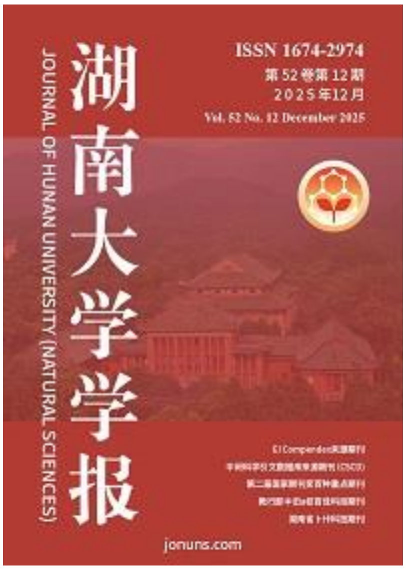

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Computational Architecture Proposal for Digital Optical Signal Processing in Human Gait Analysis

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Abstract: Markerless optical motion capture enables unobtrusive gait assessment, yet kinematic estimates remain sensitive to acquisition variability and to heterogeneous processing workflows, limiting cross-study comparability and reproducibility. This paper presents a modular computational architecture for processing markerless optical gait data, aimed at standardizing key steps from raw recordings to analysis-ready kinematic time series. Based on a structured comparison of commonly used pipelines and reported failure modes, the architecture specifies four sequential stages data acquisition, signal/pose preprocessing, gait-cycle segmentation, and representation/structuring and defines interfaces and quality-control checkpoints between modules. The pipeline integrates noise attenuation and normalization with a hybrid strategy: deterministic heuristics support rule-based quality screening and parameter initialization, while learning-based components target error-prone operations such as robust gait-cycle delineation under occlusions and variable viewing conditions. By explicitly separating concerns (capture, cleaning, segmentation, and representation) and by formalizing intermediate outputs and metadata, the proposed architecture provides an auditable foundation for implementation and subsequent experimental validation. The framework is intended to improve consistency of kinematic outputs and facilitate reproducible biomechanical analyses across laboratory and in-the-wild settings.

Keywords: markerless motion capture; gait analysis; kinematic time series; signal preprocessing; gait-cycle segmentation; reproducible pipelines.

基于计算架构的人体步态分析数字光信号处理方案

摘要： 无标记光学动作捕捉技术使步态评估能够在不干扰受试者的情况下进行，但运动学估计仍对采集过程的变异性以及处理流程的异质性高度敏感，从而限制了跨研究的可比性与可重复性。本文提出一种用于无标记光学步态数据处理的模块化计算架构，旨在将从原始记录到可用于分析的运动学时间序列的关键步骤加以标准化。基于对常用处理管线及其已报道失效模式的结构化比较，该架构明确了四个连续阶段：数据采集、信号/姿态预处理、步态周期分割，以及表征/结构化，并在模块之间定义接口与质量控制检查点。该处理管线以混合策略整合噪声衰减与归一化：确定性启发式方法用于基于规则的质量筛查与参数初始化，而基于学习的组件则针对易出错操作（例如在遮挡与视角条件变化下稳健界定步态周期）进行优化。通过明确分离关键环节（采集、清洗、分割与表征）并规范中间产物及元数据，所提出的架构为实现与后续实验验证提供了可审计的基础。该框架旨在提升运动学输出的一致性，并促进在实验室与真实场景（in-the-wild）条件下可复现的生物力学分析。

关键词： 无标记动作捕捉；步态分析；运动学时间序列；信号预处理；步态周期分割；可复现处理管线。

1. Introduction

Human gait analysis plays a fundamental role in diverse domains, including biomechanics [1], rehabilitation [2] and human–computer interaction [3], as it is essential for characterizing locomotor patterns and detecting motor impairments [4]. Recent advances in markerless optical motion capture have increased the feasibility of unobtrusively registering human movement across a wide range of environments [5]. Despite these advantages, ensuring consistent data quality remains challenging due to fluctuating environmental conditions and the heterogeneity of hardware configurations employed for acquisition [6].

