HEATGait: Hop-Extracted Adjacency Technique in Graph Convolution based Gait Recognition

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Abstract—Biometric authentication using gait has become a promising field due to its unobtrusive nature. Recent approaches in model-based gait recognition techniques utilize spatio-temporal graphs for the elegant extraction of gait features. However, existing methods often rely on multi-scale operators for extracting long-range relationships among joints resulting in biased weighting. In this paper, we present HEATGait, a gait recognition system that improves the existing multi-scale graph convolution by efficient hop-extraction technique to alleviate the issue. Combined with preprocessing and augmentation techniques, we propose a powerful feature extractor that utilizes ResGCN to achieve state-of-the-art performance in model-based gait recognition on the CASIA-B gait dataset.

Index Terms—Biometrics, Pose Estimation, Feature Extraction, Spatio-temporal Features, Biased Weighting, Hop Extraction

I. INTRODUCTION

Gait recognition is one of the most popular biometric authentication techniques since it can be used without the cooperation of human subjects [1]. In particular, model-based gait recognition focuses on extracting skeleton representation of human gait instead of using raw RGB videos. The representation consists of two-dimensional positions of key joints that are free of occlusions caused by carried items, clothing, etc., resulting in robust features facilitating gait recognition. It also utilizes less sensitive personal data.

Contemporary approaches on model-based gait recognition focus on extracting joint positions from gait video sequences leveraging the recent development in pose estimation techniques to generate a spatio-temporal graph considering the joints as vertices and the bones as edges [2]–[5]. Since joints that are not connected via bones can have strong correlations, an optimal method for gait recognition should explore both local and global joint dependencies. Existing approaches accomplish this by applying graph convolutions using higher-order polynomials of the adjacency matrix representing the joint connections. This can enable the graph convolution to consider distant joints by capturing the length \( n \) walk using the \( n^{th} \) order polynomial. However, due to the presence of cyclic walks, this formulation results in higher edge weights for closer joints compared to the further ones. As a result, the effectiveness of this method in capturing information from distant joints is reduced affecting the overall performance of the system [1], [6].

In this paper, we present HEATGait, a gait recognition system that utilizes existing pose estimation architecture to extract and model human skeleton joints which are then further refined using preprocessing techniques. We employ a graph convolutional network equipped with an improved multi-scale feature aggregation technique utilizing hop-extraction to create adjacency matrix that mitigates the effect of biased weight. Our empirical results show state-of-the-art performance in model-based gait recognition.

II. RELATED WORKS

Model-based gait recognition considers human body structure modeled using joints and bones. The key benefit here is robustness to occlusion, viewing angle, and subject distance.

Earlier approaches of model-based gait recognition relied on extracting joint positions using external devices [7], [8]. They extracted handcrafted features such as relative distance and angle between the joints in order to recognize gait using machine learning classifiers. However, due to severe feature engineering, these works are mostly concentrated on small datasets and often sensitive to environmental noises.

Recent approaches improved upon this in two ways. External devices to extract joint positions were phased out due to the recent advances in pose estimation techniques. Handcrafted features and machine learning-based classifiers were replaced with deep learning techniques. One of the earliest works in this regard utilized heatmaps generated from CNN to extract 2D features from each frame of gait sequence and fed them into an LSTM network to capture the temporal information embedded in the gait sequence [9]. In another work, a combination of CNN and LSTM was used to generate spatio-temporal features [10]. These works were further extended to include 3D gait features [2], [11]. However, these approaches depend on CNNs to extract gait features rather than utilizing pose information.

Considering the graph structure of gait features extracted using pose-estimation, graph convolutional networks (GCN) are being utilized in gait recognition [1]. Li et al. pioneered the use of GCN in gait recognition along with Joints Relationship Pyramid Mapping (JRP). They considered the joint positions as vertices and the bones connecting those joints as edges [12]. However, their best-performing model heavily depended on JRP. Later, Teepe et al. proposed standalone GCN architecture utilizing ResGCN [13], improving upon the

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performance of the earlier work. Later, Gao et al. introduced Gait-D architecture combining ST-GCN [14] and Canonical Polyadic Decomposition [15] to focus on relevant gait features to improve the recognition performance [5]. These methods combined the relative positions of the joints and their natural bone connection encoded using the adjacency matrix of the graph. Wang et al. extended this idea in multi-stream networks to integrate joint, bone and motion-based features [4].

