Gait Recognition Based on Structural Gait Energy Image

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Abstract

Gait energy image (GEI) has been proven to be an effective gait recognition feature. It has good performance on most of public databases. However, GEI ignores most of gait motion information and doesn’t contain enough human body structure information neither, which negatively affect its robustness in varying clothing and carrying conditions. We propose a new gait recognition method called structural gait energy image (SGEI), which combines the advantages of GEI and model-based methods. SGEI is generated by a fusion of foot energy image (FEI) and head energy image (HEI). A classifier fusion of GEI and SGEI is then conducted. Our method can cope with the clothing and carrying variations pretty well. We test it on CASIA(B) database and get a recognition rate of 89.29%, which is much higher than GEI whose recognition rate is 60.37% only.

Keywords: Gait Recognition; GEI; SGEI

1 Introduction

Gait is an effective biometrics and it has been proved that the individual gait is unique by early medical research [1]. Compared with other biometrics recognition methods such as fingerprint recognition, face recognition and iris recognition, gait recognition does not need a close view and it’s not necessary for human to be still for a while during data collection. However, gait recognition is a very challenging problem. A number of gait recognition methods have been proposed and can be divided into two categories: model-based methods [2, 3, 4, 5, 6, 7] and model-free methods [8, 9, 10, 11, 12, 13, 14, 15, 16, 17]. Model-based methods usually need to segment the human body into several parts and then get the structure and motion information to classify the gait patterns. Model-based methods are not so sensitive to clothing and carrying variation because the structure and motion information won’t change a lot when clothing and carrying condition varies. However, the performance of these methods is usually limited because of the noise of the gait images and the difficulty in segmenting the body parts. In model-free methods, the gait features are extracted from the silhouette images of the gait sequence using statistical approaches. Among several ways of gait feature representation, gait energy image (GEI) [4] is the most popular one. Improvement on GEI has been made and some methods based on GEI have appeared such as gait flow image (GFI) [5], enhanced gait energy image (EGEI) [6], frame difference energy image...
There are also some other methods of gait feature representation, like Shape Variation-Based (SVB) Frieze Pattern [10], motion silhouette contour templates and static silhouette templates (MSCT and SST) [11], etc. These model-free methods, especially the GEI method, trying to improve the performance of gait recognition using statistical approaches, can usually cope with the problem of low quality silhouettes. But they rarely contain the structure and motion information, so they are sensitive to clothing and carrying variation.

The GEI method can cope with the problem of low quality silhouettes, and model-based methods have an advantage of insensitivity to clothing and carrying variation. By combining these two advantages, we propose a new gait recognition method called structural gait energy image (SGEI). We model the foot and head region of human body and segment them from the gait image, then use the idea of GEI to get the mean value among a gait sequence. Experimental results on the CASIA(B) gait database demonstrate that our method can cope with the clothing and carrying variations pretty well. The rest of this paper is organized as follows. Section 2 describes our algorithm in detail. Section 3 presents our experiment results. Section 4 concludes this paper.

2 Algorithm

A GEI can be regarded as a moving probability graph of the human body, the high gray level part of the image corresponds to the region where human body appears more frequently during walking. However, this probability graph reflects the probability of the whole body rather than probability of each part of the body. For example, the swinging foot during walking may cover with the crus appeared at other frames of the gait cycle. Our method can deal with this problem well. The foot and head region of the body are segmented first and a foot energy image (FEI) and head energy image (HEI) are then got respectively. The FEI and HEI contains the moving probability information of the foot and head respectively, without covering with other part of the body. The motivation for choosing the foot and head region is that these regions, especially the foot region, are more robust than other part of the body when clothing and carrying condition varies. Both FEI and HEI contain some identification information. They can be used as gait features to recognize gait respectively. However the identification information of these two features alone are not plenty and the recognition performance are not good enough, so we combined the FEI and HEI to get a new feature called structural gait energy image (SGEI). The SGEI contains both foot and head moving probability information when walking, and it outperforms the HEI, HEI and GEI according to our tests on the CASIA(B) database.

2.1 FEI

To get the FEI, we first need to segment the foot region from the human body. The input of our experiment are foreground silhouette images. We first calculate the pixel numbers of each connected component and filter the noise by removing the connected components not big enough. Then, we get the location of the human body by finding the bounding rectangle of the biggest connected component. We record the center of the bounding rectangle here for later use, noted as $Cen$. The leg and foot region is subsequently found from the lower part of the human body, noted as $R_{foot}$. It’s noted that all subjects are walking from right to left in the database. So the foot in front can be located by finding the leftmost point of the leg and foot region, while
(a) Segment the foot region  (b) FEI  (c) SGEI

Fig. 1: Generating FEI and SGEI

the foot behind is located by finding the rightmost point of the leg and foot region. The two feet in the double-support position can be located easily after the leftmost and rightmost points are found, because the foot shape in the double-support position is always regular and has a horizontal direction. We can just locate a rectangle region around the two points as the foot region. However when the leg is swung near the mid-stance position, the foot shape and direction changes, so the task becomes a little more difficult. We propose a variable foot model (VFM) to solve this problem.

