VISION-BASED APPROACH FOR PEOPLE TRACKING USING GAIT IN DISTRIBUTED AND AUTOMATED VISUAL SURVEILLANCE

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ABSTRACT

Recent research studies have now confirmed the possibility of recognizing people by the way they walk i.e. their gait. As yet there has been little formal study in surveillance systems for identity tracking using gait signature over different camera views. We present a new approach for people tracking and identification between different non-intersecting un-calibrated cameras based on gait analysis. A vision-based markerless extraction method is being utilized for deriving the gait kinematics as well as anthropometric measurements in order to produce a gait signature. Given the nature of surveillance data, a parametric Fourier descriptor is being used to guide the extraction process of the legs. The novelty of our approach is motivated by the recent research for people recognition using gait. The experimental results confirm the robustness of our method to extract gait features in different scenarios with a classification rate of 92% for lateral views. Furthermore, experimental results revealed the potential of our method to work in real surveillance systems to recognize walking people over different views with achieved cross-camera recognition rates of 95% and 90% for two different views.

1. INTRODUCTION

Despite the fact that privacy has emerged as a major concern, surveillance technology is now becoming ubiquitous in modern society. This is mainly because of the increasing number of crimes as well as the vital need to provide a safer and secure environment. Tracking people over a network of distributed cameras has recently emerged of great interest to surveillance and monitoring applications. This is because of the impossibility of human operators to work simultaneously on multiple video scenes to track people of interest and analyse their activities within different places. Therefore, it is becoming a vital requirement for the computer vision community to research vision-based alternatives that can automate the process for object hand-off over different views including the tracking and identification of subjects as well as analyse their activities. Intuitively, a number of approaches were recently proposed to accomplish such aim based on deploying basic feature information including colour or shape. However, their practical deployment in real application is limited due the complexity of such problem. Alternatively, we propose a novel method for tracking subjects across different views by the way of their walk defined as Gait.

The use of gait for people recognition in surveillance systems has attracted researchers from computer vision. The suitability of gait identification for surveillance applications emerge from the fact that gait i.e. the way of walking, can be perceived from a distance as well as its non-invasive and less-intrusive nature [1]. In fact, early studies by Johansson [2] on human motion perception using Moving Light Displays have revealed that an observer can recognise different types of human motion based on joint motions. Moreover, the observer can make a judgment of the gender of the person, and even further identify the person if they are already familiar with their gait. Early studies by Murray [3] revealed that gait might be a useful biometric for people identification, a total of 20 feature components including ankle rotation, spatial displacement and vertical tipping of the trunk have been identified to render uniquely the gait signature for every individual. This leads to the conclusion that gait might be a potential biometric for surveillance systems.

As recent results have proven that gait can be a potential biometrics for real surveillance and forensic applications [1], we explore in this research a novel approach based on gait analysis for tracking and identification of walking subjects over a camera network. The approach is based on marker-less feature extraction to recover joint positions of walking subject from uncalibrated single cameras. Initially, the gait signature is being derived based on people being recorded from a sagittal view using the floating feature selection algorithm [4]. For later cases, the gait signature is thereafter derived in the sagittal plane by a rectification process [5] that transforms gait angular data from a particular viewpoint to the normal plane. In an unconstrained environment where camera information is not available, people are tracked from different viewpoints by matching their gait signature against a database of existing signatures. This way we can recognize people in one camera view from data derived from a different view. Thus, we can recognize and track people in non-intersected camera views.

The remainder of this paper is organized as follows. The next section summarises the previous approaches for object handoff between camera and the use of gait for tracking in surveillance applications. The theoretical description of the proposed marker-less approach for deriving gait-based tracking signature is presented in Section 3 and 4. Section 5 introduces the experimental results and analysis applied.

2. RELATED WORK

There is a large collection of literature from various disciplines that proves of the concept of people identification by their gait. The following section sheds light on the recent state of the art studies related to people tracking across multiple Field of Views (FOV) as well as people recognition using gait covering the different methodologies employed for feature extraction.

