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Research paper

Gait Recognition as Non-Intrusive Biometric Using View Invariant Methods in Multi Temporal Images

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Abstract

Gait patterns have been used widely in recent years to authenticate users. Because it doesn't require user intrusion, it is often used as a biometric to make authentication processes easier and hassle free. But there are various issues with this process. To start with, the viewing angle has to be constant which is quite difficult to achieve with limited number of cameras. Speed too can alter the way a person walks and cause inconsistencies in identification. Furthermore, complications might arise if the subject is carrying something. The weight can affect his walking pattern. Besides, a recent accident could also transform a person's walking pattern and lead to wrong identification. Other biometrics such as face detection can be combined with this technique to reduce the issues leading to erroneous identification. In this paper, we propose a system to overcome the viewing angle discrepancies. The system takes in walking sequences as input and processes them to create images. This is converted into 3D images by means of stereovision algorithms. Using which, we can effectively match the real-time image with various image sequences in the database. Side face detection can enhance the accuracy further..

Keywords: *Background Subtraction, Transformation, Gait Feature Extraction.*

1. Introduction

Gait techniques have often been used to identify people based on their walking pattern. But they are not yet employed commercially because of the various issues that arise starting from the person's clothing to his walking speed. However, there are some instances where the gait technique has been successfully used. In one such case, a burglar was caught using Gait. The footage available from the scene wasn't clear enough for a facial identification but his walking pattern was adequate. This was further fed into the system and the man was identified and arrested. But since it highly important to identify the right suspect, we cannot allow even the smallest miscalculations. Hence we need a robust software which would reduce the transformation errors to the maximum. Also facial recognition and foot pressure identification is used in addition with gait to slim identification faults.

Gait recognition is a biometric method for recognizing people's walking pattern without intrusion. Patterns can be recognised from a distance from even low quality videos, making them much more efficient than other biometric mechanisms. But there are limitations to employing them in real life. The most important being the distortions in views that generally occur in real situations. The most challenging task here is to match the pattern across diverse views.

We come across two different approaches proposed which will overcome this issue. An appearance-based approach [14], and a model-based approach [15]-[19]. Appearance-based mechanisms extract gait attributes directly from image sequences captured. On the other hand, model-based mechanisms derive model attributes from images. 3D model-based mechanisms are preferred because of their view-unvarying nature [17], [19], [20]. But it is often challenging to generate 3D modelsof high certainty from images taken using just surveillance cameras.Therefore, we concentrate on appearance-basedmechanisms in this paper.Many methods have been suggested to overcome the viewissue in appearance-based approaches [21]–[23]. Broadly, they fall into three groups: view-invariant, visual hull-based,and view transformation-based methods.View-invariant approaches can be categorised as subspace-based, geometry-based, and metric learningbased methods. Except for the view invariant approach, the remaining approaches use discrete views which are contained in the training set alone and can affect the accuracy if target views aren't from the trainingsets. View transformation methods extended to arbitrary views solve the discretion issues.3D gait sequences of multiple training views are taken and the features of the target subjects are created by projecting the sequences into 2D spaces related to the target views. The difference is employing multiple non target cases instead of target images. Also, we employ part dependant view selection which separates the gait characteristics along several body parts to fix destination views for each body part.

2. Existing Systems

Shuai Zheng et al [1] offered a solution for viewing angle variation issues. The gait energy image was used to create a robust view transformation model. The features were extracted from the energy image using the partial least square method. It eventually performed better by remaining robust to clothing, viewing angle variations and carrying condition changes.

Xiaoli Zhou et al [2] utilised the side face of a person and his walking pattern. The side angle of face isn't usually of high resolution and hence an image was constructed out of consecutive video frames called enhanced side face Image. The gait energy image was created by exploiting the spatio-temporal compact representation. The data was then fused to create parameters for recognition.

KonstantiosMoustakas et al [3] explained how Soft biometrics include systems that are used to acquire the biometric aspects which are usually easy to acquire but lack the discriminative powers of common biometric techniques. The analysis was dependent on radon transforms on gait energy images. The main features acquired here are a person's stride length and height. These methods are often clubbed with other efficient biometrics to enhance performance.

WorapanKusakunniran et al [4] proposed a framework to construct new invariant feature for gait recognition. View normalization was done on the input layer to normalize gaits from arbitrary views. Invariant low-rank textures transforms a certain view into canonical view. Later, an improved scheme on Procrustes analysis was applied on the silhouettes.

Liang Wang et al [5] proposed to build an algorithm for gait recognition using statistical shape analysis. Firstly, a background subtraction algorithm was used to reduce the working area. The silhouettes thus extracted are represented as sequences of vector configurations. These were done on a common coordinate frame which in turn is analyzed using procrustes shape analysis technique. The dynamics of gait wasn't efficiently explained but the structural characteristics were clearly interpreted.