A central difficulty in optical gait data acquisition concerns the variability of computational systems used for signal processing [7]. Research efforts frequently rely on diverse combinations of CPUs, GPUs, libraries and software frameworks, producing fragmented and often non-interoperable workflows [8].

This heterogeneity not only hinders the reproducibility of kinematic data across research groups and application settings but also complicates the validation of findings and their translation into clinical or industrial contexts. Consequently, there is a need for a standardized computational approach that provides a modular and transparent processing pipeline for optical gait signals, functioning independently of the capture devices or software platforms employed [9].

Preprocessing constitutes a critical stage in gait analysis, encompassing noise filtering, kinematic signal normalization and motion cycle segmentation, all of which directly affect the reliability of subsequent biomechanical evaluations [10]. However, existing approaches often implement these procedures inconsistently and without a coherent computational architecture [11].

To address this limitation, this paper proposes a preliminary modular computational framework that structures these processes into a unified, sequential workflow. The proposed architecture is designed to organize the digital processing pipeline following data acquisition, rather than to optimize capture parameters. It is specifically conceived for markerless gait analysis systems and provides a conceptual foundation for enhancing consistency and reproducibility across both research and applied contexts.

In parallel, the increasing use of portable sensors and advanced optical systems for lower-limb biomechanical data collection has expanded opportunities for recording gait outside traditional laboratory environments and in real-world settings [12]. This growth has introduced new challenges, including the identification of meaningful metrics from acceleration or angular velocity signals, achieving accurate sensor–segment alignment, operating with reduced sensor configurations and employing machine learning methods to estimate unmeasured variables [13].

These challenges highlight the need for computational frameworks capable of integrating acquisition, filtering, segmentation and data structuring processes in a standardized manner that guarantees reproducibility and accuracy across different environments [14]. Moreover, the incorporation of technological instrumentation into clinical gait analysis has strengthened diagnostic processes and the assessment of neuromotor disorders [15]. In this context, signal processing, feature selection and extraction, as well as machine learning–based classification techniques, have become indispensable for identifying gait phases and detecting abnormal locomotor patterns [16].

This scenario further reinforces the necessity of computational architectures that organize the stages of digital processing in a coherent, adaptable and application-agnostic manner to support clinical, sports and research scenarios.

The purpose of this study is to address the absence of standardized and reproducible computational pipelines for the digital processing of optical gait data obtained from markerless motion capture systems. The central research question guiding this work is how a modular, technology-independent computational architecture can systematically organize acquisition, preprocessing, segmentation, and data structuring to improve consistency and reproducibility in gait analysis workflows.

The novelty of the proposed approach lies in its architectural focus, emphasizing workflow organization and interoperability rather than the optimization of isolated algorithms or hardware configurations. Unlike existing studies that concentrate on performance evaluation of specific models or sensors, this work formalizes a unified processing framework that integrates methods within a coherent pipeline. The significance of this contribution resides in its potential to support scalable, transparent, and reproducible gait analysis across clinical, research, and applied biomechanics contexts.

2. Materials and Methods

Developing a computational architecture for gait signal processing requires reviewing existing methodologies and digital tools that support each stage of the processing pipeline. While the main contribution of this work is the conceptual architecture design, this section details the key computational methods and signal processing techniques that underpin each stage of the architecture.

2.1 Acquisition of optical motion data through markerless systems

The starting point for the proposed architecture is the acquisition of optical motion data through markerless systems [17]. These systems generate time-series data representing human joint kinematics, typically through pose estimation algorithms applied to RGB or depth video streams [18], [19]. The raw output from these systems often contains noise, missing data points, and inconsistencies that must be addressed prior to biomechanical analysis [20], [21]. This study does not optimize the acquisition process but assumes that the input data follows commonly used formats in pose estimation frameworks.

