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THEORETICAL ADVANCES

An aperiodic feature representation for gait recognition in cross-view scenarios for unconstrained biometrics

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Abstract The state-of-the-art gait recognition algorithms require a *gait cycle* estimation before the feature extraction and are classified as *periodic* algorithms. Their effectiveness substantially decreases due to errors in detecting gait cycles, which are likely to occur in data acquired in non-controlled conditions. Hence, the main contributions of this paper are: (1) propose an *aperiodic* gait recognition strategy, where features are extracted without the concept of gait cycle, in case of multi-view scenario; (2) propose the fusion of the different feature subspaces of aperiodic feature representations at score level in cross-view scenarios. The experiments were performed with widely known CASIA Gait database B, which enabled us to draw the following major conclusions, (1) for multi-view scenarios, features extracted from gait sequences of varying length have as much discriminating power as traditional periodic features; (2) for cross-view scenarios, we observed an average improvement of 22 % over the error rates of state-of-the-art algorithms, due to the proposed fusion scheme.

Keywords Gait representation · Multi-view gait · Cross-view gait · Aperiodic gait recognition · Gait cycle estimation · Unconstrained biometrics

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1 Introduction

There is an increasing interest in the human gait to be employed in biometrics applications. It is more suitable to be used in *less controlled* scenarios [19], characterized by the reduced quality of data. Gait recognition is an *activity-based* biometric trait [10], and represents the subjects in the way they walk. Even if the discriminating capability across humans gaits is smaller than that of classical biometric traits (e.g., the iris, or the face), there are several reasons for using the gait as a biometric trait that can be pointed out here: (1) no minutia information is used in the recognition process, leading easier to acquire the data from long distances; (2) walking is an instinctive activity of humans, reducing the possibility to imitations or deliberate changes over a large period; and (3) unlike the face and iris, a gait information is easily captured from multiple view angles, hence, reduces the possibility of having significant occlusions in a gait sequence.

A view-dependent gait recognition, where gallery and probe samples are of same view angle, makes subject registration process complex and infeasible. On one side, it restricts the probe subject to walk in a particular direction, in which gallery data were acquired and other side, it requires to have gallery data acquired in all possible view angles. It also suffers from being sensitive to the difference between angles of probe and gallery data. To overcome these problems, the gait recognition research has approached towards the direction of view-independent recognition methods, which are more suitable for unconstrained biometrics. Further, view-independent methods can be applied in two different scenarios, namely, multi-view and cross-view gait recognitions [15], which are detailed in next Sect. 2.

Conventionally, gait recognition algorithms employ the feature representation obtained from each gait cycle of a sequence and thus, it requires the step of gait period estimation. Hence, this class of algorithms falls in the category of *periodic gait recognition*. Due to high probability of having errors in the estimation of the gait cycle from a gait sequence, there would be a significant degradation in the recognition performance. One more disadvantage in this case is that a periodic feature representation technique cannot be extended or generalized to other activities, which are not periodic, e.g., jump, bend etc. In this context, *aperiodic gait recognition* algorithms become more suitable in flexible and scalable biometric applications as they do not require gait cycle estimation. In Fig. 1, system block diagrams for periodic and aperiodic gait recognition techniques are shown. The performance of an aperiodic gait recognition algorithm do not depend on the gait period estimation module, which is known to be a problematic, particularly for the samples with low-quality, view angle variations and occlusions.

So far in the existing literature work of a gait recognition, there have been no attempt of using a gait feature image without extracting the gait period. Thus, we examine and propose the aperiodic gait recognition scheme in different scenarios of view-insensitive gait recognition.

The main contributions in this paper are: (1) propose an aperiodic gait recognition algorithm for both, multi-view and cross-view scenarios; (2) perform experiments with non-uniform lengths of gait sequences, enabling the application of the proposed algorithm for unconstrained scenarios; and (3) describe an approach based on the fusion at the score level, particularly suitable for the cross-view scenario. In the cross-view scenario, view angles of probe and gallery gait sequences are different. Thus, it is most challenging case in a view-invariant gait recognition and recently been taken as a research objective for biometrics and surveillance applications. Our experiments were performed in the most widely used gait database (*CASIA Gait database B*) and the performance of the proposed algorithm was compared to state-of-the-art techniques. We used gait sequences of random length, simulating the acquisition of gait samples in unconstrained setups. When compared to related algorithms, experimental results point out a significant improvement in performance of the proposed aperiodic feature extraction scheme in both, the multi-view and cross-view scenarios. Also, the proposed fusion approach with an aperiodic feature representation proved to be particularly effective for cross-view situations and outperforms state-of-the-art recognition rates.

The remaining part of this paper is organized as follows: the review of gait recognition techniques for multi-view and cross-view scenarios is presented in Sect. 2 along with the list of research objectives. The proposed aperiodic gait recognition algorithm is described in Sect. 3 and its detailed justification is explained in same section. Section 4 details the fusion approach to be applied in cross-view scenario. The experimental results are presented and discussed in Sect. 5. Finally, Sect. 6 concludes the paper highlighting the accomplishment of the work.

2 Related work and research objectives

Gait sequence is a biometric signature, particularly suitable for applications involving long-range data acquisition. In the evolution of gait recognition methods, early research was aimed at matching the probe and gallery gait sequences, both of same view angles. There are various gait feature representations proposed in the literature for this kind of a simple gait recognition. In subsequent years of research, various gait representations were tested and validated against covariates such as distance, environment, illumination, back-pack and loose clothing. During the recent phase of research, the problem of a gait recognition

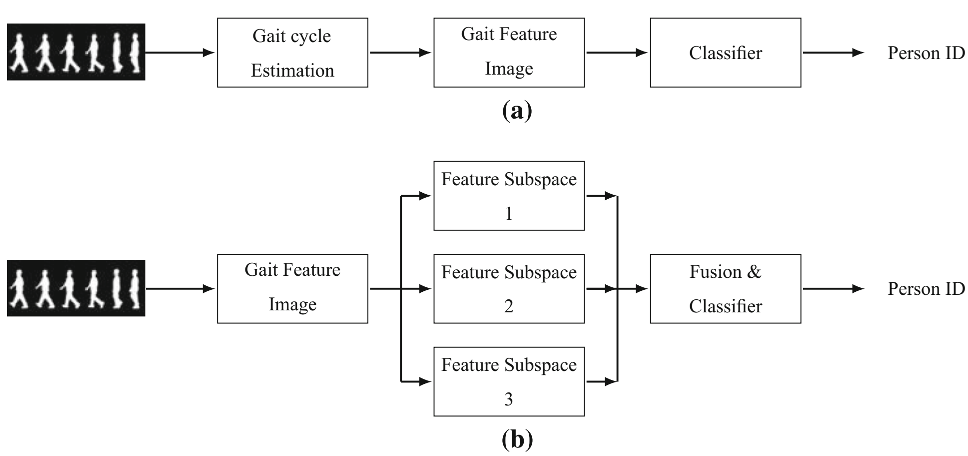


Fig. 1 Gait recognition approaches: **a** periodic gait recognition (conventional). **b** Aperiodic gait recognition (proposed)

was extended to make the system view-invariant or view-insensitive, where a system is expected to perform an identification irrespective of the angle in which subject walks. It is assumed that an angle of probe gait sequence is close to one of the angles of the gallery samples. Recently, the gait recognition problem has entered into the sub-research of exploring the way to apply a gait recognition between angles of probe and gallery with larger differences, i.e., cross-view gait recognition.

