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Gait Analysis of Human Behaviour

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ABSTRACT—

This paper presents Gait Analysis for Human Behavior, an advanced system designed for comprehensive monitoring and identification through the study of individual walking patterns. In environments where understanding human behavior is essential—such as healthcare, public safety, and behavioral research—traditional biometric systems like facial recognition and fingerprint scanning can often be limited or intrusive. In contrast, gait serves as a consistent, non-invasive biometric trait that can be observed from a distance without requiring active cooperation.

The system leverages continuous camera feeds to generate Gait Energy Images (GEIs) and applies intelligent pattern recognition techniques to analyze walking behaviors, detect anomalies, and differentiate between individuals. It not only identifies subjects but also monitors gait-related behavioral patterns over time, offering valuable insights into aspects such as health conditions, stress levels, and movement anomalies.

Gait Analysis for Human Behavior features real-time behavior recognition, entry logging with timestamps, and dynamic registration capabilities for new subjects. Designed with scalability and adaptability in mind, the system supports multi-camera input and lays the groundwork for future upgrades, including 3D gait reconstruction and predictive behavior modeling using advanced deep learning techniques.

This paper outlines the system architecture, implementation framework, and practical applications of Gait Analysis for Human Behavior across sectors like clinical diagnostics, security surveillance, and urban behavioral studies.

Index Terms—Gait Analysis, Biometric Surveillance, Gait Energy Image (GEI), Pattern Recognition, Real-time Monitoring, Multi-Camera System, Deep Learning, 3D Gait Reconstruction, Security Intelligence, PyQt5 Application

I. INTRODUCTION

Security and surveillance systems have traditionally relied on facial recognition, RFID cards, or fingerprint-based methods for identity verification and monitoring. While these approaches have proven effective, they often pose limitations in contexts where privacy, non-intrusiveness, and distance-based observation are essential. Gait recognition, which identifies individuals based on their distinctive walking patterns, has emerged as a powerful, non-invasive alternative. Gait is inherently difficult to disguise or consciously alter, making it particularly suited for long-range and continuous human behavior analysis.

This paper presents a real-time gait analysis system focused on understanding human behavior through biometric movement patterns. Leveraging Gait Energy Images (GEIs), computer vision techniques, and machine learning-based feature extraction, the system enables accurate analysis of gait dynamics for applications such as behavioral monitoring, healthcare diagnostics, and biometric identification. By combining traditional image processing methods with deep learning techniques, the system demonstrates the potential for high-accuracy gait analysis based on pre-recorded and live gait data.

Unlike conventional gait recognition approaches that often rely on fixed camera setups or controlled environments, the proposed system supports multi-angle gait capture using diverse input sources such as laptop webcams and smartphone cameras. This broader field of view enhances the reliability of gait analysis even in dynamic, real-world environments. Furthermore, future system upgrades will explore integrating 3D gait reconstruction techniques from 2D imagery using deep learning models, improving precision in cluttered or complex behavioral scenarios.

Developed using Python and a PyQt5-based graphical user interface (GUI), the system provides real-time gait visualization, behavior registration, log management, and dynamic monitoring modules. Its architecture supports scalability, making it well-suited for deployment in environments such as healthcare facilities, research institutions, and smart urban spaces where human behavior analysis is critical.

By advancing this framework, we aim to contribute toward the development of intelligent, non-invasive, and behavior-aware monitoring solutions for a wide range of applications.

II. RELATED WORK

Gait recognition has gained considerable attention in the field of biometric security due to its unique advantages—non-invasiveness, distance recognition, and difficulty to mimic. Traditional biometric systems such as facial recognition or fingerprint scanning, while effective, often face limitations in low-visibility environments or require physical contact, making them less viable for real-time surveillance. This section explores the existing approaches and technologies that form the foundation for gait recognition systems and highlights their limitations which Stride Sentinel – MKII seeks to overcome.

A. Vision Based Gait Recognition System

Early gait recognition systems relied heavily on silhouette extraction and handcrafted feature engineering. Techniques like Gait Energy Image (GEI) generation, where multiple binary silhouettes are averaged over time, became a standard representation [1]. Although these systems were computationally lightweight and interpretable, they were highly sensitive to occlusions, clothing variations, and camera angles.

