Figure 3. While using kNN classifier on the test samples, test samples are compared only with the samples corresponding to the view angle obtained from angle based classifier. Thus, the kNN classifier selects the kNN samples from training instances based on the angle of the test gait sequence, as determined from the first classifier. This method is different from the framework proposed in [2] in the sense that, former employs the fusion of two classifiers in parallel, while later one uses two classifiers in series. However, the upper bound of performance in our approach is limited by the performance given by first classifier, which outputs the view-angle class and hence, it becomes critical component in the recognition system. This classifier is expected to give more than 95% performance in typical case, additionally its output decision can be validated by additional strategy. At present, this validation strategy is kept out of scope of this paper as angle identification classifier used here is certain to provide recognition accuracy of more than 97%. The system block diagram of our approach based on two classifiers in series is shown in Figure 4. The main contributions of this approach are,

1) This is most suitable for single-view camera with unconstrained gait sequence with respect to direction of walk.
2) The samples considered in person classifier are corresponding to the angle of gait sequence classified by angle classifier in which person is walking, as opposed to the all angle view inclusion in the person classifier before fusing the results as in case of [2].

Training Samples	Testing Samples	kNN with Centroid		kNN without Centroid	
K	S	Rank-1 Accuracy(%)	Avg. Accuracy(%)	Rank-1 Accuracy(%)	Avg. Accuracy(%)
[1,3,5,6]	[2,4]	98.59	97.65	98.59	97.65
[1,2,3,4]	[5,6]	96.72	97.65	96.72	97.65
[1,2,3]	[5,6]	94.85	96.37	95.32	96.49
[2,3,4]	[5,6]	96.72	96.37	96.26	96.49
[1,2,4]	[5,6]	96.72	96.37	97.19	96.49
[1,3,4]	[5,6]	97.19	96.37	97.19	96.49
[1,2]	[5,6]	94.39	96.37	94.39	96.49
[1,3]	[5,6]	94.39	96.37	95.32	96.49
[1,4]	[5,6]	97.19	95.32	97.19	95.47
[2,3]	[5,6]	94.85	95.32	94.39	95.37
[2,4]	[5,6]	95.79	95.32	95.79	95.47
[3,4]	[5,6]	95.32	95.32	95.79	95.47
[1]	[5,6]	87.85	90.18	87.85	90.18
[2]	[5,6]	90.18	90.18	90.18	90.18
[3]	[5,6]	88.78	90.18	88.78	90.18
[4]	[5,6]	93.92	90.18	93.92	90.18

TABLE I
PERFORMANCE WITH DIFFERENT TRAINING / TESTING SAMPLES SET OF CASIA B

Training with K=[1, 3, 5, 6]	% Testing Accuracy with S=[1, 2, 3, 4, 5, 6] with view angle as follows												Testing with Non-Ortho. View with S=[1*to*6]
View Angle	0^0	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0	Avg. Accu.(%)	Avg. Accu.(%)
A=0	97.44	6.45	4.43	2.28	1.47	0.80	0.80	1.74	1.74	1.61	8.06	11.32	2.2
B=90	1.61	0.80	1.07	5.10	36.29	94.35	27.82	7.79	2.41	0.80	1.34	16.37	10.5
C=180	5.64	2.41	1.47	0.80	1.74	1.61	1.61	1.07	0.80	5.10	97.44	10.71	1.74
A+B+C	51.34	3.36	1.61	2.95	11.02	38.02	6.58	3.36	1.74	3.2	68.14	17.39	4.23
Min(A,B,C)	96.37	6.18	3.49	2.95	32.52	92.87	27.28	3.89	0.94	1.34	83.46	31.94	9.82

TABLE II
PERFORMANCE WITH ORTHOGONAL VIEW ANGLES 0^0, 90^0 & 180^0 TRAINING (CASIA B)