2.1 Related work

In the case of unconstrained scenarios, a gait signature is acquired from far distance such that subjects are free to walk in any direction. A probe gait sequence may be captured in any view angle. This kind of flexibility for probe subjects leads to two scenarios for gait recognition algorithms: *multi-view* and *cross-view*. In the former, various view angles per subject are made available as a gallery data with the assumption that an angle of probe nearly matches one of the available gallery angles. Several relevant algorithms of this kind are reported in the existing literature. In its first kind, Kale et al. [11] have used a canonical view as an intermediary view between probe and gallery of any view angle, thus making a gait recognition algorithm view-independent. Han et al. [8] also attempted to apply the principle component analysis (PCA) and multiple discriminant analysis (MDA)-based subspace on the gait energy image (GEI) feature space to achieve a view-insensitive gait recognition. Similar gait recognition objectives achieved in works [3, 6, 9, 10, 17]. Liu et al. [16] have extracted features from all views and then extracted a linear subspace, called as multi-view subspace representation (MSR) for representing a gait sequence irrespective of its view angle.

In the cross-view scenario, view angles of probe and gallery gait sequences are different. Thus, it is most challenging problem in gait recognition and recently being considered as the critical research objective for biometrics and surveillance applications. The cross-view gait recognition family is particularly important for unconstrained setups, where it has to recognize subjects for the probe gait sequence with view angle different from that are available in gallery. In an existing literature, few attempts have been reported to transform gait sequences from one view angle to another, using view transformation models (VTM). Makihara et al. [18] used singular value decomposition (SVD) to transform the frequency spectrum of the gait silhouette volume over a each gait cycle from one view angle to another. More recently, techniques based on truncated SVD (TSVD) [12], support vector regression (SVR) [13], canonical correlation analysis (CCA) [1], correlated motion regression [15] were proposed for cross-view gait recognition. There is also an attempt recently by Kusakunniran et al. [14] to extend SVM and sparse-based regression work to a neural network-based VTM construction.

In all the above-described methods, feature extraction is done from the segment of each gait cycle, i.e., the concept of *cycle* is used as a reference point. As stated earlier, algorithms used for estimating a gait cycle decrease their effectiveness for the data of low quality due to covariates (e.g., strong variations in perspective, scale or occlusions), which are more dominant in unconstrained setups. Two classes of view transformation techniques are reported in cross-view recognition methods: (1) transform the probe into the view angle of gallery, assuming that elements in the gallery share the same perspective; and (2) transform gallery data into the view angle of probe. Works described in [12–15] fall in the latter category when it is to be used with a fusion of multiple views, which significantly augments the computational burden of the recognition process, particularly in cases where large number of identities are enrolled.

2.2 Research objectives

Keeping a pace with a current research in the field of the view-invariant gait recognition, we listed out main objectives of research work presented in this paper:

– To propose the aperiodic gait feature representation, where human gait is assumed to be not periodic and thus, gait cycle estimation is not required in processing phase.
– To apply and validate the aperiodic gait recognition to multi-view scenarios.
– Since, an aperiodic feature representation could be very sensitive to the view transformation models to be used in cross-view scenarios, the important objective of our work is to develop the fusion scheme for an aperiodic cross-view gait recognition.
– To show the results for aperiodic multi-view and cross-view recognition with higher statistical significance. This is achieved using repetitions of experiments, where lengths of test sequences were drawn arbitrary across the probe sequences.

3 Proposed aperiodic gait recognition model

Most popular feature extraction techniques for a gait recognition are Gait Energy Image (GEI) [7], Radon Transform Energy Image (REI) [4, 17] and Truncated GEI (TGEI) [1]. In all these techniques, it is essential to determine the *gait cycle* of a given sequence, and several techniques have been proposed in this scope (e.g., [2, 5, 20]). As stated earlier, this step is a common source of error, and impacts negatively all subsequent phases in the processing chain. For the GEI feature in periodic (conventional) algorithms, GEI_P for the nth gait cycle of gait sequence is calculated as

$$\mathrm{GEI}_n^P = \frac{\sum_{t=1}^{T_{p,n}} \mathrm{SI}_{t,n}(m,n)}{T_{p,n}} \tag{1}$$

where $T_{p,n}$ is the gait period (in number of frames) and $\mathrm{SI}_{t,n}(m,n)$ is the silhouette image of tth frame in nth gait cycle. The overall GEI feature for any gait sequence is then averaged over the number of gait cycles (N) to be considered.

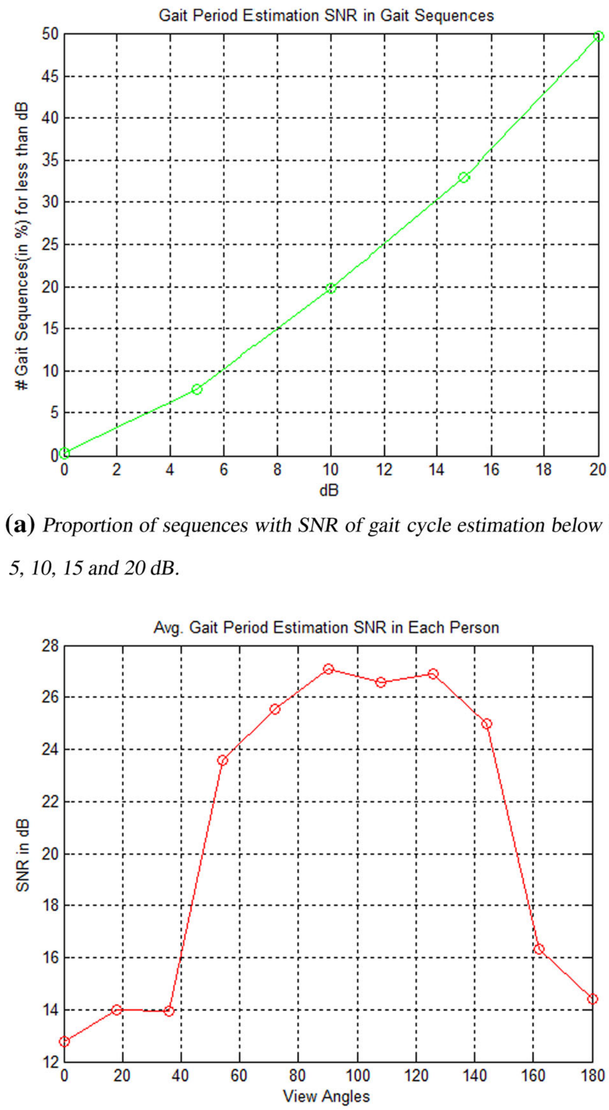
$$\mathrm{GEI}^P = \frac{\sum_{n=1}^{N} \mathrm{GEI}_n^P}{N} \tag{2}$$

While estimating a gait cycle for a gait sequence, its values obtained from gait period estimations from a gait sequence are usually averaged out. Ideally, it is the essential property of a gait cycle estimation algorithm to have no variation in estimated values for a gait sequence with the assumption that a subject is walking with a constant speed. To study the estimation accuracy, we applied the gait period estimation algorithm described in [20] to gait sequences and the variations in SNR values for all the sequences are obtained. While applying a gait cycle estimation technique, first, an aspect ratio of a silhouette for each frame is calculated. The vector formed by an aspect ratio obtained from all frames across the sequence is normalized to remove the background and then autocorrelation is computed. The autocorrelation signal is passed through the first-order derivative to detect the peaks, which are marked alternatively as gait cycle start and end instances. The signals showing outputs at various steps are shown in Fig. 3 for situations where gait period estimation fails miserably for different view angles. This algorithm is considered to be most popular and acceptable in the research community and applied in recent works, [1, 13, 15, 18].