This study assumes that the input data follows the formats commonly used in pose estimation frameworks, but optimization of the acquisition process is not included. Among the most widely used markerless optical capture systems are OpenPose, MediaPipe Pose, BlazePose, Intel RealSense SDK, and Azure Kinect SDK, which are broadly employed in clinical, sports, and research settings due to their availability, accuracy, and cross-platform compatibility [7], [17], [19], [22]. These tools implement real-time pose estimation algorithms that extract 2D or 3D joint coordinates from RGB or RGB-D sequences, forming the basis of most recent studies in gait analysis.

2.2 Digital Signal Processing Techniques

The preprocessing stage is critical for enhancing signal quality and preparing the data for segmentation and analysis. Theoretical considerations suggest the use of well-established digital signal processing techniques, such as low-pass filtering to remove high-frequency noise and Kalman filtering for adaptive smoothing [22], [23].

Additionally, preprocessing should normalize the data to account for inter-subject variability by converting absolute coordinates into relative coordinate systems centered on the subject's body and adjusting joint ranges according to anthropometric parameters [19]. These procedures aim to reduce variability caused by differences in subject size, camera placement, or session conditions.

2.3 Heuristic segmentation methods

The segmentation of continuous kinematic signals into discrete gait cycles is another fundamental task. Heuristic segmentation methods rely on the analysis of joint angles, particularly those of the knee and ankle, to detect characteristic gait events that mark the beginning and end of a gait cycle [24]. Machine learning models trained on large-scale gait datasets can also detect subtle patterns and transitions in motion data, offering improved segmentation performance in complex or noisy environments [25].

Among the most widely used tools and approaches are convolutional neural networks (CNNs) and LSTM-type recurrent neural networks, frequently implemented in environments such as TensorFlow or PyTorch, which enable automatic identification of events such as heel strike and toe-off with high accuracy. These methodologies are complemented by classical techniques for detecting peaks or kinematic thresholds, providing a hybrid framework that combines interpretability and robustness in the presence of variations in speed or gait style.

2.4 Biomechanical analysis and data sharing

Lastly, the processed data must be structured in formats that support further biomechanical analysis and data sharing [26]. Standard data structures such as CSV and JSON files provide flexibility and interoperability, enabling the resulting datasets to be integrated into various analytical workflows.

The organization of the data should include temporal alignment of signals, clear labeling of gait cycles, and the potential inclusion of extracted features such as joint angle means or stride durations [27], [28]. Overall, the preprocessing, segmentation, and data structuring methods discussed here form the theoretical foundation of the proposed computational architecture.

These core stages are modular and adaptable, supporting diverse hardware and software environments and enabling future enhancements through machine learning or domain-specific optimizations. Building on these foundational methods, the next section introduces a cohesive and flexible computational framework that operationalizes the stages discussed above.

2.5 Rationale and Implications

The research object of this study is a computational architecture for optical gait signal processing rather than a specific algorithm, dataset, or motion capture system. This selection is motivated by the heterogeneity observed in current gait analysis workflows, where preprocessing, segmentation, and data structuring are often implemented inconsistently across studies and platforms. Such variability limits reproducibility, interoperability, and cross-study comparability, even when similar acquisition technologies are used.

From a theoretical perspective, the proposed architecture provides an abstract and modular representation of gait signal processing that decouples methodological logic from specific technological implementations. This enables systematic evaluation, substitution, and extension of individual processing components without altering the overall workflow.

From a practical standpoint, the framework supports the development of scalable and low-cost gait analysis solutions suitable for real-world environments, clinical assessment, and rehabilitation monitoring, where hardware constraints and environmental variability are common.

3. Computational Architecture Proposal

The proposed computational architecture for optical gait signal processing is organized as a modular, sequential pipeline with four main stages: acquisition, preprocessing, segmentation, and data structuring. Each stage operates independently while maintaining interoperability, enabling scalable deployment across platforms. The architecture presumes access to raw data and focuses solely on downstream digital processing to convert it into structured and analyzable kinematic information.

