

FR-Former: Fast, Real-time Transformer for Efficient and Accurate Gait Recognition

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Abstract

Gait recognition is one of the most common applications in computer vision, which has been playing a crucial role in healthcare, crime analysis, and personal identification in general. In the era of deep learning, gait recognition has been empowered by neural networks and foundation models to extract meaningful feature representations. In this paper, the lightweight RTMPose model is integrated to efficiently extract 2D human poses, and a custom transformer is designed to perform accurate gait recognition upon the extracted human poses. The research goal is to develop FR-Former, a novel transformer-based architecture that outperforms state-of-the-art models in terms of runtime complexity and achieves comparable recognition accuracy in the meantime.

1 Introduction

Gait recognition, known as identifying people based on the way they walk, commonly gathered from video files [1], has multiple distinct advantages as a biometric [2]: human gait is characterized by the flexibility of being captured without physical proximity, and the permissiveness of low resolution [2]. A large number of human gait reference datasets have become available recently: a full-body gait dataset of able-bodied adults and stroke survivors has been collected to observe typical gait and aging effects [3]; another gait dataset that has combined anthropometric traits with gait parameters was acquired to facilitate patient evaluation of their physical status for health professionals [4]. Gait biometrics have been extensively studied under a standardized gait recognition pipeline: data acquisition, feature representation, dimension reduction, and classification [2]. To acquire human gait data, four devices have been widely employed: camera; accelerometer; floor sensor; continuous wave radar [2]. Feature representation can be classified into 2D representations and 3D representations based on the number of dimensions [1], or be divided into model-based representations and model-free representations depending on whether an explicit human body is defined [1], [2]. Both model-based and model-

free approaches have been well studied [1]: a set of articulated 3D point cylinders was proposed as an explicit 3D gait model with both structural features and dynamic features [5]; on the other hand, GaitSet, a model-free method, was designed to learn human gait by viewing it as a set of independent, permutation-safe silhouettes from distinct videos [6]. Dimension reduction can be classified into feature reduction and outlier removal [2]: MPCA combined with LDA has been widely used for feature reduction to filter out irrelevant features [7]; Gaussian Mixture Model has been used to partition an image into hip, knee, ankle, and outlier [8]. The outlier region shall be removed to minimize noisy signals [2]. For classification, a variety of models have been studied and utilized including Hidden Markov Model (HMM) [9], Convolutional Neural Networks (CNNs) [10], and K Nearest Neighbors (KNN) [5].

2 Related Work

2.1 Pose Estimation

Pose estimation algorithms can be classified into two modes: top-down approach and bottom-up approach [11]. With the overhead of applying an object detector to crop a human bounding box before employing the pose estimator, the top-down approach requires minimal input im-

age resolutions while preserving decent speed and accuracy [11]; on the other hand, pinpointing instance-independent keypoints directly from a given image, the bottom-up approach suffers from strict input resolution to group identified keypoints into actual human poses [11]. The estimation of poses can be reduced to different tasks: heatmap-based methods, which rely heavily on the transformation of the keypoint format between the original keypoint coordinates and the heatmaps, outperform estimates directly from the keypoint coordinates without any transformation [12]; additionally, regression-based methods are characterized by efficient computation and permissive input resolution [12]; in addition, SimCC, a classification-based method, discretizes both axes into uniform bins to locate keypoints in a bin-wise manner [13].

2.2 Gait Recognition Model

Other than statistical models, deep learning has shown substantial potential in the classification stage of gait recognition, with a variety of different neural network architectures [14]. The most widely used architecture is convolutional neural networks (CNNs), which learn body shape embeddings by generating feature maps [14]. CNNs, often combined with other neural network architectures including autoencoders and LSTMs, generally do not require complex deep layers while

still preserving sufficient encoding of gait frames [14]. Another prevalent architecture, recurrent neural networks (RNNs), can be applied in gait recognition in three distinct ways: directly learning temporal relationships of joint coordinates; combining with CNNs to learn both spatial and temporal features; learning partial representations within the same gait frame [14]. Based on the transformer architecture, deep auto-encoder (DAE) extracts bottleneck features into a latent space and minimizes the reconstruction error while decoding bottleneck features [14]. Generative Adversarial Networks (GANs), usually characterized by a generator and a discriminator, are robust to gait variations including viewpoints and clothing [14]. The generator is responsible for mixing fake samples into real ones, while the discriminator aims to distinguish between real samples and fake samples [14].