The SNR in dB is a log ratio between the mean value μ of the estimates and its standard deviation σ is given by

$$\mathrm{SNR} = 20\log_{10}\frac{\mu}{\sigma}\mathrm{dB}. \tag{3}$$

Larger the SNR, better the gait cycle estimation. We calculated the number of sequences which have SNR below the certain value (threshold). This statistic is plotted in Fig. 2a, where different threshold values from 0 dB to 20 dB are marked on the horizontal axis and number of sequences (in % of total number of sequences in dataset) having SNR below the corresponding threshold value is shown on vertical axis. Nearly 50 % of sequences have intolerable intra-sequence variations (less than 20 dB) in



(a) *Proportion of sequences with SNR of gait cycle estimation below 0, 5, 10, 15 and 20 dB.*

(b) *SNR of the estimation of the gait period for a given view angle*

Fig. 2 Illustration of the gait cycle estimation problem

the estimation of gait cycle. Another interesting observation is shown in Fig. 2b, where plot of the average SNR (vertical axis) across all the subjects for certain view angle (horizontal axis) is shown. The frontal and back view gait sequences suffer severely from the low-quality estimation of gait period. The reason behind this is illustrated in Fig. 3 and it is because of a smaller change in the silhouette aspect ratio across the sequence that makes difficult to detect peaks in the autocorrelation signal precisely. Even for other view angles, the gait cycle estimation is not good except for lateral or very near lateral gait sequences. Being considered 30–35 db to be a good estimation range in most applications like speech processing and wireless communication, maximum SNR obtained in gait sequences hardly reaches to the value of 28. These SNR values would be

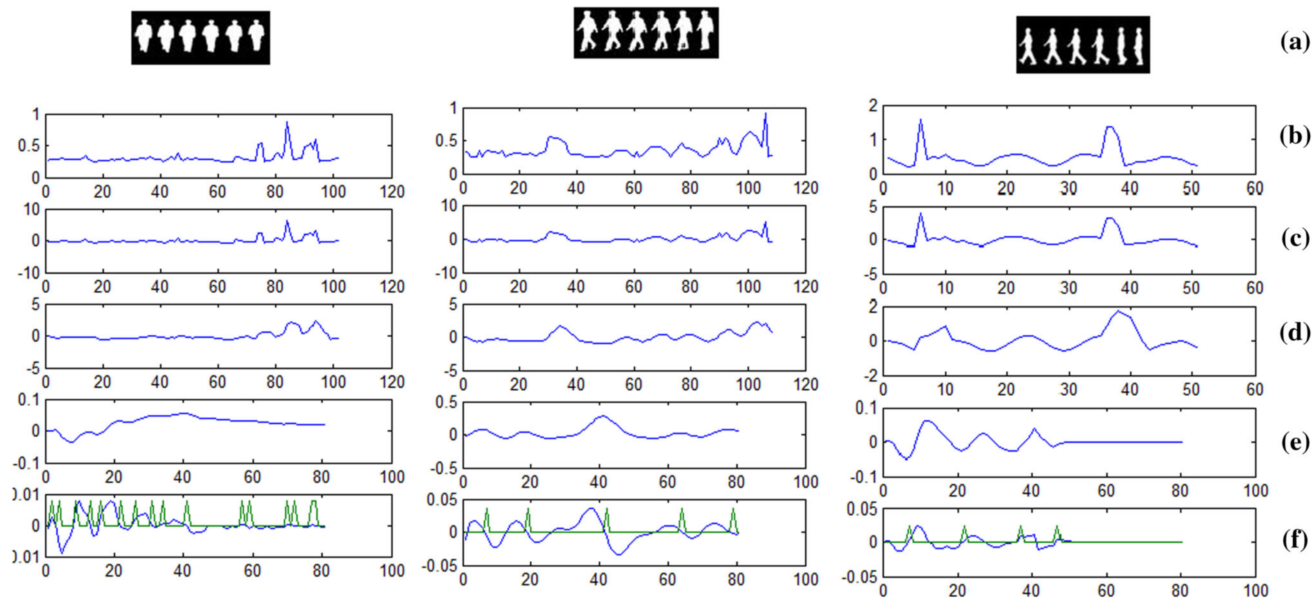


Fig. 3 Gait period estimation processing steps for different view angle gait sequences. Column-wise: *1* Frontal, *2* Oblique and *3* Lateral. Row-wise: *a* input silhouette sequence; *b* silhouette aspect ratio; *c* Normalized aspect ratio; *d* background removal *e* autocorrelation and *f* first-order derivative (*blue*) and detected peak locations (*green*)

further degraded in case of low-quality imaging hardware, occlusions, far distance and low-quality silhouette extraction techniques. Thus, it becomes important to use gait recognition systems independent of a gait period estimation module.

We propose here to extract features from gait sequences without considering the concept of cycle. Thus, the GEI feature for any gait sequence using aperiodic gait recognition, GEI^{A}, is calculated as

$$\mathrm{GEI}^{A} = \frac{\sum_{t=1}^{T} \mathrm{SI}_t(m,n)}{T} \tag{4}$$

where T is the number of frames to be considered (or available) and $\mathrm{SI}_t(m,n)$ is silhouette image of tth frame of gait sequence. The Eqs. (1), (2) and (4) can be easily extended to the other types of feature such as REI, TGEI.

We tested conventional gait sequence representations (periodic), such as GEI, REI and TGEI, using recognition experiments. For an aperiodic feature representation, we varied a length of sequences and observed the recognition performance. In particular, each sequence was divided into M equal parts and only the first N parts of each sequence were considered for feature extraction purposes. N was varied in the $[1, 20]$ interval (corresponding to 5–100 % of the available data in each sequence). Three different feature extraction techniques were tested (GEI, REI and TGEI) and nearest neighbor (kNN) algorithm used for classification purposes. Assuming a multi-view scenario, all view angles were considered for gallery and probe data, while instances of both being mutual exclusive sets of each other. The recognition rate r was used as performance measure, given by

$$r = \frac{\mathrm{TP}}{T} \tag{5}$$

where TP and T are number of true positives and gait samples tested.

The results of recognition experiments for different types of feature are plotted in Fig. 4, where the horizontal axis for the first three plots using dotted lines corresponds

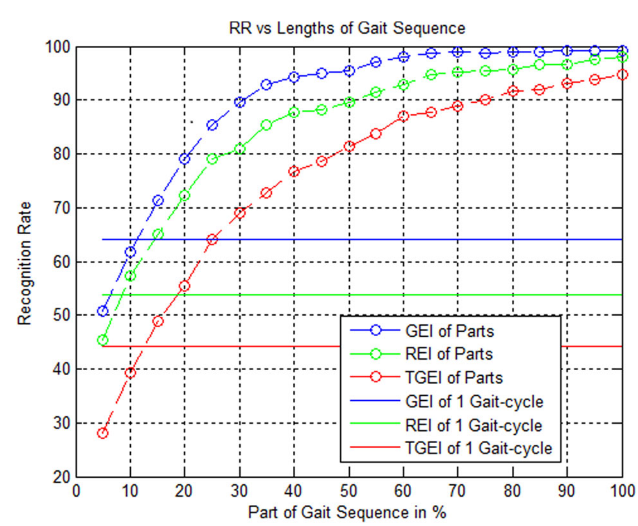


Fig. 4 Aperiodic multi-view gait recognition rate (RR) with respect to the length of sequences and periodic multi-view gait recognition with 1 gait cycle obtained from gait cycle estimation algorithm

to the proportion of data used from each sequence. The vertical axis gives the corresponding recognition effectiveness. For the sake of comparison, we give plots of constant values using continuous lines, representing the recognition accuracy results obtained when using data from one gait cycle, in a periodic recognition scheme. Results turn evident that using a sufficient amount of data from a gait sequence, the obtained results are even better than estimating the gait cycle, which might be due to inaccuracies of the gait cycle estimation module.