Shiqi Yu et al [6] explained in detail the methods to identify the gender of various humans. Prior knowledge was combined with automatic procedures which would improve classification accuracy. Also, a numerical analysis which takes into account various human components like head, hair, back and thigh helped greatly in differentiating the features.

ImedBouchrika et al [7] stated that Haar-like templates can be used to extract gait features from various viewpoints. Angular model templates which define the human motion were employed to guide markerless model. The features extracted include angular measurements for the lower legs with the displacement of the body. To enhance efficiency, a feature selection algorithm is used which relies on the proximity of the neighbours in the same class. The rate of classification was found to be 73.6% after a rectification process.

NitchanJianwattanapaisarn et al [8] proposed a method to get gait features from Microsoft Kinect. A distance function between two walking sequences was constructed using combinations of skeletal static features. Skeletal kinematic features were obtained from movements and silhouette features. Later, a function was used for classification.

SoharabHossainShaikh et al [9] said feature vector generation and subsequent classification depend on the whole silhouette and this involves a huge amount of data. They proposed a system where, the partial silhouette has enough discriminating information for gait recognition. Swinging hands of a human body was found to contain maximum discriminating features.

DaigoMuramatsu et al [12] proposed methods to reduce the faults that occur due to viewing angles. A system called Arbitrary View Transformation angle incorporated 3D images as training views and 2D images as target views. Doing so, the recognition degradation from falsely identified angles is managed. Also, Part-Dependant view selection schemes split the gait features into several parts to curtail transformation errors.

WorapanKusakunniran et al [13] proposed a method which aims to reduce the errors that might arise due to the variations in viewing angles. Normalization techniques were used to convert various views of the subject into a common view. Regression functions which employ sparse regression are elastic net for VTM construction.

3. Proposed Method

The existing system proposed a method where the 3D images of the training set was alone necessary and these can be used to map the target images to their corresponding angle deviations. We propose a system as in Figure 1, where the target images are converted into 3D images with stereovision algorithms.

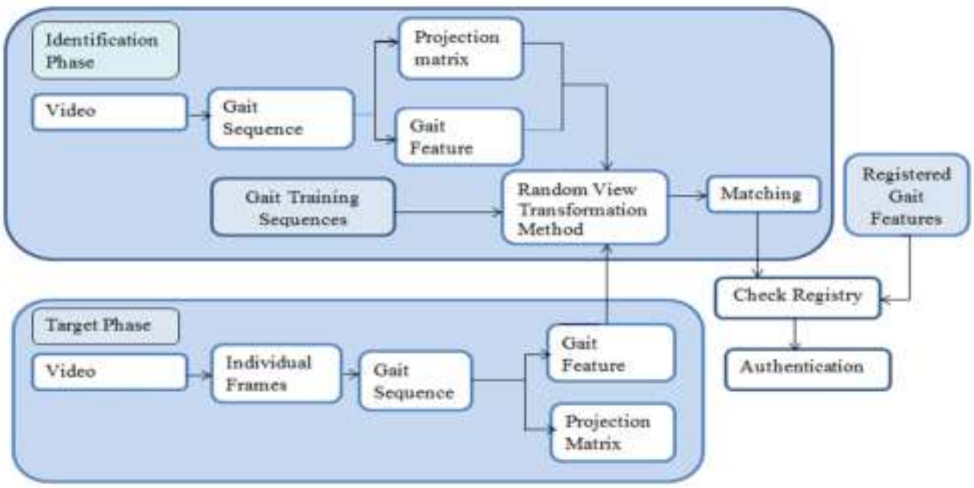

Figure 1. Architecture Diagram

3.1 Video Sequence to Frame Conversion

The video is converted to individual frames using various procedures. These would in turn be used as a sequence to differentiate one frame from the next. This difference can be exploited to make the accuracy levels higher as in Figure 2.

