



# AI-Based Gait Analysis: Intelligent Assessment of Human Movement

Dr. Mei Lin Zhou\*

Dept. of Movement Science, Shanghai Health Technology University, China

\*Corresponding author: Dr. Mei Lin Zhou, Dept. of Movement Science, Shanghai Health Technology University, China, Email: m.zhou@shtu.cn

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## Introduction

Human gait—the pattern of walking and movement—provides valuable insights into musculoskeletal health, neurological function, and overall mobility. Abnormal gait patterns can indicate conditions such as stroke, Parkinson's disease, cerebral palsy, orthopedic injuries, or age-related decline. Traditional gait analysis methods rely on clinical observation or laboratory-based motion capture systems, which can be subjective, expensive, and limited to controlled environments. AI-based gait analysis has emerged as a transformative approach, combining artificial intelligence, computer vision, and wearable sensing technologies to deliver accurate, objective, and real-time movement assessment [1,2].

AI-based gait analysis systems use machine learning algorithms to interpret complex biomechanical data. By analyzing walking patterns, stride length, joint angles, and temporal parameters, these systems provide clinicians with detailed insights that support diagnosis, rehabilitation, and performance optimization [3-5].

## Discussion

AI-based gait analysis typically integrates wearable sensors or camera-based motion capture systems. Wearable devices equipped with accelerometers, gyroscopes, and pressure sensors collect continuous data on limb movement, balance, and force distribution. Alternatively, computer vision systems use depth cameras or smartphone videos to track body landmarks without requiring physical markers. The collected data is processed using machine learning models trained to recognize patterns associated with normal and abnormal gait.

Deep learning algorithms play a central role in pattern recognition. Convolutional neural networks (CNNs) and recurrent neural networks (RNNs) can analyze spatial and temporal features of gait cycles. These models detect subtle deviations that may be imperceptible to the human eye, enabling early identification of neurological or orthopedic disorders. For example, AI systems can identify asymmetries in step timing that signal early-stage Parkinsonian symptoms or quantify

improvements during post-stroke rehabilitation.

One of the major advantages of AI-based gait analysis is remote monitoring. Patients can perform walking assessments at home while data is transmitted securely to healthcare providers. This continuous monitoring supports personalized treatment adjustments and reduces the need for frequent clinic visits. In sports science, AI gait analysis helps optimize performance and prevent injury by identifying biomechanical inefficiencies.

Despite its potential, challenges include ensuring data accuracy across diverse populations and environments. Privacy concerns must be addressed when using video-based systems, and algorithm transparency is essential for clinical trust. Robust validation studies are necessary to ensure reliability and regulatory compliance.

## Conclusion

AI-based gait analysis represents a significant advancement in movement assessment and rehabilitation. By leveraging intelligent algorithms and advanced sensing technologies, these systems provide precise, objective, and accessible insights into human mobility. Although technical and ethical challenges remain, ongoing research and innovation continue to improve accuracy and usability. As digital healthcare evolves, AI-driven gait analysis will play an increasingly important role in diagnosis, rehabilitation, and performance enhancement.

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