Some examples of GEI images, which preserve the distinctive pattern exists on GEI despite of different lengths of sequences, are considered and are shown in Fig. 5. First column shows GEI images calculated from 1 gait cycle (periodic) for different view angles. Corresponding row images are GEI images computed from different length (in %) gait sequences (aperiodic) without considering gait cycle concept. In this figure, distinctive locations in GEI are shown in each view angle across the length. It is visible that distinctive patterns in GEI are maintained in all sequences, despite of different lengths. Thus, it supports the hypothesis of aperiodic gait representation; that after sufficient length of gait sequence, GEI feature image calculated in an aperiodic manner has no variation across the lengths of sequence.

We concluded at this point that, if an accumulation of gait energy averaged over a sufficient period is provided, the recognition performance attains satisfactory values.

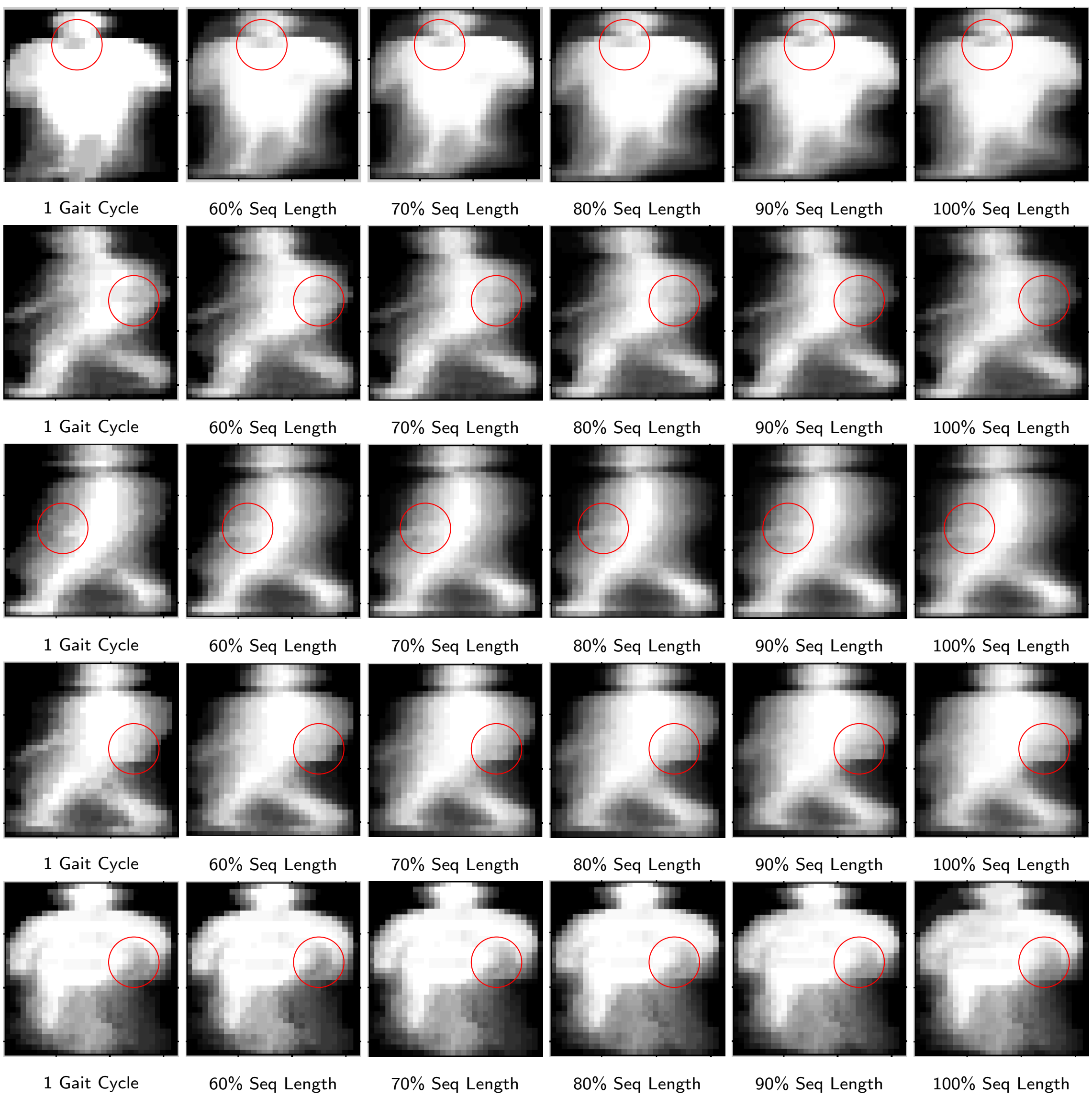


Fig. 5 GEI images for different view angles; *first column images* calculated from periodic gait cycle (periodic) and *corresponding row images* various lengths of gait sequences aperiodically (aperiodic)

Empirically, the minimal amount of data required were estimated in about 1.5 times the gait cycle for the GEI feature extraction technique. For both the REI and TGEI techniques, a value of 2 times the gait cycle was considered sufficient for attaining satisfactory performance.

It is worth mentioning here, though sufficient period is 1.5 or 2 times of gait cycle, it is not at all necessary to measure the gait cycle in a gait sequence in case of proposed aperiodic feature extraction. The approximation of sufficient period is well acceptable as the walking of any human can be accurately defined in the certain range of time required to complete one gait cycle. The typical value of gait cycle for subject can be around 2 s. Thus, accumulating gait energy over a at least (not exactly) 3–4 s can make a practical gait biometric system free from the gait cycle estimation block. In most of the practical biometrics identification or surveillance scenarios, it is reasonable to expect a subject to be walking normally for at least 3–4 s at a time in certain direction. Thus, the proposed aperiodic feature representation for a gait sequence is highly achievable.

The main advantages of an aperiodic gait recognition over a periodic gait recognition can be summarized as follows:

- The error-prone gait cycle estimation block is not required and thus, reducing the computations required for gait period estimation. In other words, it increases the reliability and reduces the computational burden.
- Since, gait feature image is accumulated at each frame and not at the gait cycle level, an aperiodic gait recognition can be used for continuous person identification.
- The negative impact of occlusions, far distance data capture and low-quality silhouette extraction technique can be reduced.
- Aperiodic gait recognition algorithms can be directly applied to the other actions, which are aperiodic in a motion profile. Thus, these algorithms become the generalized class for activity-based biometrics applications.

4 Fusion approach for aperiodic feature representation

The conventional gait recognition techniques may be suitable in case of a periodic feature extraction using gait cycle estimation. However, there is a high possibility that these techniques would give unacceptable performance in case of an aperiodic feature extraction. Degradation in the performance of aperiodic techniques is primarily because of over-fitting that occurs in the process of learning model and it becomes uncontrollable for unseen probe gait sequences. In aperiodic feature methods, there is a high probability of having variations at few pixels arbitrary in positions in their silhouette-based representation, causing over-fitting. These variations may be small, but definitely, would be larger as compared to that appear in case of a periodic feature extraction. This is the reason that conventional gait recognition techniques cannot be used in their original form for an aperiodic gait representation. Thus, there is a need to devise a strategy to handle the issue of over-fitting in an aperiodic feature extraction.