Even though the GCN-based approaches discussed above paved the way to enhance the performance of model-based gait recognition, their reliance on higher-order polynomials of the adjacency matrix for multi-scale feature aggregation makes them prone to biased weighting problem reducing the overall performance of the gait recognition system [1]. This necessitates the introduction of a novel aggregation technique to capture the long-range relationship among joint positions while also avoiding the biased weighting problem.

III. PROPOSED APPROACH

The proposed gait recognition system takes gait video of a person as input. The videos are taken from the CASIA-B dataset [16]. At first, each frame of the input video is passed through a pose estimation network to estimate the joint positions representing human pose. The pose sequence is then preprocessed to remove predictions with low confidence. The modified sequence of poses is then fed to a graph convolutional network with residual connections to generate the class label with confidence. The overall pipeline of the proposed system is depicted in Fig. 1.

A. CASIA-B Dataset

CASIA-B is one of the most common datasets used to evaluate gait recognition architectures. It provides RGB images of the gait sequence of 126 human subjects. Each subject is captured from 11 viewing angles (0°, 18°, . . . , 180°) in three walking conditions (NM: normal walking, BH: walking while carrying a bag, CL: walking while wearing heavy clothes). For each subject 6 NM, 2 BG, and 2 CL sequences are provided for each of the 11 angles resulting in (6 + 2 + 2) × 11 = 110 sequences per subject.

Since the authors of the dataset did not define any protocol to partition the data into training and test sets, we follow the split popularized by existing gait recognition literature to ensure fair comparison [2]–[5]. The dataset was split into training, validation and test set maintaining the ratio of 48:12:40.

B. Pose Extraction

A gait video of a person can be considered as a sequence of frames \( f_1, f_2, \ldots, f_N \) where each frame is an RGB image and \( N \) denotes the number of frames in the gait video. In order to perform graph convolution, the input video needs to be represented using graph, i.e., vertices and edges. To do that, each frame \( f_i \) is passed through a pose estimation that extracts \( M \) keypoints denoting the joint positions of the person. The network utilizes \( M \) heatmaps, \( H_1, H_2, \ldots, H_M \) where \( H_i \) denotes the position of the \( i^{th} \) joint in 2D coordinates.

In this work, we employ Higher Resolution Net (HRNet) [17], pretrained on the COCO dataset [18] that is able to extract 17 joint positions from each of the frames. Since the bone information is not provided, we follow the configuration followed by [3] (Fig. 2). Here, each joint is considered as a vertex and each bone is considered as an edge.

C. Preprocessing

1) Removal of Low Confidence Frames: In addition to providing the 2D coordinate of the 17 joints of a frame, HRNet generates a score for each joint denoting the confidence of the predicted joint position. The higher the score, the better the prediction. Since the relative position of the joints in subsequent frames is an important feature to recognize the gait, we hypothesize that a joint prediction with low confidence score can hamper the recognition performance. Particularly, in BG and CL walking conditions where the person is occluded by bag and clothes, respectively, the confidence of the HRNet in predicting joint positions can be significantly low. To counter this effect, we calculate the average confidence for each video frame:

\[
\text{Confidence} = \frac{\sum_{i=1}^{M} c_i}{M} \tag{1}
\]

where \( c_i \) denotes the confidence of the \( i^{th} \) joint. We remove a video frame if the average confidence is below 60%.

