GAIT RECOGNITION FOR RANDOM WALKING PATTERNS AND VARIABLE BODY POSTURES

Xiaxi Huang and Nikolaos V. Boulgouris

Department of Electronic Engineering, King’s College London, United Kingdom

ABSTRACT

In this paper, we present a gait recognition method that does not presume the existence of strict lab conditions for its operation. The proposed algorithm includes a side-view detection and extraction approach that is useful when the subject is walking randomly as well as a novel template for gait representation that is robust to body posture variations. Experimental results show that the proposed system not only has high computational efficiency, but also exhibits robust performance, especially in cases where the subject is walking along random paths.

Keywords: gait, recognition, surveillance

1. INTRODUCTION

The deployment of gait, i.e., the personal walking style, as a biometric trait has become popular during the past few years [1]. Since gait analysis is based on video sequences that are showing human beings’ walking repetitions, inevitably, it needs information about gait cycles and camera views. In other words, the number of frames in one gait cycle, as well as the starting frame of each gait cycle, and the angle between the human’s walking path and the camera’s facing direction, should be taken into account when gait feature template is constructed.

Gait Energy Image (GEI) [2] is a simple gait feature with high discriminative power. It takes into account one or all of the cycles in one gait sequence, and analyzes the silhouettes holistically. In [3], a Hidden Markov Model (HMM) is used to capture the Frame to Exemplar Distance (FED), which represents the gait information. In [4], a population Hidden Markov Model (pHMM) was introduced in order to create a generic gait walking model. Specifically, the states of the pHMM represent gait stances over one gait cycle, and the corresponding gait stances in each gait cycle over one gait sequence are averaged in order to form a dynamic-normalized gait cycle of fixed length, which the gait recognition process will be based on.

All of the above gait feature extraction approaches are based on side-view gait sequences, nevertheless, there are approaches based on sequences from other view angle. A frontal-view gait recognition approach based on a morphological operator called “cover by rectangles” is introduced in [5]. In [6], three view angles are examined by means of two gait representations: Motion Silhouette Image (MSI) and Gait Energy Image (GEI), and the results were fused at score level. In [7], GEIs of the sequences from five different view angles were calculated and a robust fusion method was proposed to generate better results. In [8], how the recognition performance is affected by view angle changes is investigated by using two typical gait features - GEI and key Fourier descriptors (KFDs).

In the existing approaches, there are two common limitations: 1) the subjects always walk in a straight line, i.e., in each gait sequence, there always is only one view angle, which facilitates the gait cycle detection process; 2) normally more than one cycle are available in one gait sequence, which helps the feature extraction process become robust. However, in practical scenarios, these two statements will not always hold. Instead, in practical scenarios, 1) the subjects will walk in a random path, i.e., the frames in the same gait sequence have different view angles, and this makes it difficult to detect gait cycles and extract efficient gait features; 2) the subjects will walk more naturally, i.e., the way they walk and the body posture they assume may be affected by their mood, body condition or other factors. Unavoidably, this will affect the shape of the silhouettes and add difficulties to finding discriminative features.

In this paper, we propose a gait feature extraction method, which aims to work in situations in which there is no strict walking protocol. Firstly, one side-view gait cycle is segmented from the whole multi-view sequence using a novel approach that is based on the subject’s apparent height in the frames. Using the segmented cycle, we construct an advanced gait representation, the Shifted Energy Image, that is robust to body posture variations. We apply the proposed algorithm on the CMU database [9] and the ACTIBIO database, which was compiled under a European Commission project 1. The experimental evaluation shows the superiority of the proposed algorithm over existing gait algorithms.

The rest of the paper is organized as follows: the proposed gait template construction method, including side-view gait cycle partitioning and advanced gait feature extraction, is described in Section 2, experimental results are presented in Section 3, and, conclusions are drawn in Section 4.

2. PROPOSED ALGORITHM

Our proposed gait feature extraction method aims at working in practical situations, in which the subjects are expected to be walking in random patterns. When a subject is walking past a stationary camera in a random path (i.e., not in a straight line), different views of the subject will be visible throughout the frame sequence. In order to extract discriminatory gait features, we need to select the most informative silhouettes and use them for the construction of gait templates. It has been shown that the side-view silhouettes contain more gait information than silhouettes taken from other view angles [6, 7]. Therefore, in our proposed algorithm, we only use the side-view silhouettes for gait feature extraction purposes.