A view transformation model is the core phase of any cross-view gait recognition method. According to the results observed in Fig. 4, the GEI-based gait representation feature was chosen here, though it can be easily replaced by TGEI, REI etc. There are two macro-level requirements in a cross-view transformation model. One is applying a transformation between two angles which are separated by smaller angular span and another is a transformation between angles with larger difference. Intuitively, the use of a feature representation in different subspaces can handle these requirements intelligently. The discriminant feature space in the form of Linear Discriminant Analysis (LDA) has been effectively used in a gait recognition. The LDA has been proved to be optimal, especially when the cross-view angles' difference is small and thus, it is important to take advantage of it along with VTM. Interestingly, we observed that representations obtained from (1) dimensionality reduction techniques (LDA subspace, as suggested in [4, 10]) and (2) the transformation model, appear to have some degree of complementarity in handing the two different requirements of cross-view scenario. The gait features in LDA subspace are particularly effective for minor view differences (between probe and gallery), whereas the view-transformed subspace obtained using transformation models outperforms in case of large angular differences. Nearest neighbor was used for classification purposes. Hence, three recognition algorithms with features in different subspaces were considered in this phase: (1) LDA subspace, GEI + LDA + kNN; (2) View-Transform Subspace, GEI + VTM + kNN; and (3) Original Subspace, GEI + kNN.

The fusion approach can be used to combine the advantages of LDA and VTM. Three individual strategies, to be used here, have been empirically found efficient, are shown in Fig. 6. It is well-known fact that LDA subspace is used to reduce the dimensionality of large dimension data. The compact representation of a gait sequences enables to calculate the most discriminative information [4]. This leads to a large decision margin between representations of any two classes and makes the classification problem more tractable. Due to a large decision margin, classification process becomes more tolerable to small variations in pose

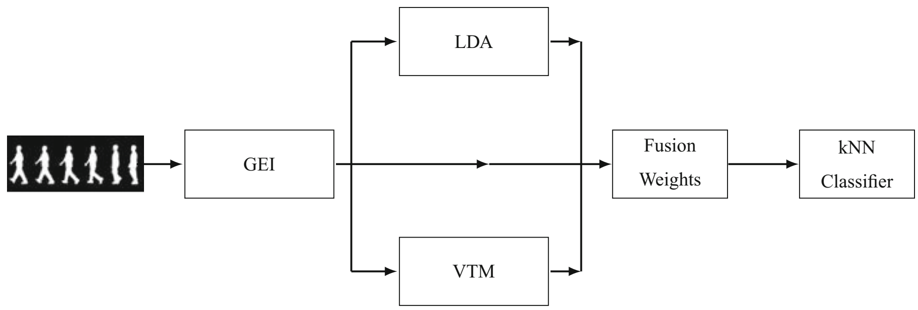


Fig. 6 Fusion of three subspaces, namely, GEI + LDA (discriminant subspace), GEI + VTM (view-transformed subspace) and GEI + kNN (original subspace)

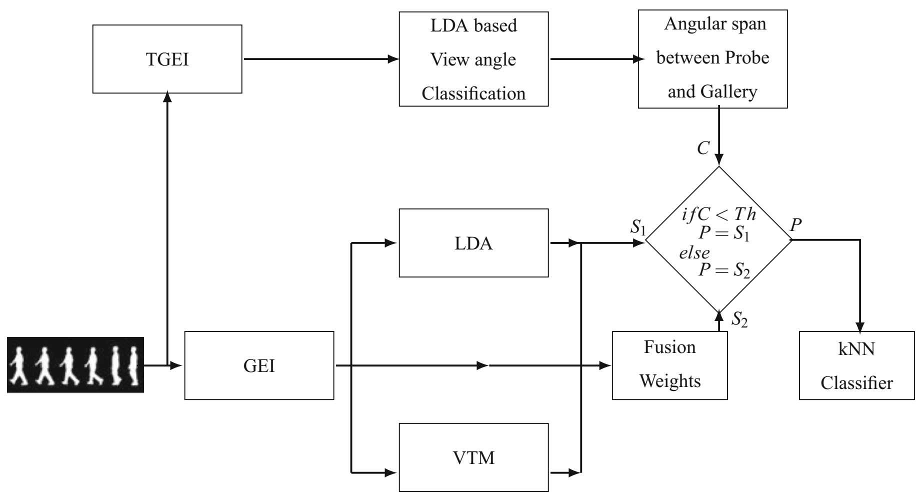


Fig. 7 Switch-based fusion using view angle classification

angles of gait sequences. The VTM is constructed to nullify the pose angle variation in gait sequences. This is especially required in the case of large pose angle difference between probe and gallery gait sequences. Thus, LDA and VTM become complementary to each other in handling the large range pose angle difference between probe and gallery. Besides LDA and VTM subspaces, the GEI feature in its original space in small extent can be a catalyst for the overall performance of the fusion approach. Fusion was performed at the score level, according to two different rules: (1) the *min* rule, corresponding to consider the best matching score among the three algorithms; and (2) according to the weighted sum rule, which is known to usually attain a maximal effectiveness. Also, the *switch-based* fusion approach was considered, to profit from the best cases of each algorithm: in case of probe/gallery similar view angles, the GEI + LDA algorithm is preferred; in the remaining cases, the general fusion rule should be considered. This switch step can be easily implemented, using a module, which estimates the view angle of a given sequence. If the *angular span* between probe angle and available gallery angle is less than a certain absolute value, the GEI + LDA is used to identify the gait sequence; otherwise, fusion of features from multiple spaces is employed. This switch-based fusion scheme is depicted in Fig. 7.

5 Experiments and discussion

The gait recognition experiments reported in this paper were carried out with the *CASIA Gait database B* [21]. It contains 124 subjects and 6 gait sequence instances per subject. We divided the dataset into two disjoint sets: training, containing the first 4 instances from each subject; and test, that contains the remaining sequences. The first 24 subjects of the training set were used for obtaining the VTM and for the view angle estimation module. The recognition experiments were performed, by randomly drawing the samples to be used as probe from test set such that length of each sequence has random length but larger than minimum length. The threshold of minimum length is 60 % of full sequence, approximately amounts to the 1.5 times the gait cycle. The training samples in a gallery were of full lengths. To bring statistical significance in the experiments of random lengths of test sequences, we performed some experiments 50 times for the aperiodic weighted fusion method for cross-view recognition (ref

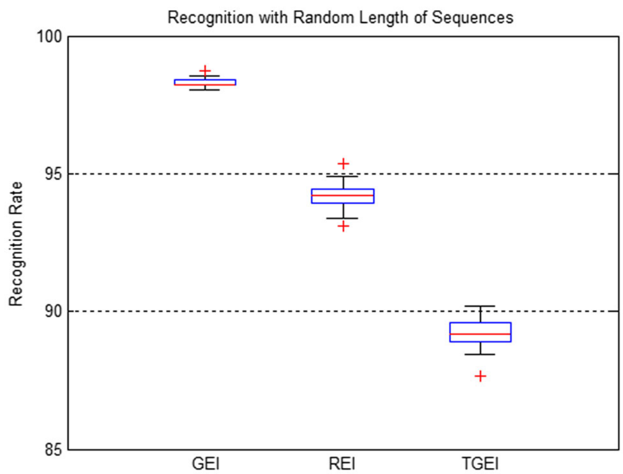


Fig. 8 Aperiodic multi-view gait recognition with random lengths of sequences (each experiment were repeated 20 times); *GEI* gait energy image, *REI* radon transform energy image and *TGEI* truncated GEI

Fig. 11) and 20 times for aperiodic multi-view gait recognition (ref Fig. 8).