2.3 Transformer Architecture

In spite of the dominance of convolutional neural networks in the field of gait recognition, transformer architectures with an attention mechanism are able to capture and emphasize features in the specific regions of an image [15]. Most transformer-based models are conceptually similar, but they can be distinguished by different ways to learn embeddings and apply attention. Different types of embeddings have been adopted

in a variety of transformer architectures. Gait-ViT starts with partitioning gait silhouettes into fragments called patches, which will be concatenated into a time series [15]; then Gait-ViT learns patch embeddings along with positional embeddings, which are crucial to preserving the structural information within the original image [15]. On the other hand, instead of using silhouettes, IIP-Transformer partitions *human skeletons* into exactly 5 parts to extract patch embeddings [16]. For attention, in Gait-ViT, both patch embeddings and positional embeddings are passed into a transformer encoder, which consists of multiple transformer blocks with the self-attention mechanism [15]. However, a large number of transformer architectures are not limited to traditional self-attention: IIP-Transformer, with a total of 5 body parts defined and spatially partitioned, proposes Intra-Inter-Part self-attention (IIPA) to aggregate both joint-level and part-level tokens and sum up their attention outputs accordingly [16].

3 Research Motivation

3.1 Problem Statement

Although a massive number of gait recognition models have been proposed, the runtime efficiency of a gait recognition model can be a potential bottleneck in many real-world applications. To

the best of our knowledge, only a few existing studies have specifically dived into developing fast, real-time, and accurate gait recognition models: for example, a simple CNN with only 4 layers has been deployed to achieve decent real-time person identification via gait analysis [17]. In this work, we attempt to address the following two problems: 1) can we develop an efficient, transformer-based neural network model while preserving competitive accuracy with different embeddings and attention mechanisms? 2) can we combine an efficient pose estimation model with our fast gait recognition transformer to build an end-to-end, fast, and real-time gait recognition pipeline? Answering these two problems in this paper can demonstrate the huge potential of even more efficient transformer architecture, challenge the persisting dominance of convolutional neural networks, and further advance the research in efficient real-time gait recognition in the real world.

3.2 Research Goals

In this work, we hypothesize that attention-aware transformer-based architectures can demonstrate competitive accuracy and efficiency as dominant convolutional neural networks. Hence, we aim to design a novel transformer architecture with effective embedding learning and an efficient attention mechanism. Additionally, during the in-

ference phase, we further hypothesize that an efficient pose estimation model that is compatible with real-time videos should be employed to further speed up inference time. After performing this research, in addition to an end-to-end gait recognition system with efficient pose estimation and real-time person identification, we also hope that within the research community, we will draw much more attention to the transformer architecture instead of CNNs to exploit the potential of transformers in developing efficient and accurate gait recognition algorithms.

4 Methodology

4.1 FR-Former: Pipeline

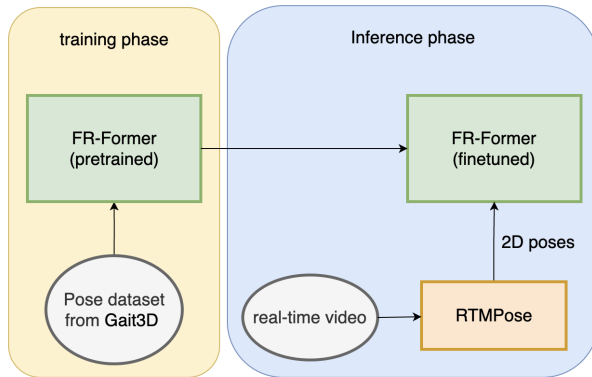


Figure 1: FR-Former Pipeline.