In a real-life gait recognition scenario, the subjects may be walking from one side to the other side of the monitored area and allowing the recording of several walking cycles. Therefore, it is reasonable to make the following two assumptions: 1) The subjects maintain a

\[1\text{http://www.actibio.eu/} \]
stable speed throughout the duration of their walking trip; 2) There is at least one, or almost one, side-view cycle in each gait sequence.

With the above assumptions, the gait feature extraction process comprises three steps: Gait Cycle Determination, Side-view Partitioning, and Gait Feature Template Construction. These are graphically depicted in Figure 1. Specifically, we first detect the number of frames in one cycle; then we use a novel method to find the first frame of a side-view cycle, based on which the side-view cycle can be segmented out of the whole sequence; finally, we construct one unique gait feature by using the side-view cycle. The proposed algorithm will be described in the rest of this section.

2.1. Cycle Determination

There are several existing approaches that can accurately detect the number of frames in one gait cycle. In our algorithm, we use the approach in [10], in which the number of pixels in the lower half of the silhouettes in the whole sequence is calculated, filtered using a median filter. The number of frames in one gait cycle is trivially calculated from the filtered signal.

2.2. Side-view Partitioning

After the determination of the number of frames \(NF_c\) in one gait cycle, we need to locate, within the gait sequence, one cycle that only, or mainly, includes side-view frames. Since \(NF_c\) is known, in practice, we only have to specify the starting frame of the side-view cycle.

When we apply foreground extraction method on the original frames, we are able to obtain the information of the subject’s apparent height in the frames, by detecting the top and the bottom edge point of the silhouette. Based on this information, we develop an algorithm to detect the first frame of a side-view cycle. If the subject is walking in a side-view direction, the apparent height of his/her silhouette, \(H_a\), in consecutive frames will change far less than when he/she is walking in other directions. Consequently, the first frame of a side-view cycle will be followed by \(NF_c\) frames the smallest variance of which in \(H_a\) will be minimum. This means that the starting frame \(N_1\) of a side-view cycle will be determined by:

\[
N_1 = \arg \min_n \left( \frac{1}{NF_c} \sum_{n=N_1}^{N_1+NF_c} (H_n - \overline{H}_a)^2 \right)
\]

(1)

where \(n\) is frame index.

2.3. Gait Feature Template Construction

In order to endow the proposed algorithm with the capacity to work in practical monitoring applications, the availability of a perfect side-view cycle should not be strictly required. In this case, the features that are extracted on a frame by frame basis do not have advantages, because the corresponding frames of the cycles from different sequences may have different view angles. Therefore, it is appropriate to use features that consider all frames in the cycle as a whole.

The Gait Energy Image (GEI) [2] is a simple, yet efficient, feature of such kind. The upper body part (i.e., the head and the torso) in a GEI reveals the shape information of the subject and the lower body part (i.e., the legs) contains the holistic dynamic information of the gait cycle. However, there are some real-life situations in which the GEI obviously exhibits poor performance. For example, as shown in Figure 2, correct recognition is difficult when the same subject’s body leans back / forward in the gallery / probe set (top row); or when the subject walks without / with a bag in the gallery / probe set (bottom row). In the above two situations, the difference, especially at the boundary of the silhouettes, between the same subject’s gallery and probe GEI is large, because the body posture was changed and the gravity centres of the silhouettes were shifted when the person was leaning forward or carrying a bag.

Therefore, in most common situations, possible differences in the body postures will generate noise in GEIs. In order to remove the effect of posture-induced differences from a GEI, while retaining the gait information included in it, we develop a novel gait features based on the GEI: the Shifted Energy Image (SEI).

The construction of the new representation is shown in Fig. 3. First, we consider that, as the silhouettes are all scaled and their heights are normalized, only the horizontal component of the gravity centre will affect the discrimination. This consideration motivated us to horizontally divide the GEI into three trunks: head, torso, and legs. According to the anatomical information in [11], the heights of a human’s shoulder and his pelvis are respectively equal to 81.8% and 48% of the total body height. Therefore, if the height (vertical dimension) of the scaled silhouette is \(H\), the head area includes the first \(0.182H\) rows of the silhouette, and the torso and legs include the next \(0.338H\) and \(0.488H\) rows respectively.

Secondly, we re-calculate the horizontal centres of those three trunks. The new horizontal centres are denoted as \(x_{ch}\), \(x_{cl}\), and \(x_{cL}\) for the head, torso and legs trunks respectively.