To contextualize the proposed architecture, Table 1 presents a structured summary of the key processing stages involved in optical gait data handling. Rather than focusing on specific tools, the table emphasizes the theoretical functions underlying each stage, along with representative implementations. This abstraction supports the identification of suitable components and guides the development of adaptable, future-proof processing pipelines.

Table 1. Overview of stages and representative implementations for the proposed computational architecture for optical gait signal processing. Source: Authors.

Stage	Primary Function	Processing Stages	Representative Implementations
Acquisition	Capture optical motion data and extract human poses.	• Synchronous data acquisition. • Pose estimation (skeleton joints). • Generation of kinematic time-series.	Pose estimation via RGB/RGB-D camera-based models.
Preprocessing	Filter noise and normalize raw kinematic signals.	• Low-pass filtering (Butterworth, One-Euro). • Adaptive smoothing (Kalman filter / AI-based filtering). • Signal resampling and interpolation • Coordinate normalization (relative coordinates, body-centered frames). • Range adjustment per subject.	General-purpose signal processing libraries or custom algorithms.
Segmentation	Divide time-series into discrete gait cycles.	• Heuristic segmentation based on joint angle thresholds (e.g., knee flexion). • AI-based segmentation (CNNs, LSTMs trained on gait patterns).	Pattern recognition techniques; may use machine learning

		• Gait cycle start-end points detection. • Event detection (heel strike, toe off).	models trained on gait cycles.
Data Structuring	Organize, label, and export processed data.	• Timestamp alignment. • Structuring of each gait cycle as independent data records. • Export to interoperable formats (CSV, JSON). • Optional feature extraction (mean joint angles, cycle duration).	Tabular data manipulation frameworks or structured export routines.

Expanding on the structured summary above, Figure 1 illustrates the sequential and modular organization of the proposed architecture. Before the four main stages of the architecture begin, a configuration or environment preparation phase is required to ensure the appropriate conditions for the correct execution of the subsequent processing.

This phase includes the configuration of optical capture devices, such as the calibration of RGB or RGB-D cameras, temporal synchronization of sensors, and definition of acquisition parameters (sampling frequency, resolution, and field of view). It also involves preparing the computational environment, installing the required libraries and dependencies (e.g., TensorFlow, PyTorch, NumPy, OpenCV), and establishing data input and output paths.

Once this initial setup is complete, the proposed workflow is executed in four sequential stages:

(1) Acquisition, responsible for capturing optical data and extracting joint coordinates using markerless systems.

(2) Preprocessing, focused on filtering, normalizing, and aligning kinematic signals.

(3) Segmentation, responsible for dividing continuous sequences into discrete gait cycles using heuristic or machine learning–based methods.

(4) Data structuring, dedicated to organizing, labeling, and exporting the processed information in standardized formats that facilitate biomechanical analysis and interoperability with other systems.

This layered representation not only reinforces the conceptual clarity of the design but also highlights its modularity, allowing researchers and developers to substitute, refine, or extend individual components according to specific system requirements, experimental objectives, or available computational resources.

Moreover, the diagram underscores the adaptability of the architecture, demonstrating how new algorithms, optimization strategies, or hardware platforms can be integrated without disrupting the integrity of the overall framework.