2.1. Tracking & Handoff Between Multiple Cameras

Most of the early approaches proposed for tracking across multiple views are limited in a way that they require information about the camera calibration as well as overlapping fields to maintain tracks between different views. Camera calibration is an expensive task and the availability of camera parameters in real life surveillance systems is difficult to provide. Therefore, subsequent methods relax the need for calibration parameters but still require the overlapping views to establish correspondences using different types of features including colour information [6] or geomtrical properties. Cai and Aggrawel *et al* [7] proposed an approach for tracking subjects from sequences of synchronized images from calibrated cameras. The correspondence across the sequence of frames is established using a set of feature points within a Bayesian probability framework. Subjects are being tracked via a single camera viewpoint until the system predicts that the active camera will no longer have a good view of the person. Features include geometric properties such as the height of the subject.

Alternatively, Stein *et al* [8] presented a new approacH h that does not require camera calibration. The camera calibration information is estimated by observing motion trajectories in the scene. Javed et al [9] presented a system for tracking people in multiple uncalibrated cameras. The system is able to discover spatial relationships between the camera fields of views and use this information to correspond between different perspective views of the same person.

2.2. Gait-Based Identification for Tracking

Much of the interest in the field of human gait analysis has originated from physical therapy, orthopaedics and rehabilitation practitioners for the diagnosis and treatment of patients with walking abnormalities. As gait has recently emerged as an attractive biometric, gait analysis has become a challenging computer vision problem. Many research studies have aimed to develop a system capable of overcoming the difficulties imposed by the extraction and tracking of human motion features. Various methods were surveyed in [10].

In 2002 BenAbdelkader *et al.* proposed a pose-free approach, where the moving person is detected and tracked and an image template corresponding to the person's motion blob is extracted in each frame [11]. Subsequently, a self-similarity plot from the obtained sequence of templates has been computed. Experimental results for outdoor sequences of 44 different candidates with four sequences of each that were recorded on two different days achieved a correct classification rate (CCR) of 77%. The method has also been tested on indoor data of seven candidates walking on a treadmill, recorded from 8 different viewpoints (from 0^o to 120^o) and on seven different days. A CCR of 78% was obtained for near-fronto-parallel views, and 65% on average over all views.

The pose-based methods, which generate the lateral view from data acquired at different arbitrary views, are the most recent approaches to 2D view-independent gait biometrics. This choice is justified by the fact that the lateral view has proven recognition capability with many approaches [12] and that the pose-free approach works on a small number of camera positions.

In 2003 the group at the University of Maryland developed a gait recognition algorithm showing that if a person is far enough from a single camera, it is possible to synthesize the lateral view from any other arbitrary view by knowing the camera calibration parameters [13]. The method has been tested on 12 people walking along straight lines at different camera views. Considering a gallery of people walking at lateral view, the video sequences where people walk at arbitrary angles were chosen as probes and the Receiver Operating Characteristic (ROC) was computed for each view.

The biometrics research group of the University of Southampton has focused attention on 2D view invariant gait recognition from 1999 [14] where a trajectory-invariant gait signature was presented. The method of Carter and Nixon corrects the variations in gait data by knowing the walking trajectory and modelling the thigh as a simple pendulum. The approach was then reformulated by Spencer and Carter [5] to provide a pose invariant biometric signature which did not require knowledge of the subject's trajectory. Results on synthesized data showed that simple pose correction for geometric targets generalizes well for objects on the optical axis. More recently, these techniques have been refined and applied on subjects wearing reflective markers with success observed from 6 different point views [5].

3. DERIVATION OF TRACKING FEATURES

3.1. Markerless Extraction of Gait Features

A new model-based approach is proposed to extract the joints' trajectories of walking people. Although, the Fourier series is the most accurate way for modelling gait motion, most previous methods adopted simple models [15] to extract gait angular motion via evidence gathering using a few parameters. This is mainly due to complexity and computational cost. Grant *et al* [16] presented a new temporal evidence gathering method to extract arbitrary moving shapes. Fourier descriptors are used to parametrize the templates of moving shapes in a continuous form.