2) Data Augmentation: To ensure the robustness of the proposed system, data augmentation techniques are used. First, we simulate the effect of a person walking backwards by inverting the order of the video frames. Again, the extracted
joint positions were mirrored based on the center of gravity of the graph along the vertical axis to imitate the same person walking in the reverse direction. Additionally, small Gaussian noise was added to each of the joints to mimic the inaccuracies introduced by pose estimation techniques. All these augmentations were performed during the training phase of the network.

D. Graph Convolution

Let, \( G = (V, E) \) be the human skeleton graph. Here, \( V = \{v_1, v_2, \ldots, v_M\} \) is the set of \( M \) vertices each corresponding to a joint, and \( E \) is the set of edges corresponding to the bones. Each vertex contains a pair of values corresponding to the \( x \) and \( y \)-coordinates of the joint. The edge information is encoded using an adjacency matrix \( A \in \mathbb{R}^{M \times M} \) where

\[
A_{i,j} = \begin{cases} 1, & \text{there exists an edge between } v_i \text{ and } v_j \\ 0, & \text{otherwise} \end{cases}
\]

Note that, since \( G \) is undirected, \( A \) is symmetric.

The human gait is represented using a vertex features set \( X = \{x_{i,j} \in \mathbb{R}^C | i, j \in \mathbb{Z}; 1 \leq i \leq N; 1 \leq j \leq M\} \) where \( x_{i,j} \) is the \( C \)-dimensional feature vector for vertex \( v_j \) at frame \( i \). Here, \( X \in \mathbb{R}^{N \times M \times C} \). Since we are using 2D coordinates of the joints, we have \( C = 2 \).

That means, \( A \) and \( X \) can represent the structural and feature information of a gait sequence, respectively.

Now, the layer-wise update for GCNs applied for frame \( f \) is defined as:

\[
X_f^{(l+1)} = \sigma \left( \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} X_f^{(l)} \Theta^{(l)} \right)
\]

where \( \tilde{A} = A + I \) denotes the conservation of identity features by the introduction of self-loops, \( \tilde{D} \) is a matrix containing the degrees of \( \tilde{A} \) in its main diagonal, \( \Theta^{(l)} \) denotes the learnable weight matrix for layer \( l \), and \( \sigma(\cdot) \) denotes the activation function. The diagonal degree matrix is used to normalize the features in order to prevent vanishing/exploding gradients [19].

E. Addressing Biased Weighting Problem

To aggregate multi-scale structural information, the spatial aggregation framework incorporates higher-order polynomials of the adjacency matrix:

\[
X_f^{(l+1)} = \sigma \left( \sum_{k=0}^{K} \tilde{A}^k X_f^{(l)} \Theta^{(l)} \right)
\]

where \( K \) denotes the scale of the aggregation, \( \tilde{A} = \tilde{D}^{-\frac{1}{2}} \tilde{A} \tilde{D}^{-\frac{1}{2}} \). Note that, \( \tilde{A}^{k}_{i,j} = \tilde{A}^{k}_{j,i} \) is the total number of length \( k \) walks between \( v_i \) and \( v_j \). That means, \( \tilde{A}^{k} X_f^{(l)} \) can be used to perform feature aggregation weighted by the number of such walks.

Unfortunately, since walks consist of hops between vertex \( i \) to vertex \( j \), where \( i \) can be equal to \( j \), there can be cyclic walks concentrated in the originating vertex. Additionally, the existence of self-loops to preserve identity features can further increase such walks. As a result, the adjacency matrix contains higher values for the vertices close to the originating vertex and lower values for that of further (Fig. 3(a)). This creates a bias in feature aggregation, rendering the process less effective in capturing long-range relationship between joints.