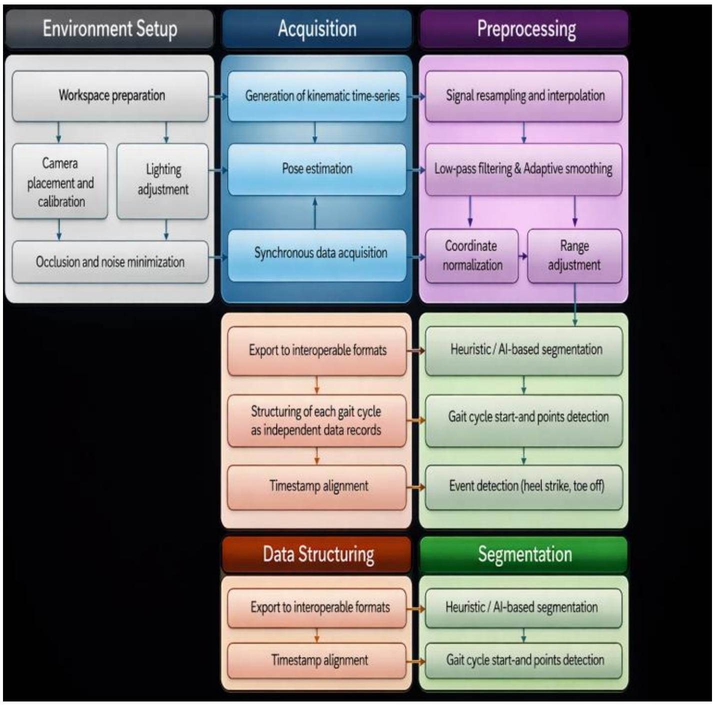

Figure 1. Modular architecture for optical gait signal processing, showing the sequential flow from acquisition to data structuring and the independence of each processing block. Source: Authors.

3.1. Stage 1: Acquisition

The Acquisition stage constitutes the pipeline's entry point. It manages the synchronous collection of motion data via markerless systems capable of real-time or offline pose estimation. These systems typically rely on RGB or depth video streams to extract time-series data of 2D or 3D joint coordinates. Widely adopted technologies in this domain include the Intel RealSense SDK, MediaPipe Pose, OpenPose, and Azure Kinect SDK [29].

While optimization of the acquisition process is beyond the scope of this work, the proposed architecture assumes that the input data conforms to standardized formats produced by these tools, ensuring downstream compatibility.

In this context, standardization protocols such as the Biomechanical Data Format (BDF), the C3D (Coordinate 3D) file format widely used in optical motion capture laboratories, and the OpenSim-compatible TRC and MOT conventions serve as representative examples.

These formats provide consistent definitions for marker trajectories, segment coordinates, and time references, enabling data interchange between acquisition, analysis, and simulation environments. By adhering to such standards, the architecture ensures interoperability across heterogeneous systems and facilitates integration with established biomechanics databases and modeling tools [26], [27].

3.2. Stage 2: Preprocessing

The Preprocessing stage aims to improve the quality and reliability of raw kinematic signals through a series of signal conditioning procedures. These include low-pass filtering to attenuate high-frequency noise using methods such as Butterworth or One-Euro filters, adaptive smoothing with Kalman filters or AI-based denoising techniques, and signal resampling to correct temporal inconsistencies [30].

Normalization steps are also applied to align coordinate systems relative to each subject’s body and to account for inter-subject anatomical variability. Commonly used libraries such as SciPy, NumPy, and PyKalman support these operations, while domain-specific enhancements can be integrated through custom algorithms.

3.3. Stage 3: Segmentation

Following preprocessing, the Segmentation stage partitions continuous motion signals into discrete gait cycles using a hybrid approach that combines heuristic and data-driven techniques. Heuristic methods identify kinematic events, such as peaks in knee flexion or characteristic ankle movements, to delineate gait phases. For more complex or noisy data, AI-based segmentation is proposed, employing convolutional or recurrent neural networks (e.g., CNNs, LSTMs) trained on gait-specific datasets. These models are capable of identifying temporal patterns that often go undetected by heuristic methods. Implementation may leverage Python-based scripts, with scikit-learn for classical models and TensorFlow or PyTorch for deep learning-based solutions.

The literature on gait partitioning emphasizes the importance of explicitly modeling the stance (support) and swing (balance) phases of gait. For example, the work of Maqbool, *et al.* [31], demonstrates a heuristic, rule-based detection of key gait events (initial contact (IC) and toe-off (TO)), enabling segmentation into stance and swing phases. Meanwhile, data-driven methods such as the Multi-Model LSTM Network for Gait Recognition Using Window-Based Data Segments exploit LSTM architectures to segment and classify gait cycles without requiring an explicit event-detection front end [32].

