Gait Recognition based Online Person Identification in a Camera Network

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Abstract. In this paper, we propose a novel online multi-camera framework for person identification based on gait recognition using Grassmann Discriminant Analysis. We propose an online method wherein the gait space of individuals are created as they are tracked. The gait space is view invariant and the recognition process is carried out in a distributed manner. We assume that only a fixed known set of people are allowed to enter the area under observation. During the training phase, multi-view data of each individual is collected from each camera in the network and their global gait space is created and stored. During the test phase, as an unknown individual is observed by the network of cameras, simultaneously or sequentially, his/her gait space is created. Grassmann manifold theory is applied for classifying the individual. The gait space of an individual is a point on a Grassmann manifold and distance between two gait spaces is the same as distance between two points on a Grassmann manifold. Person identification is, therefore, carried out on-the-fly based on the uniqueness of gait, using Grassmann discriminant analysis.

1 Introduction

In this paper, we propose a novel online distributed multi-camera person identification framework based on gait recognition. Gait recognition is a proven unique biometric for person identification. One of its main advantages over other biometrics such as iris recognition and fingerprint recognition, is that it is unobtrusive and requires no attention or cooperation from the person to be identified. It is also a preferable choice for surveillance applications over other biometrics because gait data can be captured from a far distance inconspicuously unlike face recognition data. Gait as a biometric also has typical challenges. One of the main challenges is to correctly identify a person using their gait signature as they are viewed from various angles in a camera network. Gait recognition works best in an environment where there are a fixed set of people that are allowed to enter the area under observation, a fixed set of entry/exit points. Moreover, all cameras together observe the complete area under observation at all times. In our framework, during the training phase, a global gait space of each individual is constructed incrementally, as these people move in the area under observation using Incremental Principal Component Analysis (IPCA) [1]. This gait space is view invariant and is a point on the Grassmann manifold. During the identification phase, when a person enters the area under observation, his/her gait space is constructed incrementally. A gait space is considered as an element of a Grassmann manifold and Grassmann discriminant analysis [2] is used to identify the person. Grassmannian framework gives us the benefit of working within the non-linear structure of the data with the simplicity of the vector based computation. Moreover, because our framework is a distributed framework, each camera builds the gait space of the individual based on its view and the gait spaces are merged as the object moves from one camera to another in the network based on message passing in the network. One of the advantages of our framework is that it does not require the person to remain in the view of any one camera, requires no cooperation or time of the individual, the person is identified as they move around in the area. In case, the person is not identified within a fixed time from the first moment of entry into the area, he or she is labeled as *unknown* and the security official is notified about the person's presence in the scene and his/her whereabouts in the area. Our model is scalable in terms of both the number of cameras in the network as well as the number of people that are allowed to enter the area under observation.

2 Related Work

The process of gait recognition requires recording videos of people walking, extracting the silhouettes, then extracting gait features and finally classifying the individuals based on these features. In general, for automatic gait recognition, detection and extraction of silhouettes are performed using background subtraction [3]. After the silhouettes are extracted, based on the method to be employed for gait recognition, features are extracted and selected. There are two main approaches to gait recognition, namely, model-based approach and model-free approach.

In the model-based approach [4–7], static and dynamic features are extracted from the silhouettes. These features, in general, depict the position and pose of various body parts with respect to each other as a person moves in the scene. These features are extracted by tracking and modeling the body parts such as legs, head, arms, etc. The main advantage of forming a gait signature in this manner is that it is view as well as scale invariant. These invariants are necessary in practical situations since the training sequence and test sequence need not be taken from the same camera view. The drawback in this approach is that they are highly sensitive to the quality of gait sequences and the silhouette extraction. Moreover, these methods are in general offline methods since they require large computations.

Model-free approach does not model the whole body or body-parts, but focuses on the shape of the silhouettes or the whole body motions. The advantages of model-free approach are that it is less effected by the quality of silhouette extracted compared to model based approach, and have low cost of computation.

