Long-Term Adaptive and Occlusion- Aware Gait Recognition: A Spatiotemporal Continual Learning Framework

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Abstract : An efficient biometric method for long-distance and non-contact human identification is gait recognition. However, partial occlusions and long-term gait variances brought on by aging, accidents, changing clothes, or environmental factors continue to make real-world deployment challenging. Current deep learning techniques typically rely on consistent walking patterns and clear visibility, which leads to poor performance in unrestricted situations. This study presents an Occlusion-Aware and Long-Term Adaptive (OALTA) architecture that combines a Memory-Augmented Continual Learning (MACL) approach with an Occlusion Detection and Refinement Module (ODRM).While MACL continually updates gait representations without catastrophic forgetting, the ODRM uses temporal attention and regional confidence estimation to identify trustworthy silhouette regions. To capture discriminative spatiotemporal gait features, a hybrid 3D-CNN and Temporal Transformer architecture is used. Superior robustness under occlusion and temporal gait alterations is demonstrated by experiments on CASIA-B, OU-MVLP, and a simulated Long-Term Gait dataset. Under extreme occlusion, the suggested architecture improves Rank-1 accuracy by more than 8% while preser performance.ving steady long-term recognition.

Keywords : Gait Recognition, Occlusion Handling, Continual Learning, Biometrics, Spatiotemporal Learning.

1.Introduction

Gait recognition, a behavioral biometric that uses walking patterns to identify people, has attracted a lot of interest. Gait recognition can be a feasible option for a variety of different applications as a biometric recognition technique. The most common motive for gait recognition is that it allows for discreet recording of information from a distance. As such, a primary advantage of gait recognition is its applicability for surveillance and forensic analysis. By comparing captured gait data to stored data within a database, security and law enforcement will be able to identify suspects and criminals. These applications have been identified as critical for smart city applications. Even healthcare monitoring is possible through gait recognition. The detection of different abnormalities in the gait of an individual can also help in understanding if any abnormalities exist that need medical help. This can also be helpful to understand the stability and improvement of an individual from previous injuries or other ailments. With gait recognition, contactless identification is always possible. Despite successful research works showing the successful use of gait data for identification purposes, the efficient deployment of a gait identification system presents numerous challenges. The most important prerequisite for a reliable identification result is a consistent walking pattern of the users. Hence, gait as a biometric trait needs to be based on unobstructed visibility of the data source. Several problems arise from partial occlusions in real-world settings. Furthermore, the gait traits of a specific person can change over time due to several reasons like health related issues, aging, lack of physical fitness, injuries, or different footwear. As a consequence, gait based identification systems might fail in real world scenarios and, hence raise reliability issues. In addition, gait data should be acquired in real time and on-the-fly in order to trigger appropriate actions according to the results of the identification. Given the sheer amount of data a single subject walking in different gaits generates, the devising of efficient architectures that intelligently process the data streams poses yet another challenge. The problem with the algorithms we have now is that they cannot keep up with the changes in the way people walk. When we add information to these deep learning systems that were taught with old data they often forget what they learned before. This means that over time the systems do not remember how people walk well as they used to. This paper talks, about the Occlusion-Aware and Long-Term Adaptive framework, which is called OALTA for short. The OALTA framework is a way to deal with these problems. It combines learning that never stops with a way to make sure the system understands what is important even when some information is missing. This helps the OALTA framework work better in situations that are always changing.

2. Related work

Over the past ten years, deep learning has greatly enhanced gait identification performance. While contemporary techniques use convolutional neural networks and temporal learning frameworks, earlier approaches depended on manually created characteristics like Gait Energy Images (GEIs).

2.1 Deep Learning **-Based Gait Recognition**

A set-based method that handles gait sequences as collections of unordered silhouettes was introduced by GaitSet. Strong cross-view recognition performance was attained with this approach. By segmenting human silhouettes into several horizontal regions and learning part- based temporal representations, GaitPart greatly enhanced recognition. Later models, including GaitGL and CSTL, used sophisticated spatiotemporal learning to extract both local and global gait variables. Using self-attention processes, transformer-based architectures such as GaitViT investigated long-range temporal dependency modeling. The majority of these methods are extremely sensitive to occlusions and long-term gait alterations, despite the fact that they increased recognition accuracy. When silhouettes are partially obscured or when gait characteristics change over time, performance declines dramatically.

2.2 **Occlusion Handling in Biometrics**

In biometric systems such as face recognition, person re-identification, and gait recognition, occlusion continues to be a significant problem. Attention-based feature learning, adversarial reconstruction, and silhouette completion are some of the current methods. Because the entire body contributes to the gait signature, occlusion handling in gait detection is very challenging. Although adversarial learning techniques and human mesh reconstruction have demonstrated encouraging outcomes, these techniques are computationally costly and frequently rely on precise position estimate. Without requiring explicit 3D reconstruction, the suggested OALTA framework uses a lightweight and flexible approach to dynamically assess silhouette reliability.