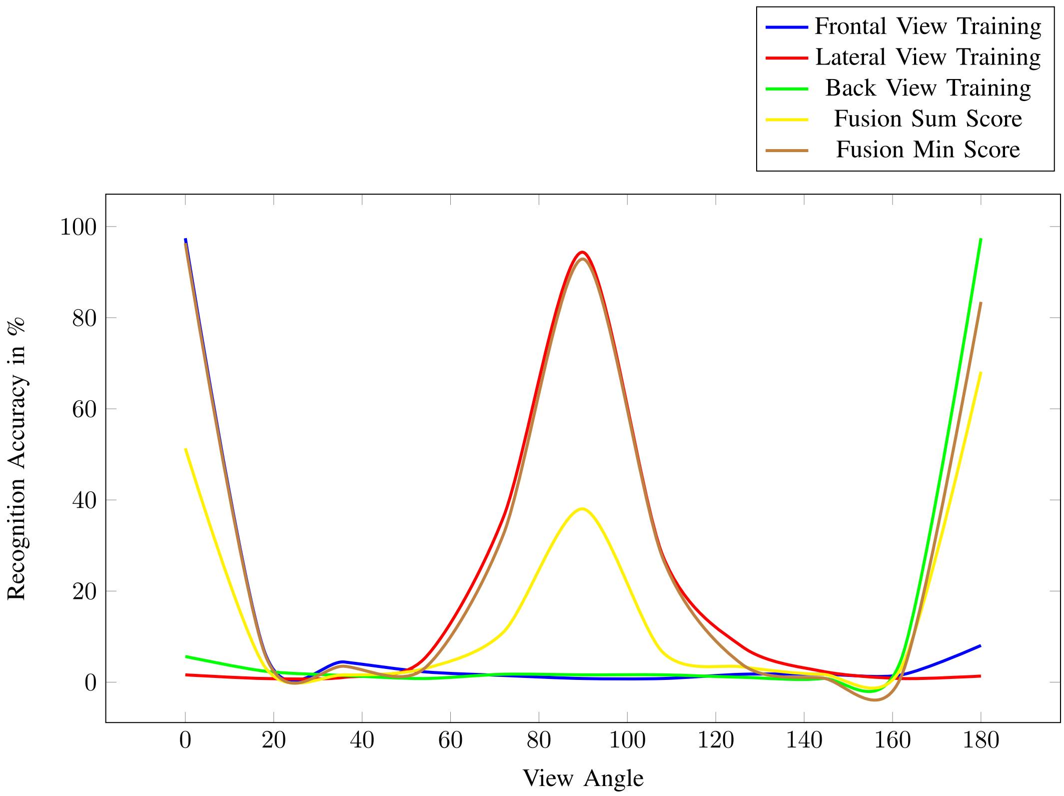

Fig. 2. Graph on Performance with Orthogonal View Angles 0^0, 90^0 & 180^0 Training (CASIA B)

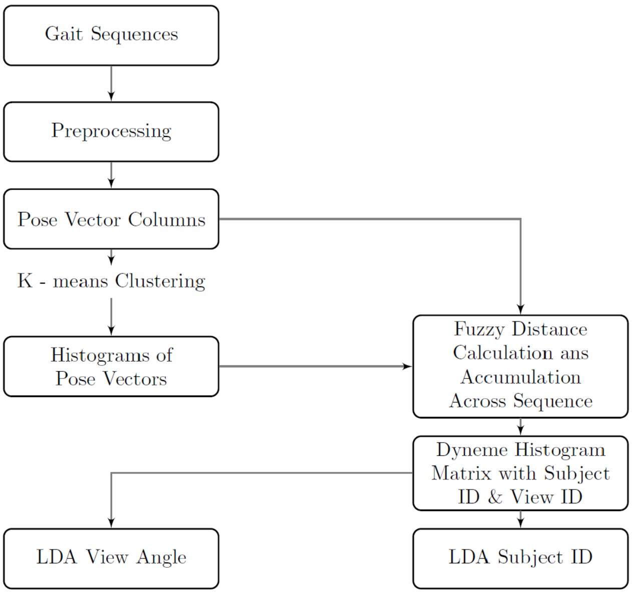

Fig. 3. Histogram Features Extraction and Two LDA Subspaces

3) The proposed mechanism of selective kNN (s-kNN) classifier improves the person identification result.
4) Significant results for non-orthogonal view angles.