However, in most cases, they are view and scale dependent. Methods such as [8] use silhouettes directly as features that are aligned and scaled. Authors in [9] propose and define motion-energy image and motion history image while [10] propose gait energy images for gait recognition. Hidden Markov Models (HMMs) [11] are also used for gait recognition as these models are able to represent the different phases of the gait cycle. Methods such as [12] based on K-Nearest neighbor classification do not take into consideration the temporal information in gait sequences. They work with a single key frame extracted from the gait sequence.

Multi-view gait recognition is gaining popularity mainly because single view gait recognition methods are many-a-time view dependent. The viewing angle at which the gait database is formed need not be the same as that used for obtaining test data. Multi-view gait recognition methods are either based on view invariant features [14], [19] or based on multi-camera calibration that extract 3D structural information. However, calibration based systems require a fully calibrated multi-camera set-up which may not always be available. Approaches to multi-camera gait recognition such as [20], [22] are based on view transformation and do not require camera calibration. Although these methods allow large changes in viewing angles by transforming the gallery and test data to the same direction, they suffer from lack of information present in views separated by large angles. Authors in [23] propose a novel gait recognition approach based on correlating gait sequences from different views using Canonical Correlation Analysis (CCA). The CCA model implicitly resolves the mapping relations between gait features from different views and projects gait sequences from different views into maximally correlated subspaces. The method in [17], forms the Eigen-gait space of training samples and for a test sample it uses k-nearest neighbor classification for classifying a test object.

In our method, we form a gait space of each individual based on the multiple view data that is recorded. We assume that cameras are mounted at various viewing angles and may observe the subjects either simultaneously or sequentially. During the training phase, the gait space is created online as the subject walks around in the camera network. The gait space is updated every time the subject walks in the view of a new camera. This gait space is view invariant and represents data from all angles in the input viewing space.

During the test phase, as a person walks through the area under observation, his/her gait space is created. Then, Grassmann Discriminant Analysis is applied to identify the person. If the person does not get identified from the first camera, his/her gait space is augmented as it moves in the views of other cameras and after a certain time interval GDA is again applied. However, we perform a cascaded classification, where in the next classification step, we use only those training classes with which the distance is less than a predefined threshold in the previous step. The probe subspace gets updated as the person walks through the network and the number of training subspaces considered for classification reduces making the system fast and online.

Authors in [15], have proposed a gait recognition method called Sparse Grassmannian Locality Preserving Discriminant Analysis (SGLPDA), where they form a gait energy image of each person. A set of gait energy images are then modeled as a collection of linear subspaces. They formulate the gait recognition problem through the graph embedding framework in [16]. They apply sparse representation along with locality preserving Grassmann Discriminant Analysis to find the inter-and intra-class variations and perform gait recognition. Our framework is an online system where a single global gait space is formed for each individual while theirs is an offline system where more than one subspace exits for the same individual. Moreover, our framework is completely distributed where each camera forms its own gait space based on its view and the gait spaces for the same person are merged to form the global gait space. GDA is applied for finding the distance of the probe gait space from the training gait spaces to be able to identify people who enter the area under observation. This identification is also carried out in real-time, as the individual is moving around in the area under observation and in a distributed manner.

3 Background

3.1 Grassmann Manifold

A Grassmann manifold denoted by, $\mathcal{G}(k, n)$ is a set of k-dimensional linear subspaces in $\mathbb{R}^n$. Each unique subspace is a point on the Grassmann manifold. Therefore, in our framework the gait space of each individual is a point on a Grassmann manifold. The distance between two gait spaces is well-defined and is computed as distance between two points on the Grassmann manifold. The basic premise is therefore, that if the test subject is one of the people allowed to enter the building, the probe gait space should be close to one of the training gait spaces.

In general, the distance between two subspaces is computed using the principle angles between the two subspaces. The distance between the two subspaces on the Grassmann manifold is calculated as the distance between two points on the manifold. Mathematically, a point on the Grassmann manifold, $\mathcal{G}(k, n)$ is represented by an orthonormal matrix $S \in \mathbb{R}^{n \times k}$, where the columns of S span the corresponding k-dimensional subspace in $\mathbb{R}^n$, denoted by $span(S)$.