Furthermore, for exoskeleton-based systems, the work of Yuxuan, *et al.,* uses a graph convolutional network (GCN) to classify multiple gait phases, including single-support, double-support, and swing in real time [33].

These studies reinforce the notion that segmentation systems should be designed with an awareness of gait-specific phase structure (support vs. swing, and potentially sub-phases) rather than relying solely on generic motion windows.

3.4. Stage 4: Data Structuring

The final stage, Data Structuring, prepares the segmented and processed data for downstream biomechanical analysis and data exchange. This involves temporal alignment of time series, labeling of gait cycles, and organizing the output into standardized formats such as CSV and JSON.

Optional feature extraction, such as average joint angles, step durations, or stride lengths, can be included to support integration with biomechanical modeling or visualization tools. Libraries such as Pandas and PyArrow facilitate the generation of structured, interoperable datasets ready for archival, statistical processing, or application within broader analytical workflows.

Together, these four stages form a coherent and modular computational architecture tailored to the processing of optical gait data. Each stage addresses a specific step in the transformation of raw motion signals into structured, analysis-ready datasets while maintaining the flexibility to accommodate various technologies and research contexts.

By decoupling the processing pipeline into discrete, interoperable components, the architecture ensures reproducibility and scalability while enabling the integration of advanced machine learning methods and deployment across diverse platforms. This framework thus establishes a foundational protocol for ensuring data quality and consistency in markerless gait analysis.

4. Discussion

The proposed modular computational architecture for processing optical gait signals offers a conceptual foundation for enhancing the reliability and scalability of digital motion analysis using markerless systems. It is structured around a four-stage pipeline (acquisition, preprocessing, segmentation, and data structuring), with each stage operating independently yet cohesively to support flexibility across hardware platforms and research protocols.

From a technology adoption perspective, the pipeline aligns with the broader shift in gait biomechanics toward accessible and non-invasive motion capture methods. As highlighted in recent reviews like Cheng et al. [7], the field is transitioning away from expensive, marker-based systems toward markerless, camera-based alternatives that rely on pose estimation algorithms such as OpenPose, MediaPipe, and BlazePose. These tools have demonstrated promising results, particularly for sagittal plane spatiotemporal parameters, though challenges remain. Ankle joint estimations, for instance, still display moderate to low reliability under certain conditions [17].

Although signal quality in markerless motion capture can be a limiting factor, the proposed architecture provides a structured foundation to mitigate such issues. While it does not yet include a dedicated quality control module, its modular and sequential design allows for the seamless integration of validation steps before preprocessing. Existing normalization and filtering routines already help reduce noise and inconsistencies, and future implementations may incorporate plausibility checks or confidence-based filtering mechanisms to further enhance robustness.

To this end, the preprocessing stage includes coordinate normalization, adaptive filtering, and interpolation routines aimed at minimizing variability and improving the reliability of 2D and 3D joint estimations from pose-based systems [19]. This is especially relevant given findings by Pardell et al. [17], who reported high error variance in lower-limb joint angles captured by markerless systems during dynamic motion. The inclusion of body-centered normalization and Kalman-based adaptive smoothing is therefore a key design feature for enhancing signal quality prior to segmentation.

The segmentation stage adopts a dual-methodology approach that combines heuristic event detection (e.g., knee flexion peaks) with data-driven segmentation using neural networks trained on annotated gait patterns. This aligns with current best practices. For instance, Dumphart et al. [25] showed that bidirectional LSTMs trained on 3D marker data can detect gait events such as heel strike and toe off with high accuracy (within 5–11 milliseconds of force plate ground truth), even in pathological cases. Incorporating such models strengthens segmentation performance across both clinical and healthy populations.

Beyond methodological rigor, the architecture emphasizes affordability and deployability, setting it apart from traditional lab-based systems. Espitia-Mora et al. [19] demonstrated that RealSense cameras combined with MediaPipe Pose yield joint trajectory estimates with error rates below 10%, making them viable for rehabilitation and sports assessment. Building on this, the proposed framework structures joint data to support interoperability and downstream analysis through features such as timestamp alignment, gait cycle labeling, and export routines (e.g., CSV, JSON), which are often missing in turnkey solutions but essential for reproducibility and cross-study comparisons [19].