We address the above issue by defining a \( k \)-adjacency matrix as:

\[
[\tilde{A}(k)]_{i,j} = \begin{cases} 1, & \text{if } d(v_i, v_j) = k \\ 1, & \text{if } i = j \\ 0, & \text{otherwise} \end{cases}
\]

where \( d(v_i, v_j) \) is the shortest distance between \( v_i \) and \( v_j \) considering the number of hops (Fig. 3(b)). Since \( G \) is undirected, the value is calculated using Breadth-First Search (BFS) algorithm to find the \( k \)-hop neighbors. Note that, \( \tilde{A}(1) = \tilde{A} \) and \( \tilde{A}(1) = I \).
Thereafter, incorporating Equation 5 with Equation 4, we get:

$$X^{(l+1)}_j = \sigma \left( \sum_{k=0}^{K} \tilde{D}^{\frac{1}{2}}_{(k)} \tilde{A}_{(k)} \tilde{D}^{\frac{1}{2}}_{(k)} X^{(l)}_j \Theta^{(l)}_{(k)} \right)$$

(6)

In contrast with Equation 4 where the total number of length $k$ walks is dependent on length $k - 1$ walks, Equation 6 provides equal importance to the vertices in closer and further neighborhoods alleviating the biased weighting problem. Consequently, this results in effective consideration of long-range relationships.

F. Model Architecture

We have adapted the ResGCN architecture that have been used for action recognition to suit our task. The architecture, as shown in Fig. 4, consists of a set of ResGCN blocks composed of Graph Convolution to extract spatial features, 2D Convolution to extract temporal features, and a set of residual connections. Some of the internal layers may contain a set of bottleneck structures. The output of the internal layers are passed through an average pooling and a fully-connected layer sequentially to map the extracted features with the class labels.

The first two blocks, Block 0 and Block 1 work as the input branch. Output from the Block 1 is fed into the next main stream block that produces the input for the final block which, in turn, produces the class-wise probabilities by normalizing the outputs.

The initial batch normalized input is given as an input to the subsequent spatial and temporal ‘Basic’ blocks. The ‘Basic’ block is a sequential set of convolution and batch normalization layers that conditionally has a residual connection. The final output of the ‘Basic’ block is produced by passing the obtained output through a ReLU activation function.

The ‘Bottleneck’ blocks are used to reconstruct the input using a sequence of up-convolution and down-convolution where each convolution layer is followed by a batch normalization layer. In case of the block being residual, a convoluted and batch normalized form of the input is added with the output. Final output is produced by passing the output through ReLU activation function.

Afterwards, the features are extracted smoothly instead of retaining more pronounced features like edges by applying an average pooling on the output feature map from the last bottleneck block of Block 2. Finally, the feature vector is mapped to the output units through a fully-connected layer.

IV. Results and Discussion

In this section, we compare our proposed approach with other state-of-the-art techniques in public gait dataset CASIA-B. The comparison is performed considering different views and different walking conditions with other model-based approaches.
A. Experimental Setup

The proposed system was trained in a Python environment in Google Colab \(^1\). Considering the noise introduced due to the approximation of joint position, we utilize Adam optimizer \([20]\). The architecture was trained in multiple cycles. Each cycle consisted of 100 epochs. The initial learning rate was set to 0.01. After each cycle, it was reduced to 10\(^{-5}\) of the previous cycle down to a minimum of 10\(^{-5}\). This was done to ensure that the model does not overfit to the training samples. Supervised contrastive loss \([21]\) was used to calculate the loss.

B. Comparison with State-of-the-Art Methods

Table I presents a comparison of our proposed system with the state-of-the-art models in gait recognition. Our system achieves a commendable performance throughout different viewing angles and walking conditions.

We implemented the architecture of \([3]\) as our baseline and performed modifications upon it for the improvement of recognition performance. According to Table I, a significant improvement can be noticed compared to the baseline. This improvement can be attributed to our conservative training process which was undertaken to ensure that the model does not overfit the training samples, a problem that is persistent in \([3]\).

In all walking conditions, our system outperforms the existing state-of-the-art for all but two viewing angles. Even in the case of 54\(^{\circ}\) and 72\(^{\circ}\) viewing angles, the performance of our system is comparable. All in all, our proposed system achieves state-of-the-art performance compared to the existing literature.

