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Information set based gait authentication system

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ABSTRACT

This paper presents the Generalized New Entropy (GNE) gait image based authentication system using Information Set concept. A GNE function with free parameters is defined and its properties are presented. A variant of this entropy function called the dynamic entropy function is used in formulating the Dynamic Information Set based Particle Swarm Optimization (DISPSO) technique to learn the parameters. Two types of entropy features called GNE features and GNE based on Histogram of Oriented Gradients (GNE-HOG) features are formulated. After the gait cycle extraction, the farmer features are derived from the probability frames corresponding to the occurrences of 0's and 1's in every pixel location from all frames (binary silhouette images) contained in a gait cycle whereas the latter features are derived from the HOG descriptors corresponding to the probability frames termed as the possibility frames. The features are validated on three databases (CASIA, OUISIR Treadmill and SOTON small database) using Support Vector Machine (SVM), Euclidean Classifier (EC) and Improved Hanman Classifier (IHC) which is an enhanced version of Hanman Classifier in the literature. The proposed features outperform the existing features using IHC.

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1. Introduction

Gait is the manner of moving on foot, which now-a-days has emerged as the most promising research area because of its non-invasiveness, non-contact and perceivable at a distance and hence suitable for surveillance. It is a behavioral biometric unlike face, iris, palm-print and fingerprint which are physiological biometric modalities that require subject cooperation, physical contacts or near proximity. However gait also has some limitations in the representation because it is affected by physical and environmental conditions. Even though the discriminating power of gait as a biometric may be curtailed by its inherent fallibility causing gait deviation under distinct conditions, yet the intrinsic gait characteristic of an individual still makes it useful for visual surveillance applications [1]. The earlier attempts on gait fall under two categories: model based and appearance based approaches.

1.1. Model based approaches

Model based approaches [2–7] usually lean on the model parameters of the human body like limb lengths, trajectories and angular speeds. The first model based approach on gait was by Cunado et al. [8] for gait recognition [9,10]. In a typical model-based approach, often a structural model and a motion model are required to serve as the basis for tracking and feature extraction. Bobick and Johnson [2] have used a structural model to recover the static body and stride parameters from the gait of a person. Lee and Grimson [5] attempt at fitting ellipses to seven regions for deriving the features. Nonetheless, as model based approaches do not detect the position of joints precisely due to highly flexible anatomy of non-rigid human body and self-occlusion [11,12], the current literature focuses on the appearance-based approaches [13–20].

1.2. Appearance/Model free approaches

Appearance based approaches operate on the gait sequences without considering any definite model. Among these approaches, the dynamic method employs the Gait Energy Image (GEI) [1,21] as the gait signature where GEI is a time-normalized accumulative energy image over a complete gait cycle of human gait subject to the unconstrained conditions. Yang et al. [11] have conducted the variation analysis for constructing a dynamic mask to intensify the dynamic region of GEI and also to reduce the noise in the insignificant regions. Chen et al. [22] compute the Frame Difference Energy Image (FDEI) by adding the positive portion of the frame difference between the consecutive frames and the Dominant Energy Image (DEI). Zhang et al. [23] propose an Active Energy Image (AEI) as the difference between the consecutive silhouette images. Lam et al. [24] construct a Gait Flow Image (GFI) by

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applying the optical flow field on the gait image sequence subject to the constrained conditions like shape variations. Bobick and Davis [25] have employed two temporal templates: Motion Energy Image (MEI) which indicates the existence of motion in a gait cycle and Motion History Image (MHI) which is a function of the regency of motion in a gait cycle. Wang et al. [26,27] have used the temporal information in a gait cycle to develop a Chrono-Gait Image (CGI) through color mapping. Lee et al. [28] propose a Time-Sliced Averaged Motion History Image from the Histogram of Oriented Gradients (TAMHI-HOG) [29] to generate gait signatures.

The first trial of Motion Energy Image (MEI) is led to GEI in [30]. A representation similar to GEI is Motion Silhouette Image (MSI). However, they are vulnerable to appearance changes of the human silhouette. To overcome this problem, Shape Variation Based (SVB) Frieze Pattern is proposed in [31]. Frieze patterns represent the information of vertical and horizontal projections. As compared to GEI and MSI, frieze pattern requires a non-trivial temporal alignment process for each gait cycle and is computationally more expensive. Other silhouette based approaches can be seen in [13,32–34].