The Fourier theory has been used for the analysis of curves and boundaries of shapes for several years. The Fourier analysis provides a means for extracting features or descriptors from images which are useful characteristics for image understanding. These descriptors are defined by expanding the parametric representation of a curve in Fourier series. Let f be the function for the boundary of a given shape, the function f is represented using elliptic Fourier Descriptors [17, 18], where the Fourier series is based on a curve expressed by a complex parametric form as shown in equation (1):

$$f(t) = x(t) + iy(t) \tag{1}$$

where $t \in [0, 2\pi]$. $x(t)$ and $y(t)$ are approximated via the Fourier summation by n terms as shown in equation (2)

$$\begin{bmatrix} x(t) \\ y(t) \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} X_t \\ Y_t \end{bmatrix} \tag{2}$$

such that a_0 and b_0 define the position of the shape's centre, and $X(t)$ and $Y(t)$ are computed as defined in equation (3) :

$$\begin{aligned} X_t &= \sum_{k=1}^{n} a_{x_k} cos(kt) + b_{x_k} sin(kt) \\ Y_t &= \sum_{k=1}^{n} a_{y_k} cos(kt) + b_{y_k} sin(kt) \end{aligned} \tag{3}$$

where a_{x_k},a_{y_k}, b_{x_k} and b_{y_k} are the set of the elliptic phasors which can be computed by a Riemann summation [18]. For a representation invariant to rotation and scaling, we need to represent f in a parametrized form to cover all the possible graphs or shapes which can be derived by applying appearance transformation to the function f including rotation and scaling. Henceforth, the function f can be rewritten in the parametric form shown in equation (4):

$$\begin{bmatrix} x_t \\ y_t \end{bmatrix} = \begin{bmatrix} a_0 \\ b_0 \end{bmatrix} + \begin{bmatrix} cos(\alpha) & -sin(\alpha) \\ sin(\alpha) & cos(\alpha) \end{bmatrix} \begin{bmatrix} s_x X_t \\ s_y Y_t \end{bmatrix} \tag{4}$$

where α is the rotation angle, s_x and s_y are the scaling factors across the horizontal and vertical axes respectively. The last equation (4) can be written concisely in its complex form as defined in equation (5):

$$\begin{cases} f = T + R_\alpha \left(s_x X_t + s_y Y_t i \right) \\ T = a_0 + b_0 i \\ R_\alpha = \cos(\alpha) + \sin(\alpha) i \end{cases} \tag{5}$$

Based on the final parametric format of f shown in equation (5), any shape can be represented using five parameters which are: a_0, b_0, α, s_x and s_y. X_t and Y_t are pre-computed using equation (3) from the original shape. In fact, the number of free parameters needed for the Hough Transform is totally independent of the complexity of shape which is defined using the elliptic Fourier Descriptors, as the defined parameters are related to the appearance transformations which define all the shapes that can be derived form the original shape.

To use the Hough transform with these templates represented via the parametric form described in equation (5), a five-dimensional space is required. Thus, the algorithm would be computationally intensive and infeasible to implement. In spite of the fact that some methods were proposed to reduce the computational requirements of the Hough Transform [19, 20], the computational load of these methods does not meet the requirements of most applications [20].

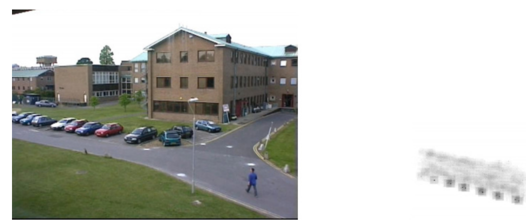

Fig. 1. The Detection of Heel Strike using the Proximity Measure in Surveillance Video

Gait knowledge is exploited via the detection of heel strikes to reduce the the parameter space dimensionality and therefore reduce the computational costs of the evidence gathering algorithm. The Hough Transform is employed to determine the free parameters through the matching process of feature points across the whole sequence of frames to the parametric function, and increase votes in the accumulator space accordingly. The parameters are deduced as the key or index of the accumulator space with the largest value. In the latter phase of the evidence gathering process, an exhaustive local search is run within every frame to locate the gait features whereby, the local search is guided by the motion pattern extracted during the first stage to restrict the search area. To more accurately extract the joint positions and reduce the search space, the lower limbs pose estimation algorithm uses as a filtering process the proportions of the human body segments.