Two subspaces, $span(S_1)$ and $span(S_2)$, are two points on the Grassmann manifold, S_1 and S_2 respectively. The distance between them is given by Equation 1.

$$d^2_{proj}(Y_1, Y_2) = \frac{1}{2}\|Y_1 Y_1' - Y_2 Y_2'\|_F^2 \tag{1}$$

where, Y_1 and Y_2 are the matrix representations of the subspaces $span(S_1)$ and $span(S_2)$. Y_1' and Y_2' are the transpose of matrices Y_1 and Y_2. This also shows that the matrix representation of S_1 and S_2 is directly used for computing the projection distances between the two gait spaces. The advantage of using the projection distance is that it is an unbiased measure as it uses all the principle angles. This is specially beneficial since we have no prior knowledge of the data and all principle angles may be important.

3.2 Grassmann Discriminant Analysis

The Grassmann discriminant analysis [2] framework is specially focused on the problems where the data consist of linear subspaces instead of vectors. As mentioned in Section 3.1, a Grassmann manifold is a collection of all linear subspaces of a Euclidean space such that the dimension of all the subspaces is the same. More formally, $\mathcal{G}(k,n)$ is the collection of all linear k-dimensional subspaces of $\mathcal{R}^n$. An element of $\mathcal{G}(k,n)$ is an orthogonal $n \times k$ matrix X. Therefore, X is a point on the Grassmann manifold. Formally, the distance between two points on the Grassmann manifold is the length of the shortest geodesic connecting the two points. However, principal angles between two subspaces provide a more computationally efficient method of defining distances between two points on this manifold.

Let S_1 and S_2 be two points on the Grassmann manifold, then the distance between the two points is computed as the projection distance given by Equation 1. Then, the projection kernel given by Equation 2

$$k_P(S_1, S_2) = ||S_1' S_2||_F \tag{2}$$

is a Grassmann kernel [2]. The Grassmann discriminant analysis algorithm uses the projection kernel in Equation 2 to perform Kernel LDA using Grassmann kernel.

The GDA algorithm assumes that the subspace bases S_i are already computed. The authors in [2] assume that the subspace bases are computed from the sets in the data using SVD. However, we use the bases computed during the gait space construction phase discussed in Section 5. During the training phase, the algorithm finds distances between subspaces S_i and S_j using the projection kernel given by Equation 2 for all subspaces S_i and S_j in the training set. These distances are stored as a matrix K_{train}. The next step is to solve for the Rayleigh quotient α using Eigen-decomposition and calculate the (C-1)-dimensional coefficients, $F_{train} = \alpha K_{train}$, where C are the class labels.

During the testing phase, first the distance between the test subspaces and all the training subspaces are calculated. Then, the (C-1)-dimensional coefficients, F_{test} are calculated. Finally, 1-NN classification from the Euclidean distance between F_{train} and F_{test} is carried out for classifying the test cases. In Section 6, we describe how we adapt GDA for gait recognition in a camera network.

4 Overview of the Framework

We assume that the area under observation is observed by multiple cameras, such that at a time one or more cameras may be observing the person under consideration. We also assume that only a certain set of people are allowed to enter and exit the area under observation.

During the training phase, as these people walk in the area under observation, their gait space is constructed incrementally in each camera of the camera network as discussed in Section 5. We apply background subtraction [3] and

Incremental Principal Component Analysis(IPCA [1]) to create the gait space on-the-fly for each object. IPCA also gives the advantage of adding new information to the already existing gait space in case new cameras are added to the system. We assume that the gallery data is present in each of the cameras and that the network has a known topology. We define neighbors of a camera C_i as those cameras that can simultaneously view the individual under consideration or view the person as it moves out of the view of C_i. When a person is about to get out of a camera's view, it passes the person's gait space and other relevant information to its neighbors. Then, the new camera augments the person's gait space incrementally using its own view. In case the new camera gets information from more than one camera about the same person, it merges the gait bases to form a single gait space of the person using the method discussed in Section 5.1 and then augments it. In such a manner, a global gait space of an individual is formed while the person is tracked across all the cameras in the network. This global gait space is used for classification using Grassmann discriminant analysis.