Even though, a lot of progress has been made using the above approaches, there is no foolproof method established yet. As stated earlier the gait recognition methods in the literature are sensitive to variations in silhouette shapes, clothing whereas GEI is easy to compute and insensitive to noise during silhouette extraction, but not robust to changes in the appearances of the human silhouette.

The GEIs are prone to uncertainty arising out of randomness over the walking cycles. Hence Shannon entropy has been used in [35] to encode the randomness of pixel values in the silhouette images over a complete gait cycle resulting in Gait Entropy Images (GEnI). The entropy values capture mostly the motion information and are robust to covariate conditions that affect the appearance. As an alternative to this, Pal and Pal entropy which is an exponential entropy is investigated in [36,37] resulting in Gait Pal and Pal Entropy Image (GPPE).

1.3. Motivation for the present work

As noted above, choice of a suitable entropy function is crucial to extracting efficient features. In this paper we are motivated to formulate a new entropy function as a generalization of the existing entropy functions to extract the gait entropy image. Using this entropy function two types of features are generated, of which the first type represents the probabilistic uncertainty and the second represents possibilistic uncertainty from the gait sequence of a gait cycle. To learn the parameters of the entropy function, we make use of Particle Swarm Optimization (PSO). Another motivation is to improve the convergence of PSO by introducing dynamic entropy function. Next we are also seized of the opportunity to improve the gait recognition rate by improving the Hanman classifier.

This paper is organized as follows. Section 2 deals with the preprocessing of gait sequence resulting in gait cycle extraction and also present the HOG and gait based authentication system. The GNE function is presented in Section 3. Section 4 presents the DISPSO for efficiently learning the free parameters of GNE function. Section 5 develops the algorithms to extract GNE features and GNE-HOG features these are derived using the GNE function. An improved classifier called IHC is presented in Section 6. Section 7 discusses with the results of gait recognition using the new features and the classifier. Section 8 gives the conclusions along with the contributions and future work.

2. Related topics

We begin with the extracted silhouette images as these are directly available in the databases. So we briefly discuss the Gait cycle extraction which facilitates the gathering of probability frames from the silhouette images contained in a Gait cycle.

Fig. 1. Samples of silhouette for normal walk, wearing coat, carrying bag from left to right.

2.1. Gait cycle extraction

The human gait can be viewed as a periodic spatio-temporal signal. Here we make use of the aspect ratio to extract a sequence of frames that forms a cycle and also consider the overlapping of frames while moving from one cycle to the next cycle to prevent information loss as it is difficult to obtain the exact end position of a cycle. A sample of gait is shown in Fig. 1 along with variation in shape of a subject due to object added like bag or clothing.

2.2. Histogram of Oriented Gradients (HOG)

The HOG descriptors were used for pedestrian detection in static images for the first time by Navneet Dalal and Bill Triggs [29] who focused on human detection from videos. These descriptors find the local shape information by extracting the gradient magnitude in different orientations with the help of kernels.

An algorithm for the computation of HOG [38,39] is now given.

Algorithm. Step 1: First compute the gradients from an image.

The gradients I_x and I_y are obtained by convolving the image with the following kernels:

$$D_x = [-1\ 0\ 1] \text{ and } D_y = D_x' \tag{1}$$

The magnitude and orientation of an image are computed from :

$$|G| = \sqrt{I_x^2 + I_y^2} \text{ and } \theta = \tan^{-1}\left(\frac{I_x}{I_y}\right) \text{ with } I_x = I * D_x \text{ and } I_y = I * D_y \tag{2}$$

Step 2: Compute the orientation bins.

The silhouette image is divided into cells of size 4x4 pixels. We consider 9 orientations from 0° to 360° at an interval of 45° in each cell and at each orientation the corresponding magnitude yields the orientation histogram.

Step 3: Perform block normalization using L2-norm given by:

Using Rectangular-HOG (R-HOG) geometry [29], a block of size 2x2 cells is formed from the neighborhood cells with an overlapping of half of the block size. This block normalization is performed by concatenating the histograms of the four cells within the block into a vector ν with 36 components (4 histograms x 9 bins per histogram). Divide this vector by its magnitude to normalize it. The block normalization using L2-norm is given in (3)

$$f = \frac{v}{\sqrt{||v||_2^2 + \varepsilon^2}} \tag{3}$$

Where f is vector of the normalized orientation magnitudes and ε is a very small value to avoid division by 0.

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