Subsequently, the three trunks are shifted according to their new centres separately, in order to obtain the SEI. If the horizontal centre of the GEI is \(x_{cGEI}\), the SEI of the head area can be calculated as:

\[
SEI_h(x,y) = GEI(x + (x_{ch} - x_{cGEI}), y), 0.818H \leq y < H
\]

(2)

The distances of the head SEI between the gallery and the probe subjects is calculated as:

\[
d_{SEI_h} = \sqrt{\|SEI_{h\text{gallery}} - SEI_{h\text{probe}}\|^2}
\]

(3)

where the operator \(\| \cdot \|^2\) denotes the average power per pixel.

![Fig. 1. Three steps in Gait Feature Extraction module.](image)

![Fig. 2. GEIs of the same subject: (a) Gallery GEI, (b) Probe GEI, (c) Difference between Gallery and Probe GEIs.](image)
Fig. 3. The construction of SEI.

In a similar way, the SEI for the torso and the leg area, $SEI_t(x, y)$ and $SEI_l(x, y)$ can be generated, and the distances based on them, $d_{SEI_t}$ and $d_{SEI_l}$, can be calculated accordingly.

As seen in Figure 3, when the SEI is used, the difference between different gait sequences of the same subject is considerably smaller than the one calculated using the GEI (see Figure 2). This is particularly noticeable in the head area, where the gravity centre undergoes a very noticeable displacement due to the difference in the body posture.

After the distances of the SEIs are calculated for each of the three body trunks, they must be combined into a single dissimilarity measure for the SEI feature ($D_{SEI}$). Since the discriminatory capabilities of the three body parts are different, we develop a weighting method based on the intra and inter variances of the gallery subjects. If the intra variance of the $SEI_h$ is denoted as $\sigma_{\text{intra},h}^2$, it can be calculated as:

$$\sigma_{\text{intra},h}^2 = \frac{1}{N_a} \sum_{s=1}^{N_a} \|SEI_{h,s} - \overline{SEI}_{h,s}\|^2$$  \hspace{1cm} (4)

where, $N_a$ is the number of subjects in the gallery. $\overline{SEI}_{h,s}$ is the average head SEI for subject $s$.

The inter variance of the $SEI_h$, denoted as $\sigma_{\text{inter},h}^2$, is calculated as:

$$\sigma_{\text{inter},h}^2 = \frac{1}{N_a \cdot (N_a - 1)} \sum_{s=1}^{N_a} \sum_{f=1}^{N_a - 1} \|SEI_{h,s} - SEI_{h,f}\|^2$$  \hspace{1cm} (5)

where $\overline{SEI}_{h,s}$ and $\overline{SEI}_{h,f}$ are the average head SEIs of subject $s$ and $f$, who are not the same subjects.

Apparently, a large intra variance leads to large False Reject Rate whereas a small inter variance leads to large False Accept Rate, our objective is to ensure the algorithm’s robustness by minimizing the impact of both situations above. To this end, we calculate the weight for the distance of the head SEI as:

$$w_{SEI_h} = \frac{\sigma_{\text{inter},h}^2}{\sigma_{\text{intra},h}^2}$$  \hspace{1cm} (6)

Similarly, the weights for the torso area $w_{SEI_t}$ and the leg area $w_{SEI_l}$ can be trivially calculated. Then, we normalize the three weights in order to make their sum to be equal to 1. The resultant normalized weights are denoted as $\overline{w}_{SEI_h}, \overline{w}_{SEI_t}$, and $\overline{w}_{SEI_l}$.

Finally, the total distance for the SEI feature is defined as:

$$D_{SEI} = w_{SEI}^T \cdot d_{SEI}$$  \hspace{1cm} (7)

where

$$w_{SEI} = [\overline{w}_{SEI_h}, \overline{w}_{SEI_t}, \overline{w}_{SEI_l}]^T$$  \hspace{1cm} (8)

$$d_{SEI} = [d_{SEI_h}, d_{SEI_t}, d_{SEI_l}]^T$$  \hspace{1cm} (9)

Since this proposed algorithm is based on the SEI and weighting, we call it weighted-Shifted Energy Image (w-SEI) method.