3.2. View-point Rectification

The method proposed by the Spencer *et al.* in [5] is based on four assumptions: the nature of human gait which is cyclic; people walk usually along a straight line; the distances between the joints of the human body are constant; as well as the fact that the articulated limbs motion is approximately planar. Therefore, multiple periods of linear gait motion should appear analogous to a single period seen from many cameras related by linear translation and the positions of the legs joints lie in an auto-epipolar configuration.

If $\mathbf{j}_i^\ell$ is the set of joints positions for each leg $\ell = \{1, 2\}$ at the i^{th} frame in the image reference system, the relationship between $\mathbf{j}_i^\ell$ and the corresponding positions in the worldspace is $\mathbf{j}_i^\ell \times \mathbf{P}_i \cdot \mathbf{J}^\ell = 0$, where $\mathbf{P}_i = \left[\mathbf{R}_\mathbf{e}^T, -i\mathbf{e}_0\right]$

and $\mathbf{R}_{\mathbf{e}}^{T}$ is the rotation matrix which is used aligning the epipolar vector $\mathbf{e}_0$ with the horizontal axis X:

$$\mathbf{j}_i^{\ell} = \mathbf{P}_i \begin{pmatrix} 1 & 0 \\ 0 & \mathbf{H}_{\mathbf{V}}^{-1} \end{pmatrix} \begin{pmatrix} 1 & 0 \\ 0 & \mathbf{H}_{\mathbf{V}} \end{pmatrix} = \mathbf{H} \cdot \mathbf{J}^{\ell} \qquad (6)$$

Expressing the plane transformation matrix of the lower legs with $\mathbf{H}_{\mathbf{V}}$ so that the two cross section plane lines are centred and normalised with respect to Y and Z axes and parallel with Y. By the assumption that the lengths of the articulated legs $\mathbf{D}_{\ell}^{2} = \Delta \mathbf{j}_i^{\ell \mathbf{T}} \Delta \mathbf{j}_i^{\ell}$ are constant over all the image sequence, the pose difference vectors for the limb segments at two adjacent frames, $\Delta \mathbf{j}_i^{\ell}$ and $\Delta \mathbf{j}_{i+1}^{\ell}$, are related by

$$\Delta \mathbf{j}_i^{\ell \mathbf{T}} \cdot \mathbf{H}^{\mathbf{T}} \cdot \mathbf{H} \cdot \Delta \mathbf{j}_i^{\ell} = \Delta \mathbf{j}_{i+1}^{\ell \mathbf{T}} \cdot \mathbf{H}^{\mathbf{T}} \cdot \mathbf{H} \cdot \Delta \mathbf{j}_{i+1}^{\ell} \qquad (7)$$

When recovering the fronto-parallel structure of subject gait, the representation of the lower joints function which is given as $\left[\mathbf{J}_x^{\ell}(t), \mathbf{J}_y^{\ell}(t)\right]$ is found by fitting a modified Fourier series to the data with fixed fundamental frequency f_0 and period T: Therefore, starting from a video stream from a single camera and without the need for calibration, the proposed markerless method, in junction with [5], estimates the gait parameters projected on the lateral view.

3.3. Feature Selection of Gait

Feature selection is a critical task for most of the pattern recognition problems. This process is aimed to derive as many discriminative characteristics as possible whilst removing the redundant and irrelevant features which may degrade the classification rate. It is practically infeasible to run an exhaustive search for all the possible combinations of features in order to derive the optimal subset for recognition due to the high dimensionality of the features space. For this reason, we utilised the Adaptive Sequential Forward Floating Selection (ASFFS) search algorithm [21]