During the test phase, as the object enters the area under observation, it is tracked and its gait space is formed on-the-fly. Then, Grassmann Discriminant Analysis is applied to identify the person based on the gait signatures created during the training phase. The details are given in Section 3.2. We define a confidence measure for identification of the person. However, in case the person does not get recognized from one view, as his/her gait space is augmented by various views, the identification process is carried out periodically. However, for each next identification step, only those training classes are used with which the distance is less than a pre-defined threshold in the previous step. This cascaded recognition makes the identification process fast. Any object that is not recognized with a certain confidence level even after the person has been in the network for a certain time period is flagged as an *unknown* person.

Using IPCA and GDA makes the system robust to addition and deletion of cameras and therefore, makes the system scalable. Deletion of camera does not affect the gallery since extra information does not mislead the system. Moreover, on addition of a camera, IPCA is used to update the gallery. Since IPCA is also used to form the probe's gait space, data of the new camera can be easily incorporated if the probe subject enters its view. Another important feature of our system is that recognition occurs online as the subject is tracked in the views of the various cameras in the network.

5 Forming the Gait Space

We form the gait space using incremental PCA [1] for creating the gait spaces as the person is tracked in each camera. In [17], background subtraction [3] is done to extract the moving object and track it in each frame. The extracted silhouette is then aligned and scaled to obtain a uniform height. This is done for taking into account the errors in background subtraction and height changes when the object moves away from the camera or towards the camera. Then, using a sequence of silhouettes the self-similarity plot (SP) of the person are detected. Then, the *Units of Self-Similarity* (USS), that is, a set of normalized feature vectors that are extracted using these self-similarity plots.

We modify this method to create the gait space incrementally. As the person is tracked, and the foreground silhouette extracted, the corresponding silhouette is scaled to a uniform height. Then, the self-similarity plot is obtained by Equation 3 between consecutive frames.

$$S(t_1, t_2) = \min_{|dx,dy|<r} \sum_{(x,y)\in B_{t_1}} |O_{t_1}(x+dx, y+dy) - O_{t_2}(x,y)| \tag{3}$$

where, $1 \leq t_1, t_2 \leq N$, B_{t_1} is the bounding box of the silhouette in frame t_1, r is a small search radius and $O_{t_1}, O_{t_2}, \ldots, O_{t_N}$ are the scaled silhouettes. Since a person's gait is periodic and continuous, the similarity plot is tiled into rectangular blocks, known as Units of Self-Similarity (USS). These USS consists of self-similarity over two periods of gait for each person. Each USS is the gait feature vector corresponding to N frames. We construct the USS's and apply IPCA on these feature vectors to incrementally find the d most significant eigenvectors that contain maximum information about the person's gait from one view. This creates the gait space of the person from one view. Each camera that observes the person creates its gait space in a similar manner. When the object is about to get out of a camera's view, the camera sends the gait space along with the identity of the person to all its neighboring cameras.

If the neighboring camera receives more than one gait space for a particular person, it merges the gait spaces as discussed in Section 5.1. Otherwise, the new camera creates its own gait space for the person and merges with the gait space(s) it received for creating a global gait space. In this manner, a global gait space is created for each individual in the training set.