5.1 Multi-view gait recognition

In a multi-view recognition scheme, all angles were included in the gallery, i.e., angles from 0° to 180°, with a step of 18°. The rank-1 recognition rates for each of the view angles of the probe sequences are shown in Fig. 8. Three line series denote the results obtained by GEI (in blue), REI (in green) and TGEI (in red) feature representations. Again, it is evident that the GEI yields maximal effectiveness. Also, having non-uniform lengths of gaits for extracting the features do not affect the performance, if a minimal length (of about 1.5 times the gait cycle) is provided. This observation was the main justification for excluding the gait cycle detection step from the recognition algorithm.

5.2 Cross-view gait recognition

For comparison purposes, the performances of techniques mentioned above were compared against state-of-the-art gait recognition methods: the GEI + VTM, being the VTM obtained by singular value decomposition [18], and the GEI + CCA, being the regression model obtained by canonical correlation analysis [1]. The regression-based methods using SVR [13] and neural network [14] are dependent on the ROI of source-view GEI for determining the every pixel in the target view. It is observed that these two methods are very much sensitive to the ROI of correlated pixels in GEI. Though these methods give better performance in periodic gait recognition methods, they have badly failed in the case of aperiodic feature representation, due to the problem of over-fitting in regression model. The performance values for considered techniques are given in Fig. 9. The results obtained for the GEI feature representation in the original, LDA and VTM spaces, and by the above-referred fusion strategies are shown in Fig. 9. The horizontal axes denote the angle of gallery data and the title above each plot gives the angle of probes. The vertical axes contain the recognition rates observed. We observed that feature representation in the LDA space gives notoriously better results than for VTM, in case of slight deviations between probe and gallery angles. Complementary, GEI + VTM outperforms in cases of large differences between the view angles of probes and gallery data. Hence, it is straightforward to consider the potential benefits of fusing both techniques. Also, as GEI feature in the original space (GEI + kNN) did not achieve best performance in any case, we decided not to include it in the plots, for clarity purpose.

The 'Minimum Fusion' in Fig. 9 represents results obtained when considering only the best matching score among the three techniques fused. In this case, we observed that this fusion scheme optimally combines the advantages of GEI + LDA and GEI + VTM for frontal / back side view angles of probes. Oppositely, it decreases its effectiveness for lateral and near lateral viewing angles. Regarding the weighted fusion rule, corresponding weight values of [0.8, 0.8, 0.1] were used (empirically adjusted). This rule was observed to achieve a more reasonable balance of the advantages of GEI + LDA and GEI + VTM, overcoming the shortcomings observed for the minimum rule fusion. It is especially evident that, for lateral and frontal view angles of probes, this technique captures the maximal effectiveness of GEI + LDA at near deviation gallery angles and of GEI + VTM at far deviation gallery angles. As such, we concluded that it achieved the most satisfactory performance.

The comparison of weighted fusion performance is also done with SVR and neural network-based regression methods in Fig. 10. It is clearly visible from these plots that these methods do not work up to the expected level in case of aperiodic feature extraction, though the methods claimed to be one the best in case of periodic gait recognition algorithms. One more disadvantage with the SVR- and NNR-based methods is the high dependency on the ROI used for regression, where localization of body parts is required.

For summarization and comprehensibility, the rank-1 recognition rates for each of the probe angles were averaged over the gallery angles and are listed in Table 1. Accordingly, our main observations were as follows: (1) the GEI + CCA method strongly decreases its effectiveness when gallery and probe view angles are strongly deviated; and (2) The weighted fusion rule is able to assimilate the advantages of GEI + VTM and

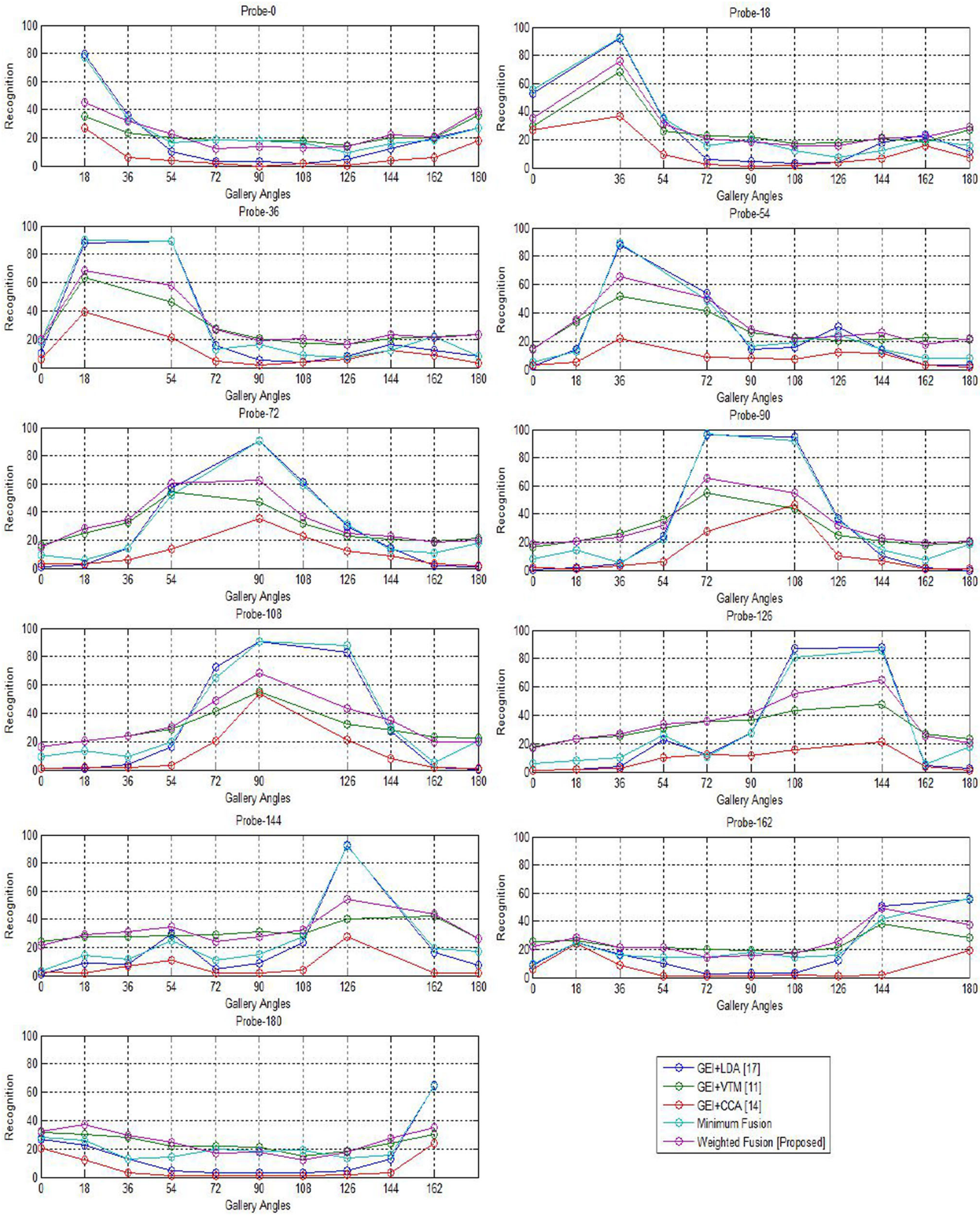


Fig. 9 Comparison of Aperiodic cross-view gait recognition rates (excluding the same-view), obtained with random lengths of sequences for each probe