The feature selection procedure is purely based on an evaluation function that determines the usefulness or discriminativeness of each feature in order to obtain the ideal subset of features for the classification process. A number of approaches [22] are based mainly on statistical metric measures which use the scatter or distribution of the training samples in the feature space such as the Bhattacharyya metric. Although, statistical methods have the benefit of low-cost implementation, they have been proved to offer poor estimate of the classification rate because of their independence from the final classifier [23]. The proposed algorithm uses a validation-based evaluation criterion to derive the subset of features that minimises the classification errors as well as ensure good separation between the different clusters. In contrast to the voting scheme used in the *KNN*, the evaluation function uses different weights or coefficients w to signify the importance of most nearest neighbours. The probability score for a sample s_c to belong to a class c is expressed in the following equation (8):

$$f(s_c) = \frac{\sum_{i=1}^{N_c - 1} z_i w_i}{\sum_{i=1}^{N_c - 1} w_i} \qquad (8)$$

where N_c is the number of instances in class c, and the weight w_i for the i^{th} nearest instance is inversely related to proximity as:

$$w_i = (N_c - i)^2 \qquad (9)$$

The value of z_i is defined as:

$$z_i = \begin{cases} 1 & \text{if } nearest(s_c, i) \in c \\ 0 & \text{otherwise} \end{cases} \qquad (10)$$

such that the $nearest(s_c, i)$ function returns the i^{th} nearest instance to the sample s_c. The Euclidean distance metric is employed to find the nearest neighbours. The subset significance based on the validation-based metric is estimated using the leave-one-out cross-validation rule.

4. EXPERIMENTAL RESULTS

For the evaluation of dynamic gait features derived using the model-based method for people identification, a gallery dataset of 160 video sequences is taken from the SOTON indoor gait database. The set contains 20 different candidates with 8 sequences for every individual. The feature selection procedure is being run on the image sequences to derive for the most discriminative subset of gait features. Based on the validation criterion function, the feature selection algorithm derived 34,261 different feature subsets which has a recognition rate of 82% based on the probability scores explained in section (3). In order to further assess the recognition potency of the selected gait features, the Correct Classification Rate is estimated using the K-nearest neighbour (KNN) classifier with the leave-one-out cross-validation rule. The KNN rule is applied at the classification phase due to its simplicity and therefore fast computation besides the ease of comparison to other existing methods.

A recognition rate of 95.7% is achieved for $k = 5$ using the set of 160 video sequences . This is achieved using solely features describing purely the dynamics of the locomotion process. The results of the classification performance are being shown in Table (1) with comparative results of other approaches which use dynamic features for gait identification. The correlation matrix is shown in Figure 1 which visualizes the separation results across the different classes. The darker squares reflect higher separation score and therefore higher discriminability. The white diagonal line reflects the zero distance between the same class. The separation distance between the different clusters is computed using the Bhattacharyya distance metric.

Method Name	Database	CCR
Our method	20 subjects, 160 sequences	95.7%
Bobick [24]	18 subjects, 106 sequences	73%
Yam [22]	20 subjects, 100 sequences	84%
Wang [25]	20 subjects, 80 sequences	87.5%

Table 1. Classification Results of Gait Recognition

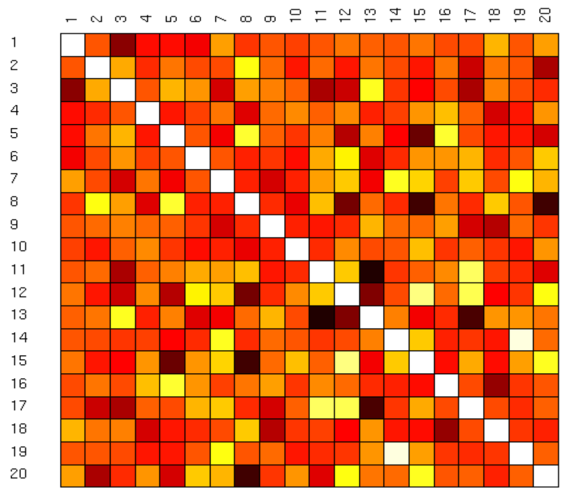

Fig. 2. Correlation Matrix for Gait Recognition using the Southampton Gait Dataset

To further assess the recognition performance of the proposed approach, a different probe data which was not used for feature selection phase, is taken from the Southampton gait database and matched against the gallery dataset. The dataset is composed of 60 sequences for 20 subjects with 3 sequences for every individual. Using the Cumulative Match Score (CMS) evaluation method which was introduced by Phillips *et al* in the FERET protocol [26], we have correctly classified 86.67% of the 60 walking sequences at rank $R = 1$. The results achieved using this evaluation are promising because the probe set has not been employed for the derivation of the dynamic feature subset. Henceforth, the derived dynamic features have a potential discriminative capability to identify people.