The system with s-kNN i.e. rank-N s-kNN classifier is shown in Figure 5.

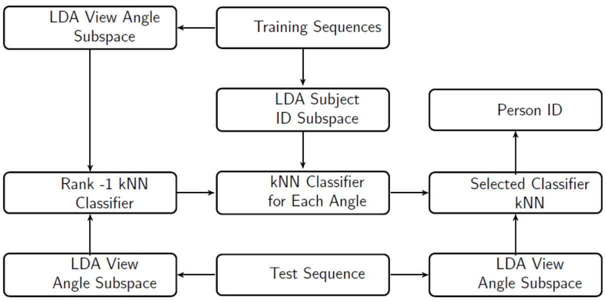

Fig. 4. S-kNN Classifier

V. Experimental Results and Discussion

Experiments performed considering normal and fast walking instances. Initially we performed experiment considering orthogonal angles 0^0, 90^0 & 180^0 in training instances $\{1, 3, 5, 6\}$ excluding instances $\{2, 4\}$. Results in terms of testing accuracy considering testing instances $\{1, 2, 3, 4, 5, 6\}$ is shwon in Table II. It is found that, the recognition accuracy infers when particular angle instance is not included in training. The average recognition accuracy for non-orthogonal view angles is also shown in Table II.

Experimentally it is found that, the orthogonal views of angles 18^0, 108^0 and 162^0 are useful for training efficiently as reported in [37]. As the dyneme representation is resilient

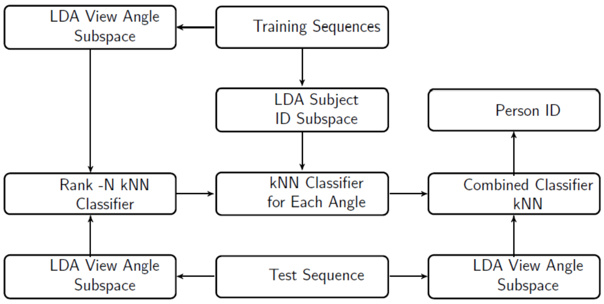

Fig. 5. Rank-N S-kNN Classifier

Fig. 6. Dynemes Poses

to noise, the set of 340 & 500 dynemes are calculated from training instances, $\{1, 3, 5, 6\}$ of 124 subjects with orthogonal view angles 18^o, 108^o and 162^o excluding instances $\{2, 4\}$. Figure 6 shows 500 dynemes for instances $\{1, 3, 5, 6\}$. The overall and across angle recognition accuracies are presented in Table III. The experiments were performed with LDA using kNN and s-kNN classifiers. Significant results obtained for non orthogonal view angles considering all instances by our method. Where, pID is person identification and VA is view angle accuracy.

The further improvement in the performance of system is achieved by rank-N s-kNN classifier. The results with different training set are shown in Table IV. It can be observed that, the rank-1 angle classification accuracy and pID rank-1 accuracy improves significantly with increased number of instances in training.

A. Comparative Work

In [37], the strategy was proposed to determine the least number of viewing angles from available maximum number of views to be used in training so that recognition with different gait angle sequences can be maximized. It is the optimization problem and training set with views from 18^o, 108^o and 162^o is experimentally found to be the best solution. We implemented our approach with these training set and compared with results obtained with their approach as reported