3. EXPERIMENTAL RESULTS

Our proposed algorithm is focusing on gait recognition for random walking patterns. In random walking patterns, it can be considered that the view angle, instead of the walking direction, changes from frame to frame, therefore, it is reasonable to compare the proposed algorithm with existing algorithms on a database with multiple view sequences. For this reason, we use the CMU database [9] for the experimental assessment of our method. Furthermore, we use the gait database that was recorded in the framework of the ACTIBIO project (Unobtrusive Authentication Using ACTivity Related and Soft BIometrics)\(^2\). Although in both of the above databases, the body posture is not an explicit covariate, the robustness of our method to different body posture has a beneficial impact on the results.

3.1. Experimental evaluation using the CMU MoBo database

In the CMU MoBo database, there are 25 subjects, 3 conditions, i.e., fastwalk, slowwalk, and walking with a ball, and 6 view angles, i.e., east, southeast, south, southwest, northwest and north. Several algorithms have been tested on this database by using sequences from one or multiple views. Among the methods that only considered the side-view, the one using pHMM [4] generally outperformed others. Among the methods that used multiple views, the method introduced in [7] gave very promising results. Therefore, in this paper, we compare our results to the ones generated by these two methods.

In our experiments, the gallery (reference) set was fastwalk and the probe set was slowwalk. We also use the walking with a ball set as reference, in order to calculate intra-subject variances. We only used the side-view, i.e., east, sequences for the proposed gait template construction. The results for the proposed algorithm and the other three existing methods are shown in Table 1. As we can see, the proposed algorithm clearly outperforms the other two methods that use side-view only (i.e., GEI and pHMM). Moreover, even only using side-view sequences, the proposed algorithm achieves the same recognition rates as the one using the combination of multiple views. This indicates that using only side-views can rival the recognition performance of a system using multiple views. Therefore, our approach of selecting one side-view cycle out of a random path is promising and efficient.

3.2. Experimental evaluation using the ACTIBIO database

In the gait database that was created in the framework of the ACTIBIO project, there are 28 subjects who are walking in an

\[2\text{For more information please see http://www.actibio.eu/}\]
Table 1. Recognition rates for the proposed and three other existing methods on the CMU database.

<table>
<thead>
<tr>
<th>Method</th>
<th>Rank 1 (%)</th>
<th>Rank 5 (%)</th>
</tr>
</thead>
<tbody>
<tr>
<td>GEI [2]</td>
<td>84</td>
<td>92</td>
</tr>
<tr>
<td>pHMM [4]</td>
<td>84</td>
<td>-</td>
</tr>
<tr>
<td>Multi [7]</td>
<td>92</td>
<td>96</td>
</tr>
<tr>
<td>w-SEI</td>
<td>92</td>
<td>96</td>
</tr>
</tbody>
</table>

Table 2. Eight different sets in the ACTIBIO database.

<table>
<thead>
<tr>
<th>Set</th>
<th>Day</th>
<th>Repetition</th>
<th>Condition</th>
</tr>
</thead>
<tbody>
<tr>
<td>Gallery</td>
<td>1</td>
<td>1</td>
<td>Normal walking</td>
</tr>
<tr>
<td>Probe A</td>
<td>1</td>
<td>1</td>
<td>Carrying a brief case</td>
</tr>
<tr>
<td>Probe B</td>
<td>1</td>
<td>1</td>
<td>Wearing a coat</td>
</tr>
<tr>
<td>Probe C</td>
<td>1</td>
<td>1</td>
<td>Wearing slippers or socks only</td>
</tr>
<tr>
<td>Probe D</td>
<td>1</td>
<td>1</td>
<td>Walking diagonally</td>
</tr>
<tr>
<td>Probe E</td>
<td>1</td>
<td>2</td>
<td>Normal walking</td>
</tr>
<tr>
<td>Probe F</td>
<td>2</td>
<td>1</td>
<td>Normal walking</td>
</tr>
<tr>
<td>Probe G</td>
<td>2</td>
<td>2</td>
<td>Stopped for a while</td>
</tr>
</tbody>
</table>

In this paper, we proposed a gait recognition method that works in practical situations. The algorithm was designed to work when the observed subjects walk in random walking paths, i.e., no strict walking protocol, and it includes a new gait feature, the Shifted Energy Image (SEI), that is robust to body-posture variations. Experimental results showed the efficiency and the potential of the proposed method.

4. CONCLUSIONS

In this paper, we proposed a gait recognition method that works in practical situations. The algorithm was designed to work when the observed subjects walk in random walking paths, i.e., no strict walking protocol, and it includes a new gait feature, the Shifted Energy Image (SEI), that is robust to body-posture variations. Experimental results showed the efficiency and the potential of the proposed method.

5. REFERENCES