Single-camera setups dominated initial research, often producing inconsistent results in dynamic environments. As a result, researchers began integrating multi-view gait datasets such as CASIA-B and OU-ISIR to improve robustness, but practical real-time deployment of multi-camera systems remained limited due to hardware and synchronization challenges.

B. Machine Learning in Gait Analysis

With the rise of machine learning, various classifiers such as k-NN, SVM, and decision trees were trained on extracted gait features to improve accuracy [2]. These models achieved promising results in controlled datasets but often failed to generalize to real-world settings with unpredictable conditions.

Furthermore, many existing systems depended on large-scale annotated datasets, making them unsuitable for rapid deployment in evolving surveillance scenarios. They also lacked adaptability, as new users had to be manually enrolled with extensive preprocessing.

C. Vector Search Engines

Recent advancements have leveraged convolutional neural networks (CNNs) and recurrent neural networks (RNNs) to capture spatial-temporal features from video sequences [3]. These models are capable of learning abstract representations directly from raw input, outperforming traditional techniques in complex environments. Nevertheless, many of them remain computationally intensive and are difficult to run in real-time without specialized hardware.

To overcome the limitations of 2D analysis, some approaches have proposed converting 2D gait imagery into 3D gait volumes using multiple viewpoints and generative adversarial networks (GANs) [4]. These techniques provide greateinvariance to viewing angles and occlusion but require careful synchronization of multi-camera inputs and calibration.

D. Multi-Camera Integration and Real Time Systems

The integration of multiple cameras to capture gait from different perspectives has shown notable improvements in recognition performance [5]. However, real-time systems that utilize such configurations often suffer from synchronization lag, bandwidth limitations, and increased system complexity. Current research continues to explore lightweight solutions for seamless multi-camera fusion, especially in portable and scalable systems.

Stride Sentinel contributes to this growing body of work by providing a practical, lightweight, and multi-camera compatible gait recognition framework. The system uses a combination of real-time camera feed acquisition, GEI-based recognition, user registration, and event logging. It aims to bridge the gap between research-grade gait analysis and deployable real-world surveillance by using scalable design principles and modular components.

TABLE I COMPARISON WITH PREVIOUS WORK

Title	concept	limitations	Comparison
Real-Time Hand Gesture Recognition Using YOLOv3	Used YOLOv3 for gesture-based threat detection	Focused only on hand gestures; not suitable for multi-angle or full-body detection	Stride Sentinel focuses on gait recognition, enabling identity-based security beyond gestures

Gesture Recognition using CNN for Emergency Detection	J CNN-based gesture classification for identifying distress in emergencies	Limited to fixed cameras and does not scale to identity verification	Stride Sentinel supports mobile and IP cameras, and performs identity verification via gait
DL-Based Gesture Recognition in Surveillance	Deep learning for gesture classification in surveillance environments	Does not support real-time identity matching	Stride Sentinel includes storage & retrieval of embeddings to verify individuals dynamically

III. METHODOLOGY

The Gait Analysis for Human Behaviour system is developed to address challenges in behavioral monitoring and biometric analysis where traditional identification methods are limited, particularly in non-intrusive and long-range observation contexts. By leveraging advanced computer vision techniques and gait recognition models, the system enables fast and accurate analysis of individuals based on their distinctive walking patterns. Its architecture is structured into four core components: Video Stream Processing, Gait Feature Extraction, Gait Pattern Database, and Behavior Recognition & Analysis Module. Each component is optimized to manage real-time, multi-angle video inputs while maintaining low latency, ensuring reliable monitoring of human gait behavior across diverse environments. This system supports a wide range of applications, from healthcare diagnostics and rehabilitation monitoring to biometric research and urban behavioral studies.

A. System Overview

1) Gait Data Processing

In security-critical environments, traditional identification methods can fail due to obstructions or poor visibility. *Stride Sentinel – MKII* overcomes this by leveraging *gait-based identification*, using continuous video streams as the primary input. The system processes video feeds captured from multiple sources such as *CCTV, laptop cameras, and mobile devices*, ensuring *multi-angle gait capture*.

Incoming video frames undergo a *silhouette extraction pipeline* where background subtraction, thresholding, and contour detection isolate the subject's walking posture. These frames are then preprocessed into *Gait Energy Images (GEIs)*, which capture the dynamic walking patterns of individuals over time, providing a consistent input format for feature extraction.