FR-Former pipeline is shown in Figure 1. During the training phase, 2D human pose data from Gait3D are fed into a pretrained FR-Former, in which its novel architecture will be designed and implemented along with this project. During the

inference phase, a real-time video can be fed into the RTMPose module to efficiently extract pose estimation, which will be the input to the finetuned FR-Former model.

4.2 Training Dataset: Gait3D

Gait3D, a large-scale gait recognition dataset consisting of thousands of subjects under an unconstrained environment, gathers 3D meshes and 3D skeletons in addition to traditional 2D poses and 2D silhouettes. Cross-camera tracking has been employed to effectively cluster sequences of the same subject across all different cameras [1]. To be able to address the issue where two people can be highly overlapped, making it challenging for person tracking, human annotators were hired to clean up such overlapping sequences [1]. In spite of various rich representations including 3D meshes provided by Gait3D [1], to our interest, only 2D pose/skeleton data are collected and utilized for training purposes.

4.3 Pose Estimation: RTMPose

RTMPose, a high-performance pose estimation framework, is used for 2D pose feature representations in our work [11]. RTMPose pipeline starts with RTMDet [18], a computationally efficient, suitable, and available real-time bounding box detector, which has eliminated the inference running time bottleneck to separate each

person within a single image [11]. CSPNeXt, a neural network that can take advantage of large kernel sizes to extract high-frequency features and use global average pooling for low-frequency feature extraction [19], was chosen as the backbone of RTMPose for its superior balance between efficiency and precision, with additional training techniques including proper pre-training and strengthening and then weak two-stage training enhancement [11]. SimCC [13], as a lightweight yet effective pipeline, was used in RTMPose to estimate keypoints within a classification framework enhanced with a larger convolution kernel and self-attention mechanism [11]. In terms of the inference pipeline, the real-time friendly skip frame detection mechanism [20], in which detection is only performed on every K frames, was used to boost efficiency while still preserving competitive performance [11]. `rtmllib`, a super lightweight library to conduct pose estimation based on RTMPose models, is employed to derive 2D human pose representations during the inference phase [21].

5 Project Timeline

The timeline for this research project is in the table below. The already finished tasks are marked as teal; the tasks working in progress are marked as blue; the future tasks are marked as gray.

Tasks	Timeline
Lit. review: gait recognition	Feb
Lit. review: pose estimation	Feb
experiment: RTMPose	Feb
experiment: Gait3D dataset	Feb
Lit. review: NN models	Feb
Lit. review: transformers	Feb
Writing: proposal	Feb to Mar
Design: transformer architecture	Mar to July
Coding: transformer architecture	Mar to July
experiment: training	May to July
experiment: inference	Jun to Aug
experiment: comparative study	Aug to Sept
writing: thesis	May to Oct
Coding: GitHub documentation	Oct
submit the paper to ICLR	by Oct
submit the paper to CVPR	by Nov
submit the paper to ICML	by Jan (next year)
submit the paper to ICCV	by Mar (next year)
4999: 2*3 credit hours	Aug to Apr (next year)
submit the paper to NeurIPS	by May (next year)

6 Personal Statement

I have had a solid research background in the field of applied machine learning with more than one year of experience in time series analysis. I am familiar with various machine learning algorithms, neural network architectures, and am comfortable with sklearn and PyTorch programming. However, I am relatively new to the field of computer vision and not familiar with gait recognition; thus, I have to do an extensive literature review on the subject of gait recognition. This project will prepare me for my future academic

career in applied machine learning with the most fundamental skills of conducting an independent study, such as doing a literature review, identifying existing research gaps, designing transformer architectures, and implementing an end-to-end machine learning pipeline. In this project, in order to develop and train FR-Former, I will be using the server from the Photogrammetric Computer Vision Lab directed by Dr. Alper Yilmaz.

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