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Clothing and carrying condition invariant gait recognition based on rotation forest☆

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ABSTRACT

This paper proposes a gait recognition method which is invariant to maximum number of challenging factors of gait recognition mainly unpredictable variation in clothing and carrying conditions. The method introduces an averaged gait key-phase image (AGKI) which is computed by averaging each of the five key-phases of the gait periods of a gait sequence. It analyses the AGKIs using high-pass and low-pass Gaussian filters, each at three cut-off frequencies to achieve robustness against unpredictable variation in clothing and carrying conditions in addition to other covariate factors, e.g., walking speed, segmentation noise, shadows under feet and change in hair style and ground surface. The optimal cut-off frequencies of the Gaussian filters are determined based on an analysis of the focus values of filtered human subject's silhouettes. The method applies rotation forest ensemble learning recognition to enhance both individual accuracy and diversity within the ensemble for improved identification rate. Extensive experiments on public datasets demonstrate the efficacy of the proposed method.

1. Introduction

Gait recognition plays a significant role in visual surveillance as it enables human identification at a distance using low resolution video sequences. However, variation in view, clothing and carried items bring main challenges to any shape-analysis based gait recognition method, as these factors considerably distort the shape of a silhouette. Human identification based on gait is also adversely affected by variation in walking speed, shadows under feet, and presence of occluding objects.

Gaussian filter is a band-pass filter, i.e., a combination of low-pass Gaussian filter (Lp-Gf) and a highpass Gaussian filter (Hp-Gf) [8]. This paper introduces a gait recognition method based on filtering which involves a Lp-Gf and a Hp-Gf at different cut-off frequencies to achieve invariance to unpredictable variation in clothing and carrying conditions in addition to other covariate factors, namely, variation in walking speed, segmentation noise, missing and distorted frames, change in ground surface and hair style, shadows under feet and occlusions. Lp-Gf causes smoothing or blurring of a silhouette and thus reduces noise. As the cut-off frequency of the Lp-Gf decreases, there is a gradual loss of boundary and exterior region. Thus, the application of Lp-Gf with decreasing cut-off frequencies gradually highlights the characteristics of inner part of a silhouette towards its central region more than its boundary, enabling the proposed method to achieve robustness against tight versus loose clothing, and clothing type variation. It also reduces the effect of shape distortions at the silhouette boundary due to small carried items. The use of Hp-Gf at the same cut-off frequencies retains the boundary and the exterior parts of a silhouette more than the central part, thus highlighting the boundary characteristics of the silhouettes. Thus, it enables improved inter-subject discrimination in the absence of change in covariate factors. The cut-off frequencies of the Gaussian filters for optimal performance are determined experimentally based on an analysis of the focus values of the silhouettes.

Several state-of-the-art gait recognition methods [3,4,27] analyse the dynamic and/or static gait characteristics of silhouettes or the extreme outer boundary of silhouettes, i.e., contours of a gait sequence for identifying a human subject. The performance of these methods largely depends on the correctness of the background segmentation techniques, presence of occluding objects in the scene and shadows under feet, as these factors considerably determine the quality of the silhouettes and the extracted contours. In addition, analysing all the silhouettes of a gait sequence individually, increases computation time and requires more storage space. Han and Bhanu [11] thus introduced a novel concept of gait energy image (GEI) which is formed by averaging all the silhouettes of a gait period to capture spatio-temporal gait

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characteristics in a single image to facilitate noise-resilient gait feature extraction in reduced space and time complexity. However, since GEI averages all the silhouettes of a gait period, it does not preserve the important distinctive gait characteristics of different phases of a gait period. To overcome this limitation, this paper introduces an averaged gait key-phase image (AGKI) by averaging key-phases of the gait periods over a gait sequence.

It has been experimentally shown in [12] that the random subspace method outperforms other ensemble classification methods, e.g., bootstrapping [2] and Adaboost [6], in the case of high dimensionality of the feature space for a small number of gallery samples. The gait recognition method in [10] demonstrated that random subspace ensemble classifier method provides improved gait recognition rate by effectively avoiding overfitting due to high dimensionality of the feature space compared to the available number of gallery samples, which are often recorded at a particular walking condition. Random subspace method combines the identification rates of the component classifiers associated with the randomly selected independent feature subsets of dimensions smaller than the original feature space using majority voting policy, and significantly outperforms single classifiers, e.g., nearest neighbour (NN), support vector machine and Bayesian classifier in gait recognition.