The markerless feature extraction method has been applied to the CASIA-B gait dataset consisting of 2270 video sequences for 65 different walking subjects with an average of 6 sessions for every viewpoint per subject. There are 6 different camera orientations (36^o, 54^o, 72^o, 90^o, 108^o, 126^o). The 90^o corresponds to the side view walking direction. The limbs pose has been extracted frame by frame whereby the hip and knee angular data have been derived for each camera position and for each candiate. Figure 3 shows an example of the legs pose estimation in the 6 different directions. A classification score of 73.6% and 100% are achieved at the 1^{st} and 11^{th} rank respectively.

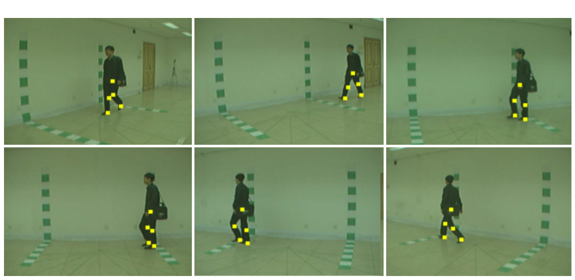

Fig. 3. Markerless Extraction of Gait Features.

	Camera 2 vs 3	Camera 3 vs 2
CCR	90%	95%

Table 2. Correct Classification Rate Analysis

To evaluate the usefulness of the proposed approach in real cases, we have used the leave-one-out cross validation with the KNN classifier to initially estimate the performance across all the 20 subjects across two different cameras. The achieved correct classification rate (CCR) is 97% for the value of $k = 1$. Further, we have matched the data from camera 3 against camera 2 and vice versa in a probe to gallery fashion. We have increased the size of people in camera 3 to include 10 more random subjects that do not exist in the 2nd camera dataset when probing camera 2 against the camera 3. In the same way, we have increased the size of dataset camera 2. The achieved classification results are over 90% for the cross-camera matching as shown in Table 1. This shows that gait features can be used in surveillance applications for identity tracking over different camera views.

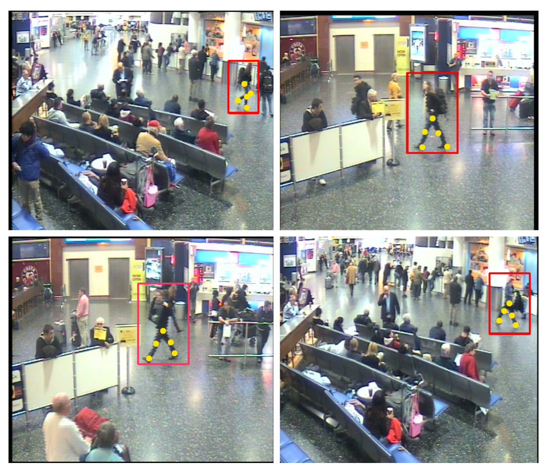

Fig. 4. Feature Extration applied on the iLids dataset. (Gatwick Airport - London United Kingdom)

5. CONCLUSIONS

We have taken a critical step in deploying gait identification for the analysis of surveillance video. An approach for people tracking between different non-intersecting uncalibrated cameras based on gait analysis is being proposed. Identification signature is derived from gait kinematical as well as anthropometric knowledge that are obtained using a marker-less feature extraction algorithm. Experimental results revealed the potential of our method to work in real surveillance systems to recognize walking people over different views using the marker-less pose recovery with an achieved recognition rate of 97%. This is an important step in translating gait biometrics into real scenarios where calibration information cannot be recovered such as in surveillance applications.

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