ORIGINAL RESEARCH PAPER

Engineering

SELECTIVE KNN BASED VIEW-INVARIANT PERSON IDENTIFICATION

KEY WORDS: Activity recognition, Person identification, Human gait.

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ABSTRACT

An activity is the signature, recently found suitable for the identification of person. Besides activity recognition, activity based person identification can add the value in bio-metrics applications. This is based on the discriminant characteristics available in the particular activity of the subjects. Some of the examples of activities, but not limited to, are: running, jumping, waving hands, sitting etc. In this paper, we present preliminary study about gait activity based person identification. We also reviewed various methods, that have been applied in activity recognition and activity based person identification. The main objective of this paper is to formulate the problems and find the solutions with the novel methods that can be employed in gait activity based person identification in unconstrained and far distance bio-metrics. The widely used publicly available CASIA A gait database is used to evaluate the proposed method.

INTRODUCTION

Bio-metrics is considered as one of the successful applica tions 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 biometric recognition systems usually operate in constrained acquisition scenarios and under rigid protocols. This scenario motivates researchers to explore the development of *non-cooperative* systems [28]. In the bio-metrics application that requires distant data (sample) capture, it becomes almost impossible to acquire the samples of fingerprints or iris. Similarly, it faces difficulties to get frontal face image capture in case of face recognition. Besides popular bio-metric modalities like fingerprint, face and iris; activity based bio-metrics [15] can add the value to the identification process, especially, in the case of bio-metric applications where far distant data capture process is involved. The gait recognition is based on the activity of person, namely walking. However, besides "walking", there are several other activities that are performed by the person in his/her daily life, such as running, jumping, waving hands, sitting etc. In 2009, the first paper [6] by Gkalelis et. al. in its kind, was published describing the approach by which person can be identified from his/her activity (not just walking activity). The action recognition techniques mostly suffer from the inter-person variation in particular activity [18].

LITERATURE OVERVIEW

In one of the early papers in the area of activity recognition [4] has presented the recognition of activities that was carried out using local appearance based features and classifying them with probabilistic classifier using Bay's rule. In [33], constructed temporal pyramid of the entire video sequence by blurring and sub-sampling the sequence along the temporal direction only and captured temporal textures using filters (plenotic functions [1]) from each subsequence of pyramid.

In [8, 9], presented the approach that assigns a value for every internal point of the silhouette, reflecting the mean time required for a random walk beginning at the point to hit the boundaries. These shape representation using Poisson's equation parameters are extended space-time shape (object) representation in the form of Hessian matrix parameters in [2, 7]. The similar work, but with difference image of consecutive frames instead of frame from video, was carried out by [26]. The neural network classifier was used in this work. Gkaleis et. al. decomposes a 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 [5]. This method was extended in [12], [14] and [13] for the multi-view videos.

The work done in [3] has proposed the scheme to make human motion classification view independent. In this method, training videos for each activity was captured using optimal view for particular activity.

In [6], features were extracted and clustered similar to as described in [5]. Later, this method was experimented with fusion of multiple classifiers in [15]. In [30], a systematic generative model for activities that accounts for variations in speed profile of an activity is generated. However, later in [31], allowable warping space was decided by learning and inference to have much general class of distributions.

In [11], the person identification is done using the group context. The group relationship was represented using the graphical model.

In one of the early papers [27] in the area of action recognition, sign of the angle of spatiotemporal trajectory is considered as sign of instant and is used to make representation view-invariant. Another interesting approach in [29], for view- invariant that image -based visual hull (VH) is computed from a set of monocular view images. Similar approach was used in [19] with different feature representation and was applied in gait recognition. In this method both learning (training) and matching (testing) sequences were captured by using multiple cameras.

To make temporal invariant recognition process, in one of the work [10], space- time interest points were extracted for each activity; as these features are based on maximization of discrimination between behaviors. In [15], the activity based person identification technique was made invariant to the temporal duration of the activity, by using the feature representation which accumulates the measure obtained from each of the final basis posture vector for the each test activity video

Inspired from their earlier work in [30], they have used the model, which is composed of a nominal activity trajectory and a function space capturing the probability distribution of activity-specific time warping transformations [31]. The distribution of possible temporal trajectory approximates the slow and fast trajectories of same type of motion profile and hence avoids the changes in temporal scaling of trajectory due to subject itself or frame rate change in camera hardware.

The Bayesian classifier [15], hidden Markov model (HMM) [20], nearest neighborhood [6], neural network 16] are used in their general form for classification of activity recognition or activity based person identification.