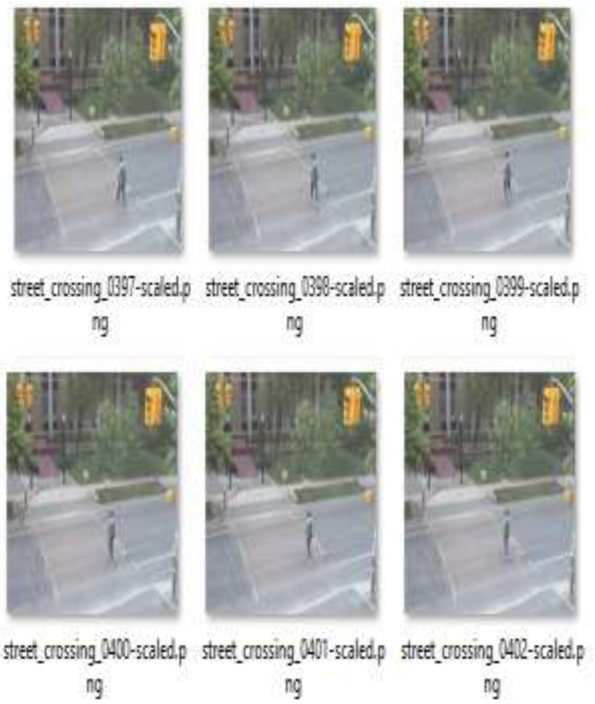

Figure 2:. Frame Conversion

3.2. Background Subtraction and Random View Method

Low Rank Subtraction or foreground subtraction is applied to get the particular person into focus. There are two phases explained here. The enlistment phase and the actual recognition phase. The gait sequences are fed in with an identification number. These usually carry the projection matrices. The matrices are utilized to provide the training data with aimed views. The background separation algorithms are used to segment the person alone. After which, the gait parameters are extracted from the silhouette sequences. These features are then enlisted with their identification number in the gallery and probe respectively. In the recognition phase, training features of the target views are provided from the multiple 3D volumes available in training sets. Here, we take the gallery and probe view as the source views. The intermediate between these views are considered destination views. The training view features are trained by the Random View Method. Also, the Part Dependent Views are used here so that the destination views selected so that the gait features are matched for each part accurately. These scores are added up for recognition. This is depicted in Figure 3.

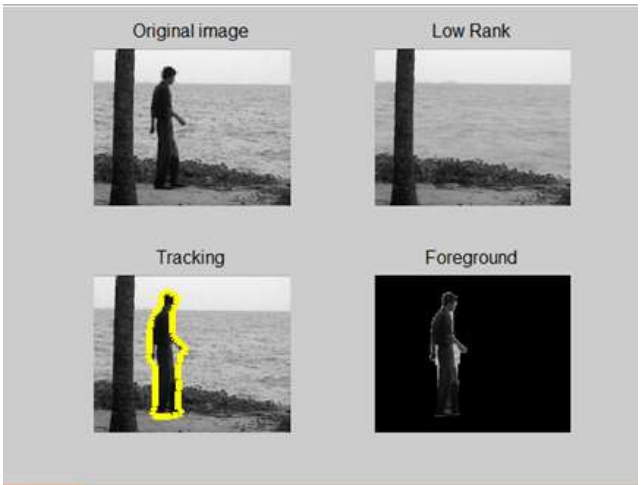

Figure 3:. Background Subtraction

3.3. Random View Framework

This approach is distinct because of its discreteness in the training views. Usually, the training dataset is made of 2D image series from various distinct views. However, it is impractical to generate 2D image sequences from random views from these 2D training datasets. Hence, we use 3D volume sequences during training itself. Using these 3D sequences, we can create 2D images in random by re-projecting the matrices. This is very essential in creating the data associated with target views. For a better classification process in a backup vector machine, input events need to be performed in a specific operation classifier algorithm to ensure a better classifier performance. Many methods have been developed to prepare input data into the classifier. Recently, the extraction and selection of features for preparation of data have been considerably taken into account. One of these reasons is that, after receiving a lot of data and many features of the test, it is not possible to directly enter the KDE classifier because it badly reduces its performance; therefore, it is necessary to extract and select the feature to prevent redundancy of information. Reducing the number of features by extracting and selecting the appropriate and useful features will be very helpful.

4. Experimental Results

4.1 Image Extraction

In partially based gait recognitions approach, the fusion occurs when they were made to walk on a treadmill and their pattern is captured. Projection matrices are created from silhouette images, where the sequences are modified manually.

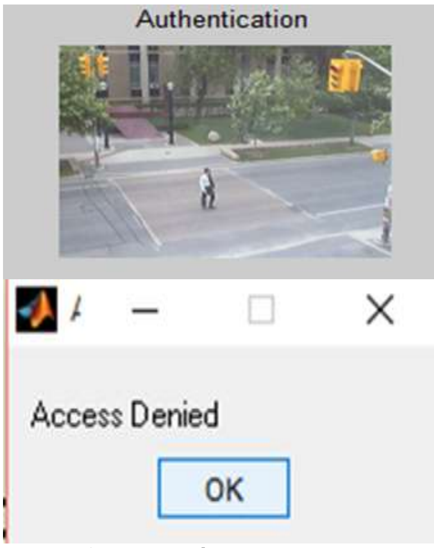

Figure 5:. Authentication System

5. Conclusion and Future Enhancement

We proposed a method for cross-view random gait recognition. There are two main advantages available in this technique. Usage of Arbitrary Views while matching when Conventional VTM's propose a discrete method which can be overcome using arbitrary techniques. Gait volumes of target individuals need not be extracted, proving the current method to be easier during matching. Part Dependant Conversion error which usually indicates The conversion error for each body part is dependant on the destination view. This paper clearly identifies the impact of view variations in the destination view. Also, the proposed random view framework modifies the precision of other methods. Adding features like side face recognition can improve accuracy rates further. The side face detection approach is also along distance nonintrusive approach which can be incorporated here. Provided, there are procedures to register faces separately.

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