Modularity also supports extensibility. In higher-resource settings, the architecture can incorporate force estimation (e.g., inverse dynamics), EMG synchronization, or sensor fusion with inertial systems. Integrating these complementary modalities enhances the physiological interpretability and biomechanical validity of gait analysis, enabling the estimation of joint torques, muscle activation patterns, and ground reaction forces that cannot be derived from optical kinematics alone [34, 35].

In particular, combining EMG signals with kinematic data enables the identification of neuromuscular coordination strategies and the detection of compensatory behaviors in pathological gait [34]. Likewise, incorporating inertial sensors (IMUs) improves temporal resolution and robustness against occlusions or visual noise, while force platforms or pressure insoles provide valuable insight into load distribution and symmetry during stance phases [36].

By fusing these heterogeneous data sources within the proposed architecture, the system can generate a more comprehensive representation of human movement, supporting clinical assessment, rehabilitation feedback, and the validation of musculoskeletal models under realistic conditions. This direction follows trends identified by Arellano-González et al. [1] and Das et al. [2], who highlight the integration of biomechanical and physiological signals such as EMG and plantar pressure as a key evolution in comprehensive gait analysis pipelines.

The architecture is also inherently extensible and supports the integration of these additional modalities. Signals such as EMG, IMUs, and force platforms can be synchronized with optical data during acquisition and processed in parallel or through feature-level fusion. Precise temporal alignment via shared triggers or event matching ensures correspondence between modalities.

Although these multimodal inputs are not yet represented in the current structural diagram or workflow logic, the architecture's modularity enables their future integration. This expands the interpretability and physiological depth of gait analysis and represents a promising avenue for future iterations of the framework.

Despite its strengths, the architecture has inherent limitations that warrant attention in future work. It assumes access to structured kinematic inputs from systems like MediaPipe or OpenPose but does not incorporate mechanisms for signal integrity verification—an important omission given real-world challenges such as occlusions, lighting variations, and pose estimation errors [7], [17]. Additionally, the framework has yet to be validated in longitudinal or free-living environments, a critical step for clinical use cases such as monitoring neurodegenerative disorders or post-surgical gait recovery, where measurement validity is essential [2].

Although designed to be hardware-agnostic, the architecture's performance under varying frame rates, resolutions, and hardware configurations remains untested. Salcedo's 2024 survey on edge-based gait recognition highlights the need for optimization in real-time, low-latency inference pipelines [11]. Furthermore, as noted by Callejas et al. [18] and Iseki et al. [22], sensor modality (RGB, depth, infrared), camera angles, and subject variability (e.g., clothing, assistive devices) introduce significant variability. While the architecture is theoretically adaptable to these conditions, its robustness under such diverse scenarios still requires empirical validation.

5. Conclusion

The proposed architecture presents a methodologically consistent framework for the digital processing of optical gait data. It offers a structured and transparent approach that supports the growing adoption of markerless motion capture technologies. As a technology-independent proposal, it does not prescribe specific hardware or software solutions but instead establishes a flexible conceptual foundation that can guide diverse analytical pipelines, regardless of the capture system employed.

By formalizing the stages of acquisition, preprocessing, segmentation, and data structuring, the architecture reinforces the reproducibility, clarity, and comparability of gait analysis workflows across research, clinical, and applied contexts. It also promotes the use of standardized data handling practices, enhancing interoperability with established biomechanical formats and facilitating the future integration of complementary sensing modalities such as EMG, inertial measurement units, and force platforms.

This broader perspective supports a richer and more physiologically informed interpretation of gait, in alignment with emerging trends in multimodal assessment, musculoskeletal modeling, and AI-assisted analysis.