C. Ablation Study

Compared to the baseline shown in Table II, our preprocessing techniques were able to improve the performance in all aspects. Specifically, considering the BG and CL walking conditions are more prone to inaccuracies in pose estimation technique, the improvement of performance in these conditions are more prominent compared to that of NM as hypothesized. In this regard, it is worth-mentioning that the preprocessing removes 0.9\% frames from the dataset. Reduction of noisy and inaccurate frames helped the model converge faster and avoid overfitting. This resulted in a 2.33\% increase of accuracy on average.

Combining the hop extraction technique with the baseline and using preprocessed dataset increases the accuracy by 11.07\% on average compared to the baseline proving the effectiveness of our approach.

1 https://colab.research.google.com/

**TABLE I**

| Gallery | NM#1-6 | Ref. | 0\(^{\circ}\) | 18\(^{\circ}\) | 36\(^{\circ}\) | 54\(^{\circ}\) | 72\(^{\circ}\) | 90\(^{\circ}\) | 108\(^{\circ}\) | 126\(^{\circ}\) | 144\(^{\circ}\) | 162\(^{\circ}\) | 180\(^{\circ}\) | Mean |
|---------|---------|------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-------------|-----|
| PSTN [10] | 34.5 | 45.6 | 49.6 | 51.3 | 52.7 | 52.3 | 53 | 50.8 | 52.2 | 48.3 | 31.4 | 47.4 |
| PSTN-3D [11] | 38.7 | 50.2 | 55.9 | 56 | 56.7 | 54.6 | 54.8 | 56 | 54.1 | 52.4 | 49.2 | 51.8 |
| PoseGait [2] | 55.3 | 69.6 | 73.9 | 75 | 68 | 68.2 | 71.1 | 72.9 | 76.1 | 70.4 | 55.4 | 68.7 |
| JointsGait [12] | 68.1 | 73.6 | 77.9 | 76.4 | 77.5 | 79.1 | 78.4 | 76 | 69.5 | 71.9 | 70.1 | 74.4 |
| GaitGraph [3] | 85.3 | 88.5 | 91 | 92.5 | 87 | 86.5 | 88.4 | 89.2 | 87.9 | 85.9 | 81.9 | 87.6 |
| Gait-D [5] | 87.7 | 92.5 | 93.6 | 95.7 | 93.3 | 92.4 | 92.8 | 93.4 | 90.6 | 88.6 | 87.3 | 91.6 |
| MS-Gait [4] | 89.4 | 91.7 | 91.6 | 90.2 | 90.6 | 90.6 | 90.4 | 90.9 | 90.4 | 88.5 | 85.6 | 90.0 |
| HEATGait (Ours) | **91.7** | **93.8** | **93.8** | **94.7** | **92.6** | **94.6** | **94.3** | **94.4** | **93.2** | **91.5** | **91.5** | **93.3** | **93.3** | **93.3** |

**TABLE II**

| Ablation Study on the CASIA-B Dataset |
|-------------------------------------|
| Strategy | Accuracy (%) |
|----------|--------------|
| NM | BG | CL |
| Baseline (ResGCN) | 87.5 | 75.3 | 67.1 |
| Baseline + Preprocessing | 88.9 | 78.2 | 69.8 |
| Baseline + Preprocessing + Hop Extraction | 93.3 | 87.5 | 82.3 |
V. CONCLUSION

In this paper, we present a novel hop-extracted adjacency technique to address the biased weighting problem persistent in existing model-based gait recognition. In this regard, we propose a gait recognition system leveraging efficient preprocessing techniques and recent advancement in pose estimation and graph convolution approaches. Our empirical results show that our system outperforms the existing architectures by a sizable margin.

Most of the existing works on gait recognition either focus on appearance-based or model-based features. Future research efforts can be concentrated on combining these two features via ensemble technique to further improve the performance. On the other hand, the existing datasets on gait recognition provide videos captured on laboratory settings, which might be essential considering the requirements to capture the same gait from different viewing angles and poses. However, videos captured in natural settings can provide much more realistic gait from different viewing angles and poses. Hence, videos should be recorded in natural environments and help researchers experiment how their systems perform in real-life scenarios.

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