2) Embedding Generation

Once GEIs are extracted, the system utilizes *convolutional neural networks (CNNs)* or pre-trained models like *OpenPose* or *GaitSet* to generate *feature embeddings*. These embeddings encapsulate the unique biomechanical characteristics of each person's walk. The model converts the visual gait patterns into *high-dimensional vectors*, ensuring consistency even under varying lighting, clothing, or carrying conditions.

3) Gait Storage

During the registration phase, each individual's Gait Energy Image (GEI) is processed to extract distinctive gait features, which are then stored as structured numerical vectors using formats such as NumPy arrays or serialized files (.pkl). These embeddings are saved alongside metadata such as user ID and timestamps in a local database or structured directory format.

When a person walks through the surveillance zone, the system generates a real-time embedding of their gait and compares it directly with the stored embeddings using similarity metrics like Euclidean distance or cosine similarity. This setup ensures quick, accurate, and dependency-free matching, allowing the system to perform identity verification efficiently, even in constrained or offline environments.

4) Recognition & Access Control

During surveillance or identity verification, live gait embeddings are generated from the camera feed and matched against the stored vectors using *nearest neighbor search*. If a match is found above a defined similarity threshold, the individual is either granted access or flagged accordingly. The system can operate in *registration mode* to enroll new users, and in *recognition mode* to continuously monitor for threats.

The recognition pipeline also logs each match event with *timestamps*, *camera source*, and *confidence scores*, providing audit-ready surveillance records. This ensures *accountability*, *traceability*, and *reliability* in high-security zones.

B. Gait Signature Acquisition and Vectorization

In Stride Sentinel – MKII, gait data ingestion is designed to handle live and recorded video streams from diverse sources such as CCTV, laptop webcams, and mobile cameras. The ingestion module processes incoming video feeds by segmenting walking sequences and extracting relevant frames where the subject's gait is clearly visible.

Each frame is preprocessed using a pipeline that includes background subtraction, binarization, and silhouette enhancement. These frames are then aggregated over a walking cycle to generate Gait Energy Images (GEIs), which capture the temporal-spatial patterns of an individual's movement.

After generating GEIs, they are passed into a deep learning model, such as a custom CNN, GaitSet, or OpenPose-based encoder, which transforms them into embedding vectors. These vectors typically range from 128 to 512 dimensions, depending on the model architecture, and preserve the unique gait signature of each person. The embeddings encode subtle distinctions in limb movement, stride length, and walking rhythm, making them robust against appearance changes or occlusions.

C. Gait Pattern Encoding

Pattern Encoding lies at the heart of Stride Sentinel – MKII, serving as the foundation for identity recognition based on walking patterns. Rather than textual data, the system operates on Gait Energy Images (GEIs)—silhouetted visual representations that encapsulate an individual's unique walking style over a gait cycle.To convert these images into numerical form, the system utilizes a custom-trained deep learning model—typically a Convolutional Neural Network (CNN)—to extract high-dimensional feature vectors that encode the spatial and temporal nuances of human gait. These embeddings capture subtle differences in stride length, limb motion, and posture, which are critical for distinguishing individuals, even when clothing, speed, or camera angles vary.

Unlike traditional biometric systems that rely on surface-level traits like face or fingerprints, this gait-based embedding process enables non-invasive, contactless surveillance, making it highly effective for security-sensitive zones. The same model is used during both the registration and recognition phases, ensuring consistent embedding quality and maximizing identification accuracy.

Gait Embedding Management and Retrieval

In Stride Sentinel – MKII, the system manages gait embeddings using an internal lightweight storage mechanism optimized for security surveillance contexts. Once the gait signatures (embeddings) are generated through the preprocessed silhouettes, they are stored in structured arrays or serialized files. This method provides fast access and easy integration with the PyQt5-based interface. The system performs real-time comparisons by calculating cosine similarity or Euclidean distance between stored and incoming gait vectors. This enables identity verification within milliseconds, ensuring that individuals walking into restricted zones are authenticated based on their unique gait patterns.