Moreover, the modular design of the framework ensures adaptability to evolving computational techniques, including machine learning–based segmentation, advanced filtering algorithms, and application-specific optimizations.

The architecture provides a unified and extensible methodological scaffold that supports the development of transparent, scalable, and interoperable gait analysis systems. It lays a solid foundation for empirical validation, technological integration, and future enhancements, ultimately promoting more consistent, robust, and rigorous practices in markerless human movement analysis.

Finally, from an academic perspective, this work contributes an original architectural abstraction for markerless gait analysis that shifts the focus from isolated algorithms toward the systematic organization of digital signal processing workflows. In contrast to existing literature that primarily evaluates sensor accuracy or model performance, the proposed framework formalizes a reproducible and technology-independent processing pipeline.

By integrating various methods within a unified modular structure, this study advances methodological clarity, interoperability, and reproducibility in gait biomechanics research, establishing a reference model for future experimental validation and multimodal system development.

6. Future Works

To advance the proposed framework, future work should prioritize three complementary directions. First, the pipeline should be evaluated across a wide range of markerless motion capture systems, spanning RGB-only, RGB-D, and multimodal configurations, to examine its consistency, cross-platform adaptability, and sensitivity to variations in acquisition conditions. Such evaluations will help determine the extent to which the architecture maintains stability when applied to heterogeneous data sources and operational contexts.

Second, collaboration with clinicians, physiotherapists, and kinesiologists will be essential for testing the framework on annotated datasets that reflect pathological gait patterns and real-world clinical variability. Applying the architecture to diverse populations, including individuals with neuromotor disorders, post-surgical patients, and older adults, will support refinement of the preprocessing and segmentation stages, ensuring that the methodology remains robust under practical clinical constraints.

Third, the Data Structuring stage can be expanded to incorporate automatic extraction of biomechanical descriptors such as gait velocity, symmetry indices, temporal–spatial metrics, and joint range of motion. Integrating these derived parameters would strengthen the framework’s applicability within broader analytical pipelines, including predictive modeling, rehabilitation monitoring, and musculoskeletal simulation.

Building on these directions, future efforts will involve implementing the full architecture in controlled experimental settings, conducting systematic comparisons across representative use cases, and exploring hybrid processing strategies that combine heuristic and machine learning–based techniques. Ultimately, these developments aim to consolidate the proposed methodology into a comprehensive, extensible, and transparent framework that supports reproducible gait analysis and promotes its integration into research, clinical, and performance-oriented environments.

The proposed architecture is inherently extensible and supports the integration of complementary data modalities such as electromyography (EMG), inertial measurement units (IMUs), and force platforms. These signals can be synchronized with optical data during the acquisition stage and processed in parallel or through feature-level fusion.

Precise temporal alignment through shared triggers or gait event matching ensures correspondence between modalities. Although these data streams and synchronization mechanisms are not yet included in the current framework, its modular design supports future multimodal integration. Such fusion enhances biomechanical interpretation by linking kinematics with neuromuscular activity and ground reaction forces.

Declarations

Author Contributions

Conceptualization, M.A.V.-G. and M.C.-C.; methodology, M.A.V.-G.; software, M.A.V.-G.; validation, M.A.V.-G., M.C.-C., and A.C.A.-A.; formal analysis, M.A.V.-G.; investigation, M.A.V.-G.; resources, M.A.V.-G.; data curation, M.A.V.-G.; writing, original draft preparation, M.A.V.-G.; writing, review and editing, M.C.-C., A.C.A.-A.; visualization, M.A.V.-G.; supervision, M.A.V.-G.; project administration, M.A.V.-G.; funding acquisition, M.C.-C. All authors have read and agreed to the published version of the manuscript.

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Institutional Review Board Statement

Not Applicable.

Conflicts of Interest

The author declares that there is no conflict of interests regarding the publication of this manuscript. In addition, the ethical issues, including plagiarism, informed consent, misconduct, data fabrication and/or falsification, double publication and/or submission, and redundancies have been completely observed by the authors.

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