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A Review of Fatigue Detection Methods by Identifying Gait Features

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***Abstract*--** **Fatigue is a significant factor in unexpected incidents that incur considerable economic and human losses for societies. Consequently, various methods have been developed to detect fatigue, among which gait features analysis is one of the most common. Gait features can be assessed by several techniques, but the most prevalent ones include force plates, wearable sensors, and image processing. This review paper has revealed the different techniques for fatigue detection by categorizing the different methods of gait feature measurement. It has evaluated the strengths and weaknesses of each technique and identified the challenges and future directions for fatigue detection research. The final goal of this study is to investigate and determine the gait features that vary significantly with fatigue and are relevant for fatigue assessment. The study aims to establish the relationship between gait features and fatigue level and to evaluate the reliability of these features and methods for fatigue detection. It also discusses whether further research is needed to develop more valid methods based on gait analysis.**

***Index Terms*--** **Fatigue, Fatigue detection, Force plates, Gait features, Image processing, Wearable sensors**

I. Introduction

Fatigue is a frequent concern that impacts subjective and objective aspects of human performance, such as perceived tiredness, exhaustion, lack of energy, and cellular, tissue, or organ function after repeated or excessive stimulation, stress, or activity[1]. It has been examined in various domains as an everyday construct [2,3] that can also entail economic consequences by impairing efficiency and production [4-6], especially in labor societies [7]. Fatigue in the workplace [8] results in mishaps and permanent injuries in construction [9], transportation (implicated in 13% of truck crashes and up to 21% of fatal crashes [1]), and healthcare, where fatigue among medical professionals can lead to critical errors during surgeries and patient care [11].

Fatigue encompasses both physical and mental components, each with distinct characteristics and detection challenges. Physical fatigue results from prolonged physical activity or medical conditions such as hypothyroidism, autoimmune disorders, liver or renal diseases, or cancer. Mental fatigue occurs after prolonged periods of cognitively demanding activity and is defined by a general sense of exhaustion [12]. While several studies have investigated fatigue and low energy as separate categories with biological overlaps [13–18], both types of fatigue can be detected through gait analysis, as walking patterns reflect both physical and cognitive states.

Walking is a common daily activity [19–21] and benefits health [22]. Gait analysis has proven effective for identifying various medical conditions, including Parkinson's disease (PD) [23–27], multiple sclerosis (MS) [28–32], and joint arthrosis [27, 33–35]. The emerging field of fatigue detection through gait analysis builds upon these established methodologies, offering potential for both physical and mental fatigue assessment.

This study provides a comprehensive review and classification of gait analysis methods specifically for fatigue detection. While existing literature has explored gait analysis for various purposes, a focused review on fatigue detection methods addressing both physical and mental fatigue is less common. This research aims to establish a foundation for developing more accurate and reliable fatigue detection systems by extracting and analyzing gait parameters that vary with different types of fatigue.

According to the type of gait features measured, the methods for detecting fatigue are analyzed and categorized into three groups: detection using force plates, wearable sensors, and image processing. This review aims to ascertain the gait features that are susceptible to fatigue-induced changes so that both physical and mental fatigue can be detected during walking by assessing these parameters.

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II. Review Methodology

A. Search Strategy

A systematic literature search was conducted in September 2024 using multiple electronic databases, including PubMed, IEEE Xplore, Web of Science, and Google Scholar. The search strategy employed a combination of relevant keywords and Medical Subject Headings (MeSH) terms related to fatigue detection and gait analysis. The search terms included: ("fatigue detection" OR "fatigue assessment" OR "fatigue monitoring") AND ("gait analysis" OR "gait features" OR "walking pattern" OR "locomotion") AND ("force plate" OR "wearable sensor" OR "image processing" OR "computer vision" OR "biomechanics").

