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Exploring Artificial Intelligence-Driven Gait Analysis for Suspect Identification in Forensic Video Footage

Dr. Anu Singla[*1]
[*1]*Associate Professor & Head, Institute of Forensic Science & Criminology, Bundelkhand University, Jhansi, India Email: anusingla@bujhansi.ac.in*
Zeeshan Khan[*2]
[*2]*Student, Dept of CSE, Bundelkhand University, Jhansi, U.P, India*

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Corresponding Author:
Dr. Anu Singla

Abstract:
In our digitally connected world, surveillance cameras record massive amounts of visual data on a daily basis. This paper takes a close look at how artificial intelligence, particularly methods centered on gait analysis, could be harnessed for criminal investigations when facial recognition proves insufficient. Our primary focus is to assess how a person's distinctive walking pattern can aid in identifying a potential suspect in video footage used for forensic purposes. We provide an extensive background on both conventional and emerging approaches to gait recognition, then outline a unified methodology that incorporates denoising, feature extraction, and neural network-based classification. We also present experimental evaluations that illuminate the reliability and shortcomings of gait-based investigative techniques, with specific attention to real-world complications such as altered viewpoints, clothing variations, and partial obstructions. Overall, the aim here is to furnish a comprehensive picture of AI-powered gait analysis and to underscore its potential to augment existing forensic methods while emphasizing the practical steps required to ensure its efficacy and reliability in real investigations.

Keywords: artificial intelligence, gait analysis, forensic video, suspect identification, computer vision, deep learning, biometrics, surveillance.

1. Introduction

The omnipresence of cameras in public spaces—ranging from city streets to airports—has made video footage a critical resource in criminal investigations. Yet, even with high-quality technology at our disposal, identifying persons of interest in such visual data can be tricky. While face recognition has long been a prime candidate for verifying individuals, its success depends heavily on capturing a clear, unobstructed view of a person's face. In countless real-world situations, faces can be concealed, or the camera's position can be too distant or skewed to acquire usable facial details. These practical issues spur interest in alternative biometrics like gait analysis, which examines the distinctive ways individuals walk and move.

Researchers have studied human gait for decades, but in recent years, computational techniques have become more sophisticated thanks to advancements in neural networks and large-scale data processing. Gait is attractive because it often remains identifiable even when other markers are unavailable or severely degraded. Yet there are still hurdles, including changes in how someone walks due to footwear, clothing, or injuries, and environmental factors like camera angle or lighting. Through this paper, we investigate the feasibility of applying AI to gait analysis for practical suspect recognition in forensic scenarios. We start by reviewing literature that addresses both traditional silhouette-based techniques and more recent deep-learning-based systems. We then describe our proposed methodology, which includes sophisticated feature extraction procedures, classification strategies, and validation protocols. Finally, we share experimental findings that show what works, where the pitfalls lie, and how the method might be deployed to assist law enforcement or forensic teams in diverse situations.

2. Literature Review

The notion that a person's walking style can offer clues to identity is not new. Conventional methods often revolved around examining features like stride length and body geometry. These handcrafted characteristics were typically processed through statistical models, which could categorize individuals by matching these measured patterns to an existing record. Although these earlier attempts established the rudiments of gait recognition, they struggled with variability in clothing or footwear, as well as subtle changes in how one walks.

The arrival of more powerful computer vision techniques ushered in a wave of improvements. Background subtraction and optical flow-based methods made it possible to isolate individuals from busy backgrounds and analyze movement patterns in a more automated manner. One of the breakthroughs was the development of silhouette-based representations like Gait Energy Images. However, even these early automated methods were vulnerable to occlusion and inconsistent lighting.

The recent advent of deep neural networks has transformed the field by enabling the extraction of more robust and discriminative features. Researchers have explored 3D CNNs for directly processing video clips and RNNs for capturing the time-dependent aspects of walking. These newer models substantially boosted recognition accuracy in controlled laboratory tests.

Forensic contexts introduce complexities that academic research data typically does not. Surveillance footage is often low resolution and subject to a range of environmental noise. Additionally, suspects can appear at arbitrary angles or walk in irregular ways. In response, some approaches aim to reconstruct missing details using generative adversarial networks, though such methods raise concerns about evidence authenticity. Skeleton-based analyses that track the positions of key joints in the body can better withstand clothing differences but may fail when joints are obscured or the resolution is insufficient. Multi-view systems that consolidate data from several cameras have shown promise but are rarely an option in everyday surveillance settings, given logistical constraints. Much of the current work thus explores strategies for augmenting data, learning robust representations, and developing interpretability measures that can make the technology acceptable in a legal context. Overall, this evolving field aims to bridge the gap between solid results in controlled experiments and the realities of law enforcement applications.

3. Case and Methodology

Our approach to building an AI-driven gait recognition tool for forensic usage encompasses an integrated series of steps: from extracting frames and cleaning the raw footage, to selecting features and training a deep network that can differentiate among individuals based on gait. Below is an overview of the entire pipeline, distilled into concise modules.

Video preprocessing is the first line of defense against noisy and unstable footage. By applying filters to remove grain and adjusting frames to account for camera jitter, we enhance the chances of isolating a clear silhouette or pose. Out-of-focus frames or those with extensive obstruction may be excluded to avoid compromising the later stages. Following preprocessing, the system moves into feature extraction, which may proceed through silhouette-based or skeleton-based methods, or a blended approach. Silhouettes can offer comprehensive shape details, while skeleton-based analyses concentrate on joint-level data, yielding a kinematic portrait of an individual's walk.