5.1 Merging Two Gait Basis

Our method for merging two gait spaces is based on the method for merging two subspaces as proposed in [18]. Let the two sets of observations be $\mathbf{A}_{n\times N}$ and $\mathbf{B}_{n\times M}$. Then, their corresponding Eigenspace models are denoted by $\varOmega = (a, S_{np}, \varLambda_{pp}, N)$ and $\varPsi = (b, T_{nq}, \varDelta_{qq}, M)$, respectively. The goal is to merge the two spaces and to compute the combined Eigenspace $\varPhi = (c, U_{nr}, \varPi_{rr}, P)$ for the combined observation $C_{n(N+M)} = [A_{nN} B_{nM}]$ using only $\varOmega$ and $\varPsi$. Then, using the Gram-Schmidt orthonormalization [21], we first construct the orthonormal basis set γ_{ns} that spans both $\varOmega$ and $\varPsi$ and $x - y$. The basis $\varGamma_{ns}$ differs from the required basis U_{ns} by a rotation R_{ss} as given in Equation 4

$$U_{ns} = \varGamma_{ns} R_{ss} \tag{4}$$

We then derive another Eigenproblem using the basis $\varGamma_{ns}$ whose solution gives the eigenvalues $\varPi_{ss}$ that are required for the merged model. The corresponding eigenvectors R_{ss} form the rotation matrix that is required in Equation 4. Using R_{ss}, we compute the eigenvectors U_{ns} as given by Equation 4. The r non-negligible eigenvalues and their corresponding eigenvectors form U_{nr}. Thus, the merged Eigenspace is computed in this manner.

6 Person Identification through Gait Recognition

Each person walks with a gait that cannot be replicated by another person, making gait a unique biometric. In our framework, during the training phase, the gait space of all the people allowed in the area under observation is formed and stored in each of the cameras.

Person identification is performed online as the person moves in the area under observation. When a person comes into the view of a camera, it starts getting tracked and its gait space is formed incrementally as described in Section 5. As a person walks in the area observed by multiple cameras, we assume that the subject is viewed by multiple cameras simultaneously or sequentially. For each of the individuals that are allowed to be present in the area under observation, their gait space is created in the training phase using IPCA. As mentioned before, IPCA gives us the flexibility of adding new cameras without having to re-compute the complete gait space of an individual. For Grassmann discriminant analysis, we form the matrix $K_{train} = k_P(X_i, X_j)$ for all training subspaces X_i and X_j. We then compute the Rayleigh quotient and F_{train} as described in Section 3.2.

During the test phase, when an object is detected to have entered the area under observation, its gait space constructed using the method outlined in Section 5. After a certain time interval, the distance between this test subspace and the training subspaces of all the people allowed in the area is computed, and the (C-1)-dimensional coefficients, F_{test} are computed. The Euclidean distance between each F_{train} and F_{test} is computed as $d(F_{test}, F_{train}(i))$. We define a confidence measure, given by Equation 5, as a distance decay function based on the distance between F_{train} and F_{test}.

$$CM(i) = e^{-(d(F_{test}, F_{train}(i))} \tag{5}$$

The dimension of the gait space of the probe individual changes as the person moves in the area under observation and gets recorded by various cameras in the system. We assume a match with the i^{th} individual, if the confidence measure is above a threshold. However, we perform recognition in a cascaded manner wherein, as the person moves in the area under observation, recognition is performed at fixed time intervals. All the training classes are used in the first attempt, after that in every interval only those training classes are used with which the confidence measure of match is above a per-defined threshold, t_{elim}. In this manner, as the test data increases the dimension of the gait space formed on-the-fly also increases and the chances of a correct match increases. An individual is said to be correctly recognized if the confidence measure of a match is above another pre-defined threshold t_{match}.

An important point to be taken into consideration is that the distance on the Grassmann manifold is measured between two subspaces of the same dimension only. However, the dimension of the training gait spaces is much larger than the test gait space. Therefore, we consider only the first n basis vectors of all the training gait spaces where, n is the dimension of the test gait space in that time interval.

7 Experimental Results

We used the CASIA gait dataset B [13] for our experiments. The dataset consists of 124 subjects. This dataset is a multi-view gait dataset as it was captured from 11 viewing angles. The viewing angles are 0°, 18°, 36°, 54°, 72°, 90°, 108°, 126°, 144°, 162° and 180°. Moreover, 6 gait sequences are captured for each individual under each viewing angle. Therefore, there are a total of $11 \times 124 \times 6$ or 8184 gait sequences. For each person, we form the gait space using two gait sequence for each angle. We started with 0° to form the gait space and then, incrementally create the gait space using two gait sequences for all the views.