B. Inclusion and Exclusion Criteria

Inclusion Criteria:

- Studies published in peer-reviewed journals and conference proceedings
- Research focused on fatigue detection or assessment using gait analysis methods
- Studies employing force plates, wearable sensors, or image processing techniques for gait feature extraction
- Articles published in the English language
- Studies involving human subjects
- Research published from September 2000 onwards to ensure comprehensive coverage of contemporary methodologies

Exclusion Criteria:

- Editorial articles and opinion papers
- Studies not specifically addressing fatigue detection through gait analysis
- Research focusing solely on pathological gait without fatigue assessment
- Animal studies
- Studies with insufficient methodological details
- Conference abstracts without full-text availability

C. Study Selection Process

The systematic search process followed the guidelines outlined in Fig. 1. A total of 307 studies were initially identified through database searches. Following screening of titles and abstracts for relevance against the inclusion and exclusion criteria, 111 studies were selected for detailed review and inclusion in this comprehensive analysis. The complete selection process is illustrated in Fig. 1.

D. Data Extraction and Analysis

From each included study, the following information was systematically extracted: study design, participant characteristics, fatigue induction methods, gait analysis techniques employed, specific gait parameters measured, key findings related to fatigue detection, and study limitations. The extracted data was then categorized according to the three primary gait analysis approaches: force plates, wearable sensors, and image processing techniques.

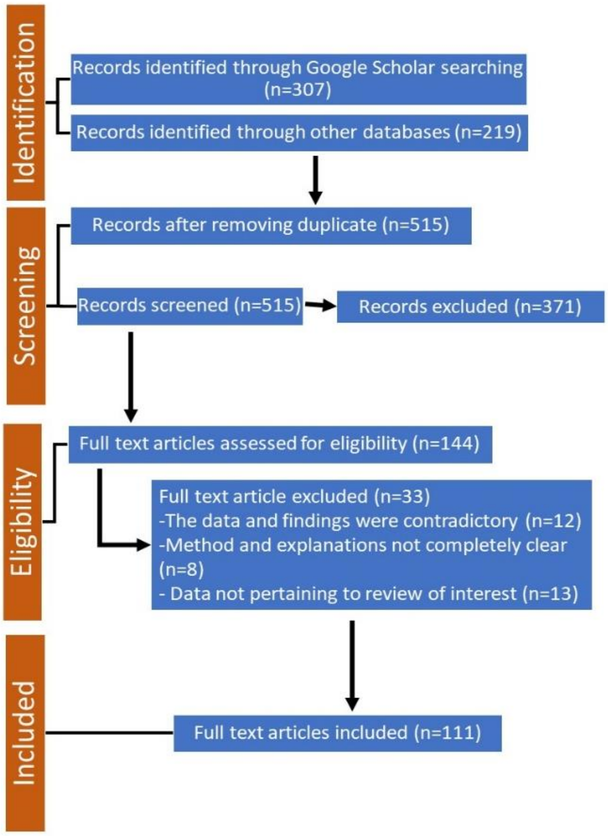

Fig. 1. Flow diagram illustrating the literature search and selection process for identifying relevant studies on fatigue detection methods based on gait features.

III. FATIGUE DETECTION ACCORDING TO GAIT FEATURES

Previous studies have shown how fatigue affects human physical condition [41-44], with balance impairment being the most common consequence [45-49]. Fatigue may induce alterations in gait patterns [41-44,50-57], particularly in the presence of lower limb fatigue [42,58]. These gait parameter modifications are more noticeable in older adults [12,59-61] and [62,63]. Moreover, these studies indicate that these alterations are more prominent in the spatiotemporal aspects of gait, such as stride length, speed, and cadence [64-66], especially when gait dynamics change due to muscle fatigue [67-69], which impairs muscle coordination and responsiveness [70].

A. Comparison of Gait Analysis Methods for Fatigue Detection

In the field of gait analysis for fatigue detection, three primary methods are commonly employed: force plates, wearable sensors, and image processing. Each method has its own set of advantages and limitations:

Force Plates: These measure ground reaction forces using pressure sensors in platforms. They are highly accurate (e.g., ±0.1% of load) but expensive (€4,000–€54,000) and limited to laboratory settings, capturing only a few steps, which may not reflect natural walking.

Wearable Sensors: These include devices like inertial measurement units (IMUs) and pressure sensors worn on the body. They are portable, cost-effective (e.g., €91.30 for inertial sensors), and suitable for real-world use, but require battery management and complex data processing.