Relying on the basic principle of random subspace method, the main motivation of introducing the rotation forest ensemble classifier in [21] is to simultaneously encourage member diversities and individual accuracy within a classifier ensemble. Although the superiority of random forest over bagging and AdaBoost has been demonstrated on 33 datasets from the UCL repository in [21] and three widely used datasets, i.e., NASAs Airborne Visible Infra-Red Imaging Spectrometer, Reflective Optics System Spectrographic Imaging System, and Digital Airborne Imaging Spectrometer for hyperspectral image classification in [28], its efficacy has yet to be explored in gait recognition. Thus, the paper introduces the use of rotation forest ensemble classifier in gait recognition, and experimentally demonstrates its superiority to random subspace method in this field by simultaneously encouraging individual accuracy and diversity within the ensemble in addition to overfitting avoidance.

The rest of the paper is organised as follows. Section 2 discusses related works and Section 3 presents the proposed method. Section 4 presents the experimental results, and Section 5 concludes the paper.

2. Related work

Various markerless gait recognition methods (model-based and model-free) have been proposed in the literature to address one or more covariate factors of gait. Model-based methods (e.g., [9,17,23]) use a structural model to measure time-varying gait parameters, e.g., gait period, stance width and stride length, and a motion model to analyse the kinematical and dynamical motion parameters of the subject, e.g., rotation patterns of hip and thigh, and joint angle trajectories, to obtain gait signatures. The model-free gait recognition methods in [3,4,27] analyse the dynamic and/or static gait characteristics of silhouettes or the extreme outer boundary of silhouettes, i.e., contours of a gait sequence. The performance of these methods largely depends on the correctness of the background segmentation techniques, presence of occluding objects in the scene and shadows under feet, as these factors considerably determine the quality of the silhouettes and the extracted contours. In addition, analysing all the silhouettes of a gait sequence individually, increases computation time and requires more storage space. Hence, the introduction of GEI [11]. Since then many promising model-free gait recognition methods have been proposed based on a GEI, e.g., [1,5,15,24,26,29] to outperform the original method of GEI.

The boundary shape distortions due to variation in clothing of the same subject decrease the identification rate. Therefore, the method in [13] applies part-based strategy to adaptively assign more weight to body parts that remain unaffected due to clothing variation and less weight to affected body parts based on a probabilistic framework. However, it is unrealistic to train the model with all known clothing types in realistic scenario. The method in [14] assigns depth information to binary silhouettes using 3-dimensional (3D) radial silhouette distribution transform and 3D geodesic silhouette distribution transform. The gait features extracted by radial integration transform, circular integration transform and weighted Krawtchouk moments are fused using a genetic algorithm (RCK-G). RCK-G is robust to limited clothing variation, but sensitive to carrying conditions.

The methods in [3,4,20] aim to achieve invariance to carrying conditions. The method based on spatio-temporal motion characteristics, statistical and physical parameters (STM-SPP) [3] analyses the shape of a contour using Procrustes analysis at the double support phase and elliptic Fourier descriptors (EFDs) at ten phases of a gait period. The method in [4] combines model-based and model-free approaches to analyse the spatio-temporal shape and dynamic motion (STS-DM) characteristics of a subject's contour. A part-based EFD analysis and a component-based FD analysis based on anthropometry are respectively used in STM-SPP and STS-DM to achieve robustness to small carried items. The method in [20] uses an iterative local curve embedding algorithm to extract double helical signatures from the subject's limb to address shape distortion due to a specific carrying condition, e.g., a briefcase in upright position.

While existing gait recognition methods have only considered the predefined and limited variation in clothing and carrying conditions, the proposed method achieves robustness against unpredictable variation in clothing and carrying conditions as well as several other covariate factors.

3. Proposed method

3.1. Module 1: Feature extraction

3.1.1. AGKI formation

The normalised and centre-aligned silhouettes provided by the publicly available datasets are used as the input gait sequences of the proposed method for feature extraction. A gait period starts with the heel strike of either foot and ends with the subsequent heel strike of the same foot and comprises two steps. Each foot in a gait period transits between two phases: a stance phase when the foot remains in contact with the ground and a swing phase when the foot does not touch the ground. The components of stance phase are: initial contact, mid-stance and propulsion. The components of swing phase are: pre-swing, mid-swing and terminal swing. A detailed description of these phases are provided in [3].

The gait periods are determined from the video sequence of lateral view of the subject by the number of frames between two frames of a gait sequence with the most foreground pixels enclosed in the region bounded by bottom of the bounding rectangle and the anatomical position of just before the subject's hand measured from the bottom (i.e., 0.377H where H is height of the bounding rectangle) because this foreground region, i.e., the bottom segment of the bounding rectangle is not distorted by self-occlusions due to arm-swing (see Fig. 3 of [4]). After estimating the gait period, its five key-frames (i.e., double support, midstance, midswing, ending swing and propulsion) which capture most of the significant gait characteristics, are extracted using region-of-