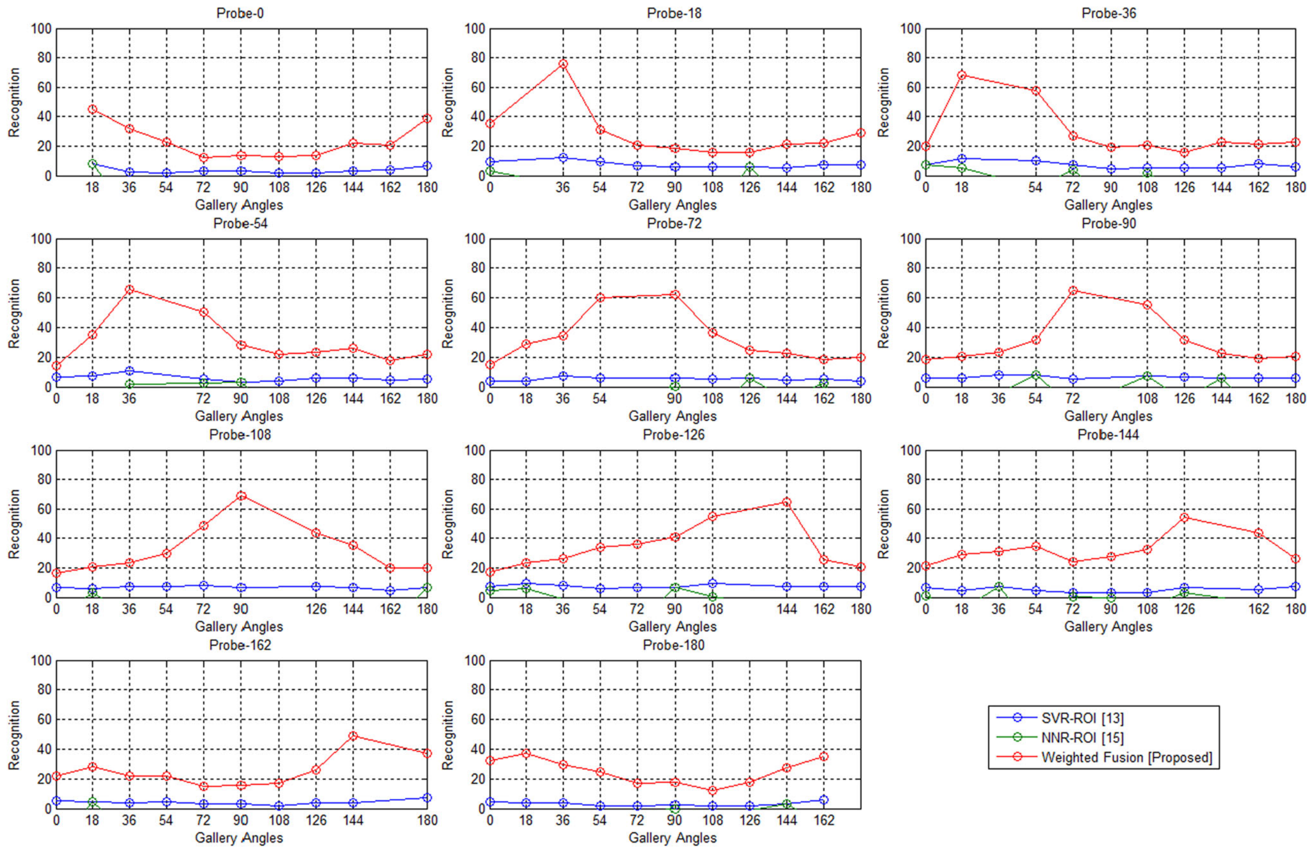


Fig. 10 Comparative recognition performance with SVR and NNR VTM and proposed approach of weighted fusion aperiodic gait recognition

Table 1 Recognition rate (averaged over all cross-view gallery angles) for each of the probe angles

Method	Cross-view probe angles°											Avg.
	0	18	36	54	72	90	108	126	144	162	180	
GEI + LDA [4]	19.70	24.89	25.67	23.85	27.26	26.98	29.87	25.04	20.08	18.79	15.97	23.46
GEI + VTM [18]	22.38	27.07	27.48	27.55	29.08	28.07	29.37	31.02	30.55	23.87	24.15	27.32
GEI + CCA [1]	6.77	11.08	10.60	8.22	10.84	10.36	11.33	8.14	5.96	6.45	6.77	8.77
Min. Fusion	25.14	28.72	28.43	24.68	30.58	31.46	35.12	27.86	23.64	22.41	23.26	27.39
Weig. Fusion [Proposed]	23.34	28.51	29.62	30.37	32.28	30.87	32.66	34.40	32.53	25.34	25.00	29.53

GEI + LDA in small/large deviation angles, turning its performance better than any of the individual state-of-the-art approaches. The results of weighted fusion are obtained again by repeating the experiment 50 times as each time test sample of drawn of different lengths randomly. The error plots with mean and standard deviation for the statistical results with weighted fusion method for each probe angle with respect to gallery angle are shown in Fig. 11. It shows the high statistical confidence in the results as each random experiment almost gives same result (very less variations). In this context, it should be stressed that even better performance might be possible, if more sophisticated optimization techniques, either linear (e.g., regression) or non-linear (e.g., neural networks), are used to find the optimal values for the weights of each algorithm.

5.2.1 View angle classification and switch-based fusion

As stated earlier, in cross-view scenarios, it is necessary to know the view angle of the probe, which can be used in the fusion scheme to decide the weights given to each basis algorithm, with respect to the deviation between gallery and probe angles. It is essential to have an accurate view angle of probe