Image Processing: This uses cameras to analyze gait nonintrusively, offering high-resolution data but being computationally intensive and costly (e.g., €160–€18,440), with challenges like calibration issues.[71]

TABLE I
Summary of Gait Analysis Methods[71]

Method	Accuracy	Cost (€)	Limitations
Force Plates	High (±0.1% of load)	4,000–54,000	Expensive, limited to a few steps, may alter natural gait
Wearable Sensors	Varies (R > 0.95 for some)	91.30–350	Power consumption, complex algorithms, potential noise
Image Processing	Varies (2.66%–9.25% EER for ToF)	160–18,440	Expensive, computationally intensive, calibration issues

Each method faces unique challenges in data collection, particularly concerning experimental conditions, environmental variables, and individual differences.

Force Plates: The primary challenge is ensuring participants step fully on the plate without altering their gait pattern. This targeting effect can lead to unnatural walking, potentially skewing the data [72]. Additionally, the laboratory setting may not reflect real-world walking conditions, limiting the ecological validity of the findings.

Wearable Sensors: Data collection with wearable sensors is influenced by sensor placement, which must be consistent across participants to ensure comparability. Environmental factors such as magnetic interference can affect sensor accuracy, and individual differences in gait patterns may require personalized calibration to achieve accurate measurements [73]. Recent advancements, such as those by Dai et al., highlight machine learning-assisted wearable electromechanical sensors improving gait recognition accuracy [74], while Mu et al. emphasize real-time monitoring capabilities. [75]

Image Processing: For image-based systems, environmental variables like lighting and background complexity can significantly impact data quality. Proper camera calibration is essential, and variations in clothing or body shape can affect the accuracy of pose estimation [5]. Moreover, individual differences in gait kinematics necessitate robust algorithms that can account for variability among subjects.

In summary, while each method offers distinct advantages for gait analysis in fatigue detection, researchers must carefully consider their specific needs, including the required accuracy, cost constraints, and the context in which data will be collected. Force plates provide high accuracy but are limited to laboratory settings, wearable sensors offer portability at the cost of potentially lower accuracy, and image processing provides detailed kinematic data but requires significant computational resources and controlled environments.

While each method offers distinct advantages for fatigue detection through gait analysis, a critical evaluation reveals significant trade-offs that influence their practical utility. Force plates, with their superior accuracy (±0.1% of load), provide a reliable benchmark for controlled studies, making them ideal for establishing baseline gait parameters under fatigue. However, their high cost (4,000-54,000 €) and confinement to laboratory settings severely limit their scalability and real-world applicability, particularly for continuous monitoring or large-scale population studies. Wearable sensors, in contrast, excel in portability and affordability (91.30-350 €), enabling real-time data collection in naturalistic environments, which is critical for detecting fatigue in occupational or clinical contexts. Yet, their variable accuracy (e.g., <5% error in stride length) and susceptibility to noise introduce challenges in achieving the precision needed for diagnostic purposes, often requiring advanced signal processing to mitigate these drawbacks. Image processing offers a middle ground, with its non-intrusive nature and potential for detailed kinematic analysis, but its wide cost range (160 € to 18,440 €) and environmental sensitivity (e.g., lighting issues) make it less practical for widespread deployment outside controlled settings [71]. The computational burden further complicates its use in real-time applications. Thus, while force plates provide unmatched precision in controlled research, wearable sensors stand out for their practical versatility despite accuracy trade-offs, and image processing holds promise for detailed analysis if cost and environmental challenges can be addressed. Future advancements, such as integrating wearable sensors with machine learning to enhance accuracy, may bridge these gaps, offering a balanced solution for fatigue detection.