We then feed these features into neural network architectures designed to grasp spatial and temporal aspects of gait. If silhouettes are used, 3D convolutional layers can capture motion dynamics, whereas skeleton-based input can be channeled through LSTM or graph-based layers to process the interplay between various joints. The trained model ultimately assigns a probability of identity or computes a similarity score relative to known gait signatures. In open-set conditions, the system flags anyone not resembling the profiles in the database.

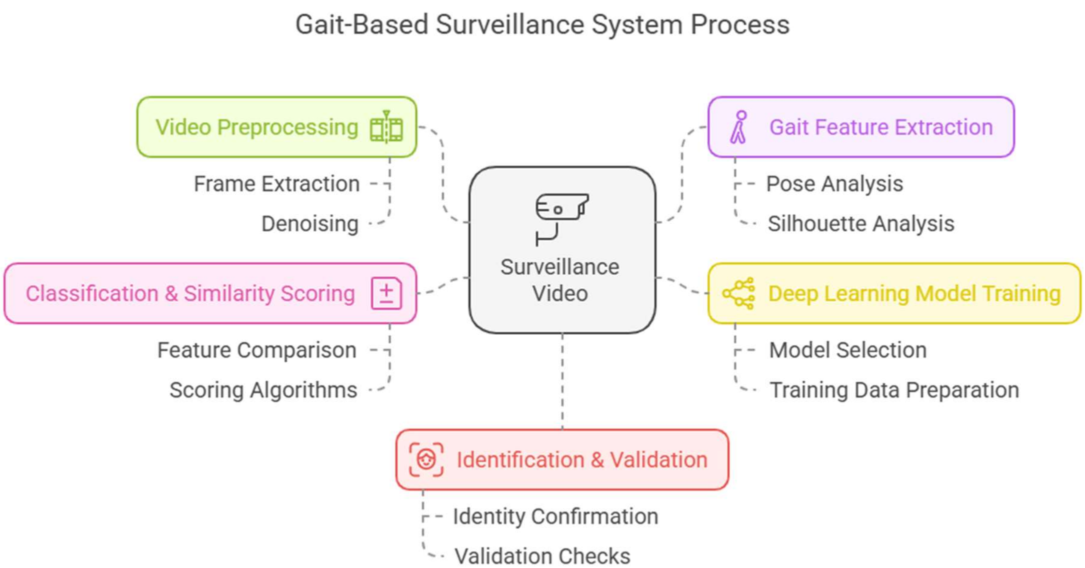

Figure 1

We emphasize the classification and validation segments since they define how the system's results are interpreted in a forensic context. Metric learning techniques may be introduced to better handle individuals who are not in the training set, producing an embedded representation where known identities form clusters. Finally, performance metrics such as precision, recall, and false acceptance rates are computed to quantify the reliability of the model. This comprehensive approach is designed to cope with the unpredictable challenges of real-world footage while still exploiting the robust pattern recognition capabilities of deep learning.

4. Results & Analysis

To assess the performance of our proposed method, we conducted tests in both laboratory conditions, using the CASIA-B Gait Database, and under real-world conditions, using video collected from a regional transit hub. The lab-based experiments allowed us to calibrate the model against a standardized dataset with multiple viewpoint variations and diverse subject profiles. The real-world footage, conversely, was riddled with complications such as uneven lighting, partial blockage by crowds, and frequent camera shakes.

We evaluated our deep learning architectures—one using 3D CNNs on silhouettes and another involving LSTM for skeleton-based data—against two classical baselines: an HMM-based approach and an SVM trained on handcrafted features. On the curated CASIA-B set, both deep networks surpassed the older methods by a comfortable margin in terms of accuracy. Although the skeleton-based approach took slightly less time to run compared to the 3D CNN, it lagged a bit in accuracy. The difference may be attributed to how well silhouettes can capture overall shape dynamics when the footage is not heavily cluttered. That said, in the transit footage, which featured more clutter and obstructions, the skeleton-based approach demonstrated better resilience, provided it could extract adequate joint data.

In nearly every scenario, the neural network solutions outperformed the older systems, highlighting the advantage of data-driven representations. We found, however, that both new methods dipped in accuracy when tested on surveillance footage that deviated significantly from the training data, emphasizing the need for ongoing efforts to develop robust domain adaptation methods. Additionally, partial occlusions—think of a suspect briefly moving behind a column—particularly tested the silhouette-based approach, producing distorted outlines that yielded false identification in a handful of cases. Further improvements may involve incorporating temporal coherence checks, so that classification decisions can factor in multiple continuous frames.
To put our findings into context, the appended table shows how different techniques fared on key metrics. The advanced models achieved impressive gains in terms of precision and recall, though at a higher computational cost. From a forensic standpoint, the increased processing time is often acceptable if it significantly boosts accuracy in suspect identification.

5. Conclusion

By integrating deep learning with the study of human gait, this paper contributes to the broader conversation on future directions in forensic video analysis. While traditional methods of biometric identification remain pivotal, especially in well-lit and high-resolution environments, there is a clear advantage in exploring alternative markers like gait in situations where facial data is unreliable. Our experiments illustrate not only the viability of silhouette-based and skeleton-based approaches but also how a fusion of these methods could yield a more robust solution in the face of complex, real-world conditions.

It is critical, however, to acknowledge the challenges that remain. As the experimentation shows, model performance can degrade sharply when subjected to footage that differs significantly from the data on which the model was trained. Ethical and legal questions surrounding AI-driven identification also call for a considered approach, including transparent reporting of error margins and a framework for interpretability. These precautions are especially vital if gait analysis is to hold weight in legal proceedings. With continued refinements in pose estimation, data augmentation, and interpretability techniques, we expect AI-powered gait systems to evolve into a trusted component of forensic investigations, assisting agencies in pinpointing suspects quickly and reliably while minimizing unwarranted privacy intrusions.

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