Unlike traditional large-scale vector databases, this embedded approach prioritizes simplicity and low overhead. It’s ideal for edge devices, standalone systems, and environments with limited infrastructure, all while maintaining high accuracy and low latency. The storage structure supports updates, enabling administrators to register new individuals or modify existing profiles dynamically without reinitializing the system.

This efficient retrieval mechanism enhances real-time surveillance operations, ensuring secure, scalable, and accurate gait-based identification.

Real Time Recognition and Access Control Interface

The Stride Sentinel – MKII integrates a PyQt5-based graphical interface called **GaitDemo**, which allows real-time recognition and monitoring. Through this interface, security personnel can register new individuals, view live camera feeds, and receive alerts when unregistered gait patterns are detected.

When an individual enters the surveillance zone, the system captures their silhouette, computes the gait embedding, and compares it against the stored database. If a match is found, access is granted; otherwise, a visual/audio alert is triggered.

The entire recognition process is designed to be fast, secure, and intuitive. By combining the robustness of gait biometrics with a user-friendly interface, Stride Sentinel provides an effective solution for identity verification in high-security environments.

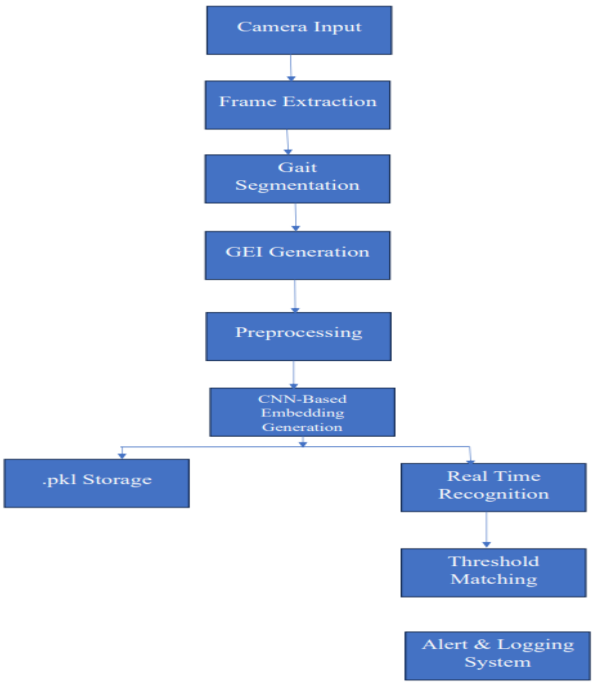

Fig1:Workflow

Results

Fig. III (a): Initialization

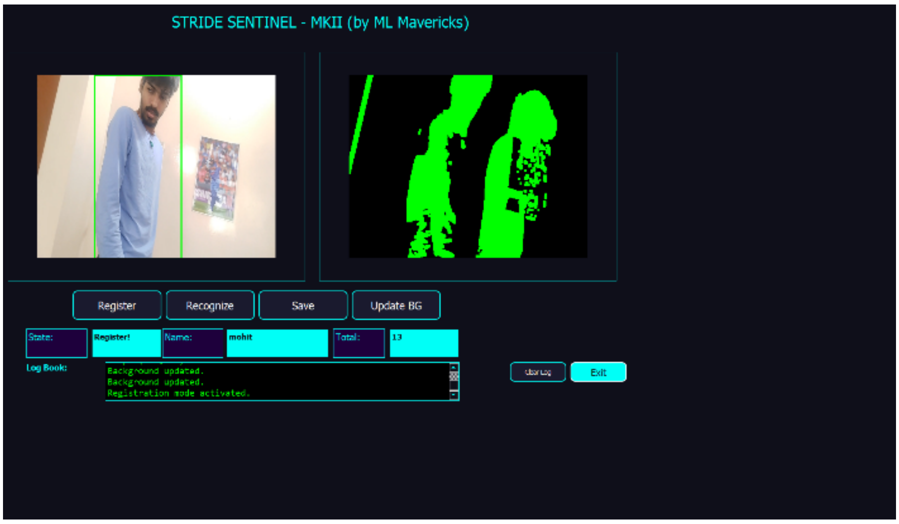

Fig. III (b): Registration

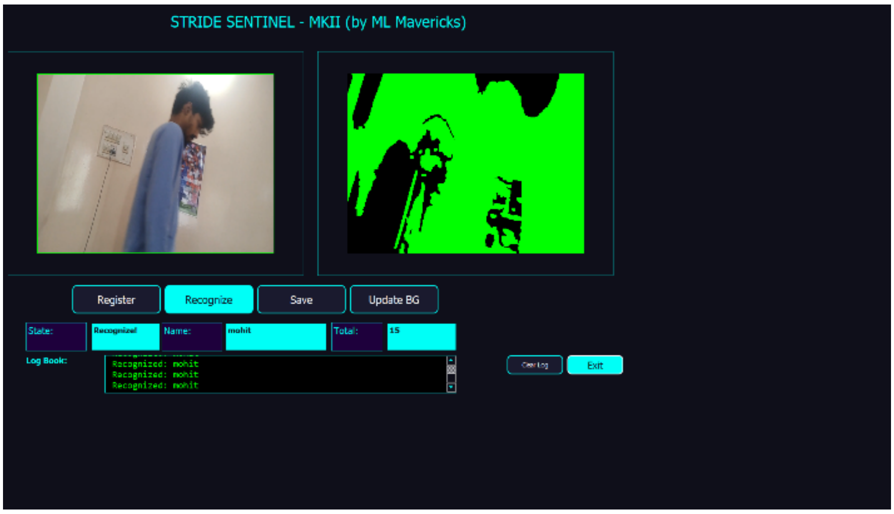

Fig. III (c): Recognition

Conclusion and Future Work

The Gait Analysis for Human Behaviour project presents an advanced system that leverages gait analysis as a non-invasive biometric method for studying and monitoring human movement patterns. By using Gait Energy Image (GEI) extraction techniques and integrating a real-time recognition and behavior analysis system with a PyQt5-based graphical interface, the system enables accurate, contactless identification and behavioral assessment across diverse environments. Unlike traditional biometrics such as facial recognition or fingerprints, gait patterns are challenging to consciously alter or mimic, making gait analysis highly effective even under conditions involving occlusions, variations in clothing, or changing environmental factors.