B. Using force plates to extract gait features to assess fatigue

In numerous papers, force plates are used to measure various gait features [76–78]. Fabio et al. conducted a detailed investigation into the effects of fatigue on gait characteristics by examining both free walking and obstacle-adapted walking modes along an 8-meter path. Participants walked at a self-selected speed, with gait parameters measured using a force plate and an EMG sensor to capture biomechanical and neuromuscular data. To induce fatigue, participants performed repeated sit-to-stand movements, which are known to target lower body musculature and simulate real-life fatigue scenarios. Following the induction of fatigue, several notable changes in gait parameters were observed. Specifically, walking speed increased, stance time decreased, and step length was reduced. These findings suggest that fatigue significantly alters the biomechanical efficiency and control of gait.

In addition, the study revealed important insights into the role of physical activity levels in fatigue resistance. It was observed that young, active individuals displayed a higher resistance to fatigue compared to their inactive counterparts, underscoring the protective effects of regular physical activity on physical performance. Furthermore, the obstacle-adapted walking mode introduced additional challenges to participants' gait. Compared to free walking, the obstacle mode was associated with a noticeable decrease in step length, walking time, and speed, alongside an increase in double support time. This suggests that navigating obstacles while fatigued further amplifies the challenges posed to gait stability and coordination, providing valuable information for designing interventions aimed at minimizing fatigue-related risks in complex walking environments. [78]. Similarly, Fabio et al. utilized the same testing protocol to examine and compare the effects of knee muscle fatigue on gait parameters in both young and older adults within a controlled experimental setting. The study provided valuable insights into how age-related physiological differences influence the impact of fatigue on gait. The findings revealed that while stride length remained relatively unchanged in younger participants, it increased significantly in older adults, suggesting a compensatory mechanism in the elderly to maintain stability or efficiency under fatigue. Stride time, on the other hand, decreased in both groups, but this reduction was more pronounced among the older participants, highlighting their altered temporal gait patterns under fatigue.

Moreover, the study observed an increase in stride speed across all age groups, although the change was more substantial in the elderly. This may indicate an age-related difference in motor strategies or energy expenditure in response to fatigue. Interestingly, the crossing step length, an essential parameter for gait stability and obstacle negotiation, decreased for all participants regardless of age, underscoring the universal impact of knee muscle fatigue on specific aspects of gait. Beyond these findings, the study also emphasized the variability of knee muscle fatigue effects with age, reflecting the complex interplay between aging, muscle function, and motor control. These insights are crucial for understanding how fatigue impacts gait differently across the lifespan and may inform the development of tailored interventions to mitigate fatigue-related risks in both young and older populations [79]. Behmaram et al. conducted an insightful study to explore the differences in fatigue induced by backpack carrying between students with flat feet and those with normal foot arches. The research aimed to investigate how varying backpack weights influence fatigue levels and gait parameters in these two groups. Backpacks weighing 7.5%, 10%, 12.5%, and 15% of the participant's body weight were used in the experiment, with the fatigue level being assessed after 10 minutes of walking at a standardized mean backpack weight of 10% of body weight. The study primarily focused on ground reaction force (GRF), a critical parameter that reflects the force exerted by the ground on a body in contact with it, as a key indicator of gait changes due to fatigue.

The findings revealed significant differences in how fatigue affected students with flat feet compared to those with normal feet. In participants with flat feet, GRF decreased after fatigue when carrying backpacks weighing 15% of their body weight, indicating a possible decline in gait stability or efficiency under heavier loads. Conversely, GRF did not show significant variations in students with normal feet under the same conditions, suggesting better fatigue resistance and load adaptability in this group. However, when comparing pre-fatigue and post-fatigue states, GRF in students with flat feet exhibited a substantial increase, highlighting the pronounced impact of fatigue on their gait dynamics. These results underscore the importance of considering individual biomechanical differences, such as foot arch structure, when evaluating the effects of load-induced fatigue, particularly in contexts like school or daily activities where backpack carrying is common. This research provides valuable insights for designing ergonomically appropriate load limits and interventions for individuals with varying foot structures. [80].

The document provides a thorough overview of fatigue detection methodologies with a focus on gait-based features, highlighting the significant impact of fatigue on human performance and safety in areas like healthcare, transportation, and workplace environments. As a unique biometric indicator, Gait is particularly sensitive to physical and mental states, making it a promising avenue for objective, non-invasive fatigue detection. The study emphasizes the use of wearable sensors, computer vision, and machine learning for precise fatigue assessment. Wearable devices such as accelerometers and gyroscopes offer detailed kinematic data, while computer vision techniques enable non-contact analysis through video-based gait pattern recognition. Machine learning models further enhance these methods by providing real-time and predictive capabilities.