3. Proposed Methodology

There are three main parts to the suggested OALTA framework: 1. Extraction of Spatiotemporal Features 2. Module for Occlusion Detection and Refinement (ODRM) 3. MACL, or Memory-Augmented Continual Learning.

3.1 System Overview

Preprocessing is the first step in the system, where raw video sequences are transformed into normalized gait silhouettes. The hybrid feature extraction network, which consists of a Temporal Transformer and a 3D-CNN, receives these silhouettes. The ODRM, which highlights observable gait information and detects unreliable or obscured locations, is used to refine the retrieved features.

Lastly, in order to facilitate long-term adaptation, the MACL module continuously changes gait representations.

3.2 **Spatiotemporal Feature Extraction'**

Both temporal and spatial information are present in human gait. OALTA incorporates a hybrid architecture in order to successfully capture these qualities:

3D-CNN: Extracts local spatial and short-term temporal features.
Temporal Transformer: Models long-range temporal dependencies across gait cycles.

Let the gait sequence be represented as: $S = \{s1, s2, \ldots, sT\}$

where each silhouette frame is processed sequentially to generate discriminative gait embeddings.

The Transformer concentrates on global sequence relationships, whereas the 3D-CNN records body movement patterns including stride and limb motion. Even in difficult situations, the combination yields reliable feature representations.

3.3 **Occlusion Detection and Refinement Module (ODRM)**

The purpose of the ODRM is to lessen the effect of partial occlusions when extracting features. There are two main parts to it.

Regional Confidence Network (RCN)
The trustworthiness of various silhouette regions is assessed by the RCN. Lower confidence scores are given to loud or obscured areas.

Reliability Masking
Unreliable areas are suppressed and informative areas are highlighted based on confidence estimation. Stable gait frames throughout the sequence are also given priority by temporal attention systems. This technique improves recognition robustness by allowing the framework to concentrate on observable and reliable gait information.

3.4 Memory-Augmented Continual Learning (MACL)

Adaptation to changing gait patterns is necessary for long-term gait recognition. Two memory structures are used in the MACL technique to solve this problem.

Global Identity Memory (GIM)

This system keeps a record of how each person walks over a period of time. It stores these walking patterns. What we call gait prototypes for each individual person. In this section, we present a system that encodes long-term gait prototypes and supports updating them for identity recognition. We first introduce the Adaptive Buffer (AB) that stores gait embeddings over time and describe the memory updating process using exponential moving averages. We then discuss the bi-level optimization and how to compute existing long-term prototypes for the OALTA framework.

4. Experimental Design

4.1 Dataset and preprocessing

CASIA-B is a dataset that people use a lot for recognition. It has lots of walking conditions and viewpoints. OU-MVLP is a dataset that was made to test how well gait recognition works when the view is different. The Long-Term Gait Dataset is a dataset. It was created by changing gait parameters a little at a time to make it look like how a persons changes over a long time. When they got the data ready they used video matting and background reduction to get the silhouettes. Every silhouette was made to be 64, by 64 pixels. To make it more like life they covered up some parts of the silhouettes on purpose to create fake things that block the view.

4.2 Implementation Details.

For the implementation PyTorch 2.1 is used and trained on GPUs.

Parameters:

- Embedding dimension: 256
- Transformer heads: 4
- Encoder layers: 2
- Batch size: 32
- Learning rate: 10−4
- Optimizer: Adam

The MACL module kept an Adaptive Buffer containing recent gait embeddings and a Global Identity Memory with 10,000 prototypes.

5. Results and discussion

Method	0%	10%	20%	30%	40%
GaitSet	95.1	90.3	85.2	78.9	71.2
GaitPart	96.2	92.5	87.8	81.5	74.1
GaitGL	95.8	91.9	86.5	80.1	72.8
CSTL	96.5	93.1	88.5	82.3	75.5
GaitRef	96.0	92.0	87.0	80.5	73.5
OALTA	**97.3**	**94.8**	**91.1**	**89.2**	**83.5**

The findings show that OALTA performs steadily even in situations with extreme blockage. OALTA significantly outperformed current methods, achieving 89.2% Rank-1 accuracy at 30% occlusion.

5.2 Long Term Adaptions

Over long periods of time, the MACL method successfully adjusted to changing gait patterns. In contrast to conventional static models, OALTA continuously learned new gait representations while maintaining good recognition stability. For realistic gait identification settings, the combination of continuous learning and temporal attention proved to be quite successful.

6. Conclusion

The Occlusion-Aware and Long-Term Adaptive (OALTA) framework for reliable gait identification in unrestricted contexts was introduced in this research. The two main obstacles to gait recognition—partial occlusions and long-term gait variations—are addressed by the suggested method, which combines memory-augmented continuous learning with occlusion- aware feature refinement. Significant gains over current state-of-the-art techniques were shown by experimental results on benchmark datasets. The framework successfully adjusted to changing gait patterns over time while maintaining excellent recognition accuracy in situations of extreme occlusion. Future research will concentrate on combining privacy-preserving gait analysis methods, real- time deployment optimization, and multimodal biometrics.

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