In our VFM model, a rough position is got by locating a rectangle region around the left and right most points. Then the coordinate relative to the point $C_{en}$ and the detection of each foot is calculated. This information can be used to get the accurate position of the feet. Based on the fact that the foot area won’t change a lot when the foot swings while walking, we decrease the width and increase the height of the foot region when the foot swings near the mid-stance position and has a big angle with the horizontal direction. By conducting this VFM model, we get a precise position of both feet. We then segment the foot region and save it to a foot image, noted as $F$. Then a registration procedure is conducted to make sure the point $C_{en}$ of each gait image is aligned to the same coordinate. To achieve this goal, we first move the point $C_{en}$ to the center of the image, then move the foot region to keep the relative position to the point $C_{en}$, which makes a new registered foot image, noted as $F_{r}$. We have also tried to register each gait image to the centroid of the human body. But the center point is more stable than centroid especially in the vertical direction, so we use the center point at last. The experimental result shows the registration to the point $C_{en}$ gets higher recognition rate. The FEI is then generated.

\[
FEI_{Sequence} = \sum_{k=1}^{N} \frac{F_{rk}}{N} \tag{1}
\]

In order to reduce the complexity, we obtain the sequence foot energy image $FEI_{Sequence}$ rather than the FEI among each gait period. $FEI_{Sequence}$ is calculated as formula (1), where $F_{rk}$ is the $kth$ registered foot image, $N$ is the number of images in the sequence. We borrow this idea from Toby et al. [5], they have proposed a gait recognition method called GFI, and when they calculate the GFI, they obtain the exemplar GFI, which is some like our sequence FEI. Fig. 1(a-c) shows three examples of finding the foot region, where the blue point is the center point and the red point is the centroid. Fig. 1(b) is an example of FEI and Fig. 1(c) is an example of SGEI.

2.2 HEI

It’s much easier to get the HEI because the head won’t swing largely while walking. So we get the HEI just by setting a head region parameter noted as $R_{\text{head}}$ and cutting the top region of the bounding rectangle of the human body. Because this bounding rectangle has been found at
previous procedure, the work here gets simpler. We’ve done some experiments to make sure we get the optimal head region parameter, which can distinguish the gait patterns best and gets the highest gait recognition rate. A registration to the point \textit{Cen} is also conducted for the HEI.

### 2.3 SGEI

After the FEI and HEI are got, we make a fusion of these two features and combine them into a new feature called structural gait energy image. Because the FEI and HEI are both registered to the point \textit{Cen}, the two images can be simply added to get the new SGEI. The SGEI contains both foot and head information, and the relative position information of these two parts is retained. Each feature can distinguish the gait patterns in some degree, but the combination of these two features gets much better performance, which is validated by our following experiments.

### 2.4 Classification

Huang et al.\cite{12} combined principal component analysis (PCA) and liner discriminant analysis (LDA) to get the best data representation and pattern separation. In our paper, we follow their method. PCA is used to reduce the dimension of SGEI and LDA is used to separate the patterns. After this, Euclidean distance is used as the similarity measure and a nearest neighbor classifier is used to classify the samples.

By conducting the steps above, we can get an SGEI nearest neighbor classifier. Aiming at achieve best performance on all probes, we carry out a fusion of the SGEI nearest neighbor classifier and the GEI nearest neighbor classifier. The GEI nearest neighbor classifier is got just like the SGEI nearest neighbor classifier. The only difference is that the SGEI is replaced by the GEI. The image distance in both GEI and SGEI classifier are calculated, the image distance in SGEI is multiplied by an adjustment parameter \( \gamma \) to get the normalized image distance. We compare the normalized image distance and choose the classifier which has a small distance.

### 3 Experiments

Our method was tested on the CASIA(B) database \cite{14}. The CASIA(B) database has 124 subjects, every subject walked 10 times in the scene (6 normal + 2 with a coat + 2 with a bag). The videos were captured from 11 different view angles(\(18,36,\ldots,180\)). So it has 13640 video sequences in total. In this paper, we chose the 90 degree view angle samples to accomplish our experiments, which contain 1240 videos. We chose the first three normal walking videos of each person as the gallery set and the left seven videos as probes, which include three normal walking videos, two videos walking with a bag and two videos walking with coat for each person. We compared the performance of our method with GEI \cite{4} which had the same setting of gallery and probes.

We employed the cumulative match characteristics(CMCs) \cite{18} to evaluate the recognition performance. Fig. 2 shows the cumulative match score in different ranks when using GEI and our method respectively. It’s obvious that our method outperforms the GEI method. We’ve achieved an average rank 1 recognition rate of 89.29\%, which is much higher than GEI’s 60.37\%; and we’ve got an average rank 5 recognition rate of 96.08\%, which is much higher than GEI’s 74.65\%.
Fig. 2: Comparison of cumulative match scores

Fig. 3: Rank 1 Recognition Rate

We also did some experiment to prove the effectiveness of the feature fusion and the classifier fusion. Fig. 3 shows the recognition rates of GEI, HEI, FEI, SGEI and the integrated classifier on three different probes. It shows that the recognition rate of HEI, FEI and SGEI on the bag probe and coat probe are higher than GEI, and the integrated classifier gets even higher performance.

4 Conclusion

This paper describes a novel gait recognition approach called as structural gait energy image (SGEI). We first get the FEI and HEI, then combine these two features into an SGEI. PCA and LDA are subsequently used and a classifier fusion of GEI and SGEI is then conducted. Experiments on the CASIA (B) database show our method outperforms GEI. The experimental results demonstrate that our method is much more robust to clothing and carrying variations. Our future work will model more parts of the body and expand more structural information into the SGEI.

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References