The successful implementation of user registration, GEI-based recognition, and behavior logging modules demonstrates the project's strong conceptual foundation and practical viability. It also shows promising potential for deployment in healthcare diagnostics, rehabilitation monitoring, sports science, and behavioral research. Although full-scale performance validation awaits hardware integration and broader dataset testing, the established architecture provides a solid basis for real-world application.

Looking ahead, several enhancements are planned to further improve the system's accuracy, scalability, and real-time responsiveness:

- **Hardware Integration and Multi-Angle Gait Capture**: Future versions will integrate synchronized multi-camera setups to capture gait patterns from multiple viewpoints, enabling comprehensive evaluation under naturalistic conditions.
- **3D Gait Reconstruction**: Deep learning-based approaches for reconstructing 3D gait models from 2D imagery will be explored, facilitating depth-aware behavior analysis for complex and dynamic scenarios.
- **Model Optimization and Advanced Training**: The recognition models will be refined using hybrid deep learning architectures, such as CNN-LSTM models, to better capture the spatial and temporal aspects of gait sequences.
- **Scalability for Broader Applications**: System optimization will focus on ensuring low latency and consistent analysis performance even when monitoring large populations across various settings.
- **Privacy and Ethical Data Handling**: To address privacy concerns in behavioral monitoring, encryption techniques and secure data protocols will be incorporated to protect biometric and behavioral data.
- **Hybrid Behavioral Authentication**: Future enhancements may consider integrating gait analysis with other behavioral and physiological metrics to develop multi-modal, holistic monitoring systems.
- **Deployment on Edge Devices**: The system will be optimized for deployment on low-power edge devices such as Raspberry Pi or NVIDIA Jetson platforms, supporting real-time offline analysis in healthcare centers, clinics, or urban environments.
- **Quantitative Performance Evaluation**: Upon hardware deployment, rigorous evaluation using metrics such as accuracy, precision, recall, and response latency will be conducted to benchmark system effectiveness and reliability.

Through these developments, the Gait Analysis for Human Behaviour project aims to evolve into a robust, scalable, and intelligent human monitoring framework, capable of advancing healthcare, research, and behavioral analytics. Its foundation blends technical innovation with practical utility, offering new perspectives in non-invasive and ethically aware human behavior analysis.

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