Training with K=[1, 3, 5, 6] with 124 Sub.	Testing % Accuracy with S=[1, 2, 3, 4, 5, 6] with view angles as follows											Testing with Non-Ortho. Views with S=[1 to 6]
	0^0	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0	Avg.%
340-LDA-kNN	95.83	96.23	95.56	94.62	87.76	85.61	87.09	92.33	93.81	93.27	95.56	92.52
500-LDA-kNN	95.16	96.37	96.63	95.29	88.97	85.88	89.65	94.48	94.48	93.95	96.10	93.36
340-LDA-S-kNN	97.58	97.31	96.10	96.63	94.62	89.65	91.66	95.43	94.48	93.27	96.77	94.85-pID
340-LDA-S-kNN	97.84	98.25	97.44	97.17	97.71	97.58	6.10	96.50	94.75	94.35	97.58	96.84-VA
500-LDA-S-kNN	97.17	97.58	96.50	96.77	94.22	89.51	93.01	95.56	94.35	93.95	97.74	95.06-pID
500-LDA-S-kNN	97.84	98.92	97.17	97.04	97.84	97.98	96.23	96.50	94.75	94.35	97.71	95.94-VA

TABLE III
PERFORMANCE WITH LDA USING kNN AND S-kNN CLASSIFIERS WITH NO. OF DYNEMES 340 AND 500 TRAINED BY ORTHOGONAL VIEW ANGLES 18^0, 108^0 & 162^0 (CASIA B)

Training and Testing Sets 124 Subjects	Rank-1 Angle Classification Accuracy		Person ID-Rank - 1 Accuracy(%) with Different S and K with Rank - N Classification where N is as follows										
K and S Sets	Testing Sample	Rank-1 Angle Accu. %	1	2	3	4	5	6	7	8	9	10	11
K=[1], S=[2, 3, 4, 5, 6]	6660	6366 (95.58)	64.09	64.09	64.81	64.86	64.83	64.87	64.90	64.89	64.87	64.86	64.81
K=[1, 3] S=[2, 4, 5, 6]	5321	5118 (96.18)	78.81	78.18	79.57	79.64	79.74	79.75	79.75	79.79	79.81	79.39	79.92
K=[1, 3, 5] S=[2, 4, 6]	3991	3861 (96.73)	87.59	87.59	88.37	88.49	88.62	88.67	88.79	88.82	88.79	88.82	88.84
K=[1, 3, 5, 6], S=[2, 4], 124/104 Subjects	2675 /2341	2592 (96.89) /2287 (97.68)	91.25 /92.39	91.25 /92.39	92.07 /92.95	92.26 /92.99	92.29 93.03	92.33 93.07	92.37 /93.07	92.33 93.07	92.33 /93.07	92.33 /93.07	92.29 93.07
K=[1, 2, 3, 5, 6],S=[4]	1329	1290 (97.07)	93.00	93.00	93.22	93.52	93.60	93.82	93.82	93.90	93.90	93.90	93.90

TABLE IV
RANK-1 ACCURACY OF PERSON IDENTIFICATION WITH DIFFERENT SETS OF K AND S WITH RANK-N CLASSIFIER FOR ORTHOGONAL VIEWS 18^0, 108^0 & 162^0 (CASIA B)

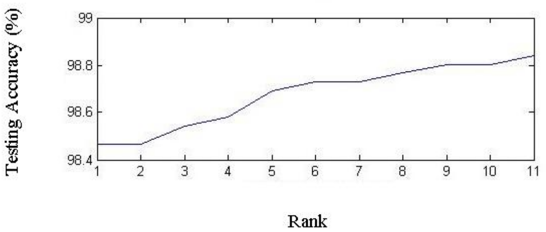

Fig. 7. Testing Accuracy of Angle Classifier for angle 180^0

in the Table V. It can be seen that, our approach gives slightly improved performance over this method.

In [39], the correlation motion analysis for each point in GEI is done across the views and the sparse regression is carried out with the help of correlation coefficient. Once the regression GEI features across any view-angle is obtained, the view classifier estimates the angle of test gait sequence walked in any direction. This classifier is based on the GEI features projected on the PCA and later PCA transformed features are used in constructing LDA subspace. Using projection of training images in LDA subspace to compare with that of test images, angle is estimated. This step is similar to angle based classifier used in our algorithm, with only difference of using dynemes histogram as a features in place of GEI features and using LDA subspace directly instead in PCA transformed space. In this approach, sparse regressive GEI data corresponding to the estimated angle refined by ROI selection based on motion correlation is used in classifier after projecting it on PCA. The Euclidean distance as a similarity measure, is used in the classifier for identifying the person. We have compared our approach with this method reported in [39]. To be fair with comparison, we used first 24 classes to make the dynemes model and remaining 100 classes used for view-angle classification and person identification as specified in their work. Figure 7 shows testing accuracy of angle classifier for angle 180^0. From the results it can be seen that, our approach outperforms almost at every place. The variant of this