PROPOSED METHODOLOGY

The main complexity of the activity based recognition lies in three components, namely, 1) Dynemes Calculation, 2) Feature Extraction and 3) Classifier and fusion. Our proposed approach uses only three orthogonal views in multi-view capture or multi-view gait environment. The dynemes were used to calculate its histogram using distance measure and its fuzzification as described in [15]. kNN training instances with different gait-angles or view angles can give enough variation in their features to overlap 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 1. This method is different from the framework proposed in [15] in the sense that former employs the fusion of two classifiers (in parallel), while later one uses two classifiers in series. The system block diagram of our approach based on two classifiers in series is shown in figure 2.

The further improvement can be achieved in the S-kNN classifier using Rank- N angle classification results to build next selective classifier, where the samples of angles obtained from rank-N angle group are included in gallery image. The improved version of S-kNN i.e. Rank-N S-kNN classifier is shown in figure 3.

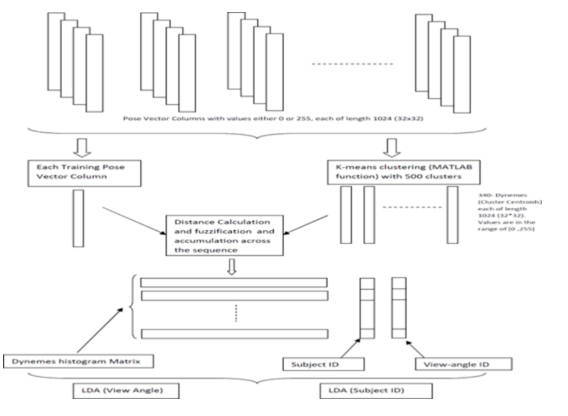

Figure 1: Histogram features extraction and two LDA subspaces

RESULTS

In order to evaluate the proposed classifier strategy for sparse representation of gait sequence, we experimented our approach with sparse representation and LDA subspaces presentation using CASIA data set A. This data set has 20 subjects and 4 instances of each of the three angles; 0°, 45° and 90° making total gait sequences in this data set as 20x4x3=240. The performance result is shown in figure 6.

CONCLUSION

Gait activity is the individual signature and can be used for the identification of person. Besides other activity recognition, gait activity based person identification can add the value in bio-metrics applications. In this paper, we presented preliminary study about gait based person identification. We also reviewed various methods, that have been applied in activity recognition and activity based person identification. The problem of in-variant gait person identification is addressed in this work. The view angle optimization framework and sKNN classifiers improve the view angle classification and person identification rate.

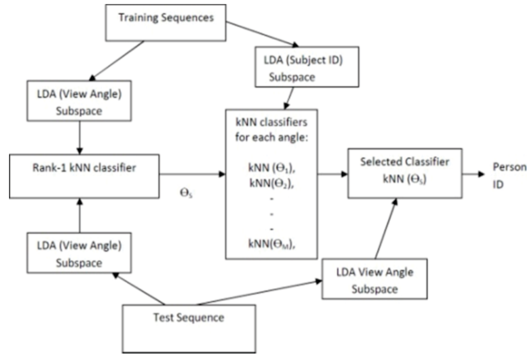

Figure 2: S-kNN Classifier

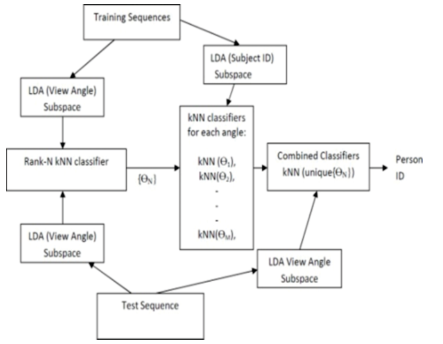

Figure 3: Rank-N S-kNN Classifier

Table 1: Sparse and LDA based with kNN and S-kNN classifiers

Training	Method	Overall Accuracy, S={3, 4}, 120 samples	0^0 S={1,2,3, 4}, 80 Samples,		45^0 S={1,2,3, 4}, 80 Samples,		90^0 S={1,2,3, 4} 80 Samples,	
			VA	pID	VA	pID	VA	pID
CASIA Dataset A No. of subjects=20 Dynemes=340 from DyAng={0, 45, 90} K={1, 2}	LDA	70.83	-	85.00	-	88.75	-	82.5
	Sparse	70.00	-	85.00	-	85.00	-	85.0
	S-kNN LDA	79.16	98.75	90.00	100.0	93.75	97.50	85.0
	S-kNN Sparse	74.16	97.50	86.25	98.75	90.00	100.0	85.0

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