For the identification phase, we use a gait sequence of each person that was not used for training. We start with the 0° view and create the gait space of the test subject. We check for identification using the GDA algorithm and then, add data from each of the viewing angles and re-checking the identification using the algorithm in 6. We find that the identification rate improves as the number of views are increased as shown in Figure 1. We calculate the Ambiguity resolution measure as given by Equation 6

$$\text{Ambiguity resolution} = \frac{\text{no. of objects correctly classified}}{\text{total no. of objects}} \tag{6}$$

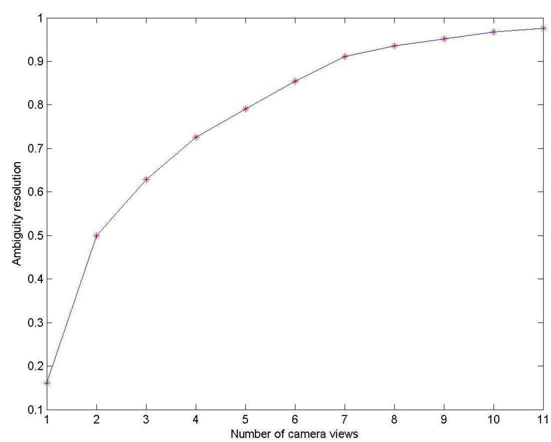

Fig. 1. The graph shows that as the number of views are increased, the recognition rate increases. It can be seen that initially there is a steep rise in the number of subjects correctly classified as the number of views increase, however, after a certain number of views have been considered the graph saturates. The x-axis shows the number of views considered and the y-axis represents the ambiguity resolution calculated by Equation 6.

We also use the Cumulative Match Characteristic(CMC) to present our results for the GDA based gait recognition. We find that for each person the identification rate increases as the number of views taken in the creating the test gait space is increased. This can be seen by the different curves in Figure 2. In general, we see that for all the 124 subjects, not all 11 views are required for the identification. In most cases, 5 views were the maximum that was required for recognition while in a few cases 7 views were required for the person to be correctly classified.

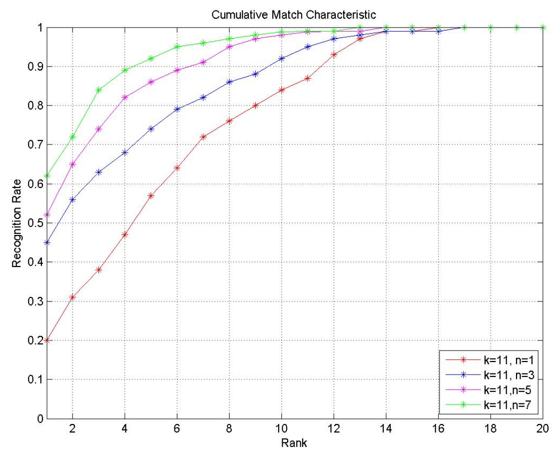

Fig. 2. The graph shows that as the number of views are increased, the recognition rate also increases. $k = 11$ are the number of views taken into consideration for forming the gait space during the training phase. n indicates the number of views taken into consideration during the identification phase.

8 Conclusion

In this paper, we have proposed a novel online, distributed framework for person identification in a camera network. Our framework is based on gait recognition using Grassmann discriminant analysis. During the training phase, a known set of people move in the area under observation and a gait space for each individual is created, by merging the gait spaces from all the cameras viewing the person. During the test phase, as an individual moves in the area under observation, his/her gait space is created on-the-fly and Grassmann discriminant analysis is applied for classifying the individual. Therefore, as a person moves in the area under observation, our system is capable of identifying him/her. In case, the person does not get identified after a certain time interval, we label the person as an *unknown* person.

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