Training with K=[1, 3, 5, 6] with 124 Sub.	Testing Accuracy with (S=[2, 4])		Testing Accuracy(%) with S=[2, 4] with view angle as follows										
	Correct	% Accu.	0^0	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0
Method [37]	-	90.72	87.9	96.37	94.35	87.1	84.68	91.94	97.18	88.31	87.9	97.18	85.08
Proposed Method	2425	91.25	94.67	95.93	92.68	95.49	86.53	73.06	84.08	95.85	95.78	92.85	97.13

TABLE V
COMPARISON WITH METHOD [37]

Training with K=[1, 3, 5, 6] with 124 Sub.	Testing Accuracy with (S=[2, 4])		Testing Accuracy(%) with S=[2, 4] with view angle as follows											Avg. Accu.(%)
	Correct	% Accu.	0^0	18^0	36^0	54^0	72^0	90^0	108^0	126^0	144^0	162^0	180^0	
Method [39]	-	90.5	88			95		88		91				90.5-pID
			90	91	91	98	99	91	93	94	92	93	91	94-VA
Proposed Method	1971	92.22	91.41	94.94	95.45	95.91	92.38	77.15	85.27	95.87	96.82	93.26	95.91	92.22-pID
			98.86	98.98	96.96	95.42	98.98	94.41	94.41	100	97.35	94.81	98.46	97.22-VA

TABLE VI
COMPARISON WITH METHOD [39]

work is also presented in [38] using different type of regression method to select the optimized feature representation.

In [2], authors proposed the framework for person identification based on various activities like; jump in place, wave one hand, jump forward, run, walk (gait). Although, we focused on gait activity only. The features extracted in [2] are the histogram of dynemes (centroid of clusters) calculated and accumulated from each of the frame throughout the video sequence. This algorithm doesn't need to calculate the gait cycle and thus it is shift invariant in time. Two subspaces are created using LDA from the dynemes histogram features. One for subject class and another for view-angle. The kNN classifier with centroid is applied to each of the view of probe subject to decide its view angle and its subject class. These two labels obtained from N camera views are fed to the Bayesian Framework to obtain final output in terms of person class. It is important to mention here that our feature extraction method is very much adopted from this work because of its shift-invariant property. It can also be used for continuous person identification. However, the classification strategy used in our approach is hard than the one used in [2]. We compared our algorithm with the results provided in this paper. The experiment includes the 5 sample instances as training and testing is done on remaining one instance as mentioned in [2]. The recognition accuracy is reported in this paper is 93.27%, while our approach gives the accuracy of 94.19%. This shows the slight improvement can be gained with our approach.

VI. CONCLUSION

We have explored the view-invariant gait recognition system which use three orthogonal views of gait signature for the person identification. It is observed that, training with orthogonal views becomes very effective in multi-view gait recognition. Another proposed mechanism of selective kNN (s-kNN) to fuse the two classifiers have been successful in improving the gait recognition accuracy. Initially, we performed experiment considering orthogonal angles 0^0, 90 and 180^0. It is observed that, the recognition accuracy decreases abruptly if test instance of a particular view angle not included in training. The testing accuracy for non-orthogonal view angle was also infer. Next, we use optimized view angle framework with orthogonal view angles 18^0,108^0 and 162^0 for training. Various experiments were performed considering 340 and 500 dynemes for kNN and s-kNN classifier. We got significantly improved results even for non-orthogonal view angles. We report 97.07% maximum rank-1 angle classification accuracy and 93% maximum rank-1 person identification with different sets of K and S for rank N s-kNN classification. It is observed that s-kNN perform better than kNN in pID (person identification) and VA (view angle accuracy).

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