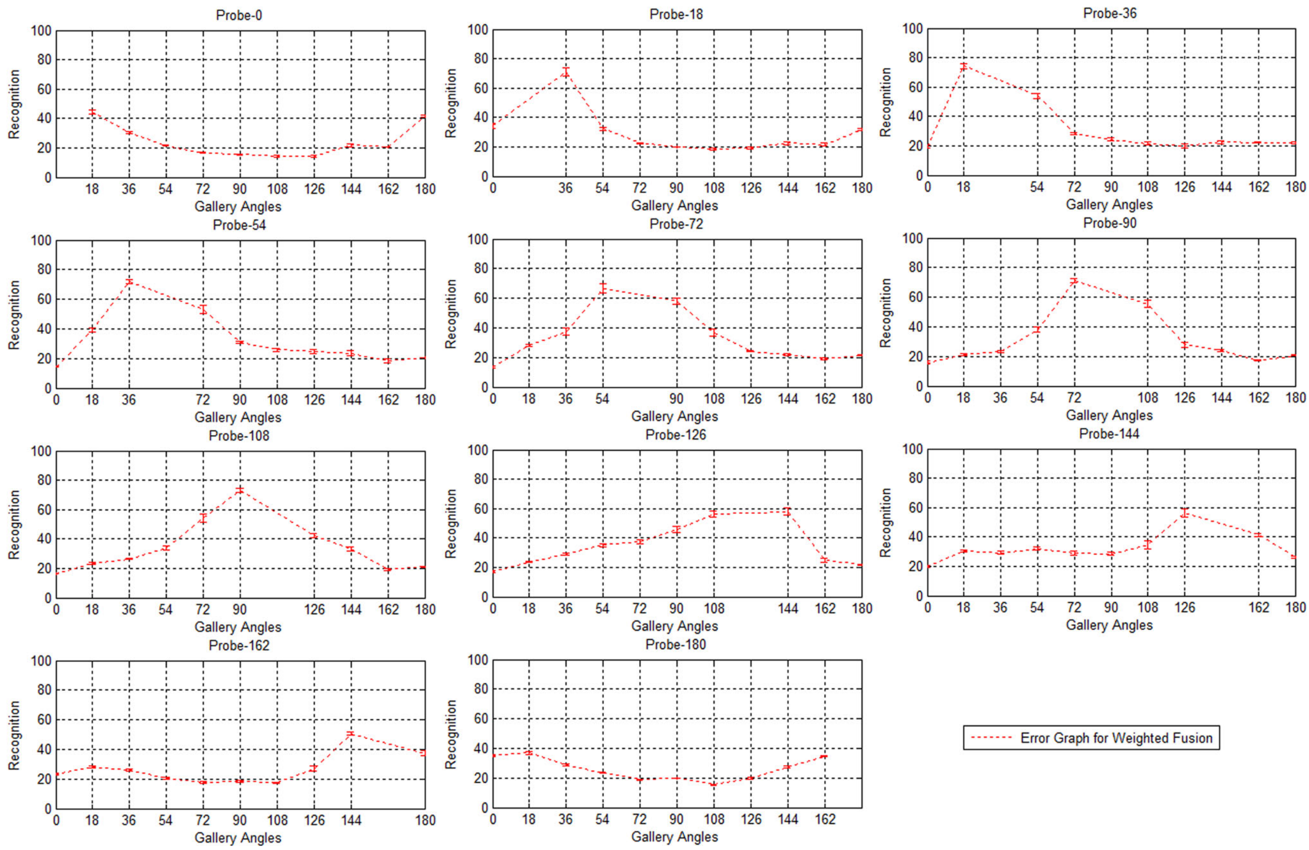


Fig. 11 The error plots with mean and standard deviation showing statistical confidence in results (no of experiments = 50) with weighted fusion method of aperiodic gait recognition

Table 2 View angle classification rate (VA)

Method	Probe angles°											Avg total
	0	18	36	54	72	90	108	126	144	162	180	
VA, GEI + LDA	55.23	47.32	52.67	48.13	44.39	48.53	34.16	42.30	35.62	55.60	46.61	46.43
VA, TGEI + LDA	96.65	97.11	84.36	89.21	92.94	84.10	91.25	94.87	92.27	97.41	99.15	92.63

Table 3 Cross-view recognition rate (CV) using switch fusion

Method	Probe angles°											Avg total
	0	18	36	54	72	90	108	126	144	162	180	
CV, switch fusion with angle span of ±18°	26.82	31.85	34.73	32.98	34.77	37.86	38.79	39.87	33.64	27.32	28.00	33.33
CV, switch fusion with angle span of ±36°	27.23	32.22	32.67	29.50	35.22	37.61	40.41	36.41	30.81	25.99	26.56	32.24

sample so that appropriate weights can be applied to multi-algorithms. The Table 2 gives the view angle classification rates, obtained by the GEI + LDA and TGEI + LDA techniques. In this case, it is obvious that TGEI should be preferred over a GEI for view angle classification. For further improvement, the view angle classification estimator can be used as a switch for the selection between the GEI + LDA and fusion approaches. The rank-1 recognition rate was obtained for two different angular spans: ±18° and ±36°. On observing the last rows of Table 3, it is evident that the switch-based fusion with span angle of ±18°

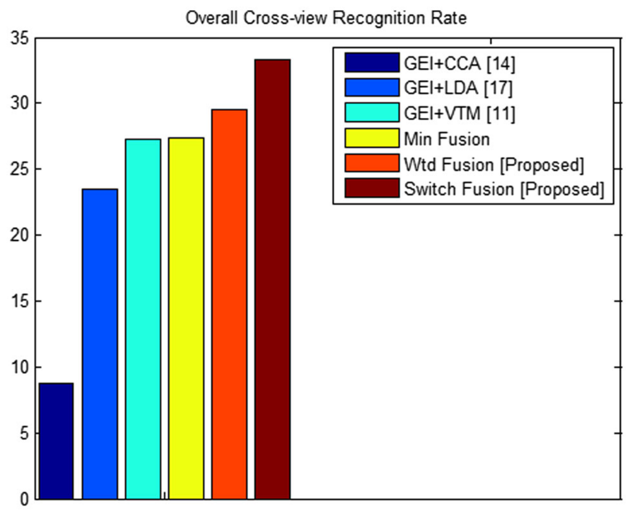


Fig. 12 Comparison of the cross-view recognition rates (excluding the same-view)

significantly improves the cross-view recognition performance, when compared to the weighted sum fusion rule.

5.2.2 *Summary*

To conclude, the summary of the overall cross-view recognition rates (excluding same-view recognition rate) obtained in this work is shown in Fig. 12. Each bar denotes a recognition algorithm and the vertical axis gives the rank-1 recognition rates, which justifies such low rates, if the plot is regarded at a glance. At the end, we observed that the techniques proposed in this paper achieved significantly better results over the existing state-of-the-art approaches. Quantitatively, the overall of 6 % additional recognition accuracy is improved using a fusion strategy over GEI + VTM method. This amounts to the almost 22 % improvement over the result of GEI + VTM technique, which was the best method in existing techniques when applied to the aperiodic feature extraction. The qualitative comparison for the state-of-the-art and proposed techniques applied to the aperiodic gait representations is tabulated in Table 4. Also, it is noteworthy to mention that results were obtained using arbitrary lengths of gait sequences in probe set, to test the robustness of aperiodic gait recognition for unconstrained biometrics applications.

6 Conclusions

In this paper, we focused on a gait recognition to be used in low-quality gait data obtained in the unconstrained setups. In these situations, it is difficult to have a reliable estimate of a gait cycle. Hence, three major contributions are reported here: (1) we proposed an *aperiodic* recognition scheme, neglecting the concept of *cycle*; (2) for multi-view scenarios, our experiments showed that satisfactory performance can be obtained by aperiodic recognition algorithms when a sufficient amount of data are used (≈1.5 times of the average gait cycle), eliminating the need to segment data in terms of cycles; (3) for cross-view scenarios, we fuse the responses attained from different feature subspaces of aperiodic feature representations at the scores level, yielding improvement in the recognition performance of around 22 %, when compared to the best of state-of-the-art gait recognition algorithms. These contributions are regarded as achievements toward the development of robust gait recognition algorithms, able to work in data of reduced quality and with significant deviations between the view angles of probes and gallery samples, as often occurs in visual surveillance scenarios and in unconstrained biometrics.

Table 4 Qualitative comparison of gait recognition techniques in periodic and aperiodic gait representations

Method	Subspace formation	Performance in periodic gait representation	Performance in aperiodic gait representation	Computational efficiency
GEI	Original	Low	Low	Moderate
GEI + CCA [1]	CCA	Moderate	Low	Moderate
GEI + LDA [4]	LDA	Moderate	Moderate	Low
GEI + VTM [18]	SVD	Moderate	Low	Moderate
GEI + SVR [13]	SVR	Better	Very low	High
GEI + NNR [14]	NNR	Best	Very low	Very high
Min fusion (original, LDA, SVD)	Subspace selection	Not applicable	Moderate	Moderate
Weighted fusion (original + LDA + SVD) [proposed]	Subspace addition	Not applicable	Better	Moderate
Switch fusion (weighted fusion and GEI + LDA) [proposed]	Subspace addition and selection	Not applicable	Best	Moderate

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