During testing, ground reaction force (GRF) data collection played a key role in analyzing gait features. Participants were required to avoid actively aiming their feet toward the force plate to ensure accurate data. The trial was excluded if the right foot failed to land in the middle of the plate or participants displayed active aiming behavior (Fig. 2A1). Once a successful trial was completed for the right foot, the same process was repeated for the left foot until three valid GRF datasets were collected for each side (Fig. 2A2). This meticulous data collection process highlights the precision necessary in evaluating fatigue-induced changes in gait parameters.

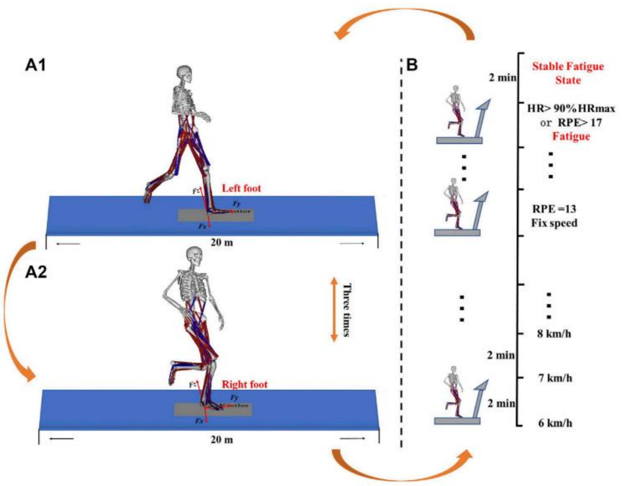

Fig. 2. Bilateral data collection process: (A1) Procedure for collecting GRF data from the right foot. (A2) Procedure for collecting GRF data from the left foot. (B) Implementation process of the running-induced fatigue protocol test [81]

Changes in gait features, such as reduced stride length, increased variability, and altered joint angles, are highlighted as key indicators of fatigue. These insights find applications in diverse domains, including monitoring worker fatigue in industrial settings, diagnosing fatigue-related health conditions, and ensuring the safety of drivers and pilots by identifying early fatigue signs. The document also discusses the challenges in this field, such as the need for diverse datasets, generalization across populations, sensor limitations, and ethical concerns surrounding data privacy. Despite these challenges, it concludes that advancements in sensor technology and computational methods will continue to enhance the efficacy and practicality of gait-based fatigue detection systems [81]. Table II includes a summary of these studies.

TABLE II
Summary of Studies using Force Plates to Extract Gait Features

Study	Objective	Methods	Key Findings
Effect of muscle fatigue and physical activity level on motor control of the gait of young adults. [78]	To investigate the effects of fatigue on gait in free and obstacle-adapted walking modes.	Force plate, EMG; fatigue via sit-to-stand; 8-meter path at self-selected speed.	Post-fatigue: ↑ walking speed, ↓ stance time, ↓ step length in free walking; obstacle walking: ↓ step length, ↓ speed, ↑ double support vs. free walking; active individuals more resistant.
Interactions of age and leg muscle fatigue on unobstructed walking and obstacle crossing. [79]	To compare knee muscle fatigue effects on gait in young and older adults.	Same as [78]; force plate, EMG, sit-to-stand for fatigue.	Older: ↑ stride length (young unchanged), greater ↓ stride time, larger ↑ stride speed; all: ↓ crossing step length.
Effects of backpack-induced fatigue on gait ground reaction force characteristics in primary school children with flat-foot deformity.[80]	To explore backpack-induced fatigue differences in flat vs. normal feet students.	Force plate; fatigue from walking with backpacks (7.5%–15% body weight); GRF assessed after 10 minutes at 10% body weight.	Flat feet: ↓ GRF post-fatigue with 15% BW; normal feet: no significant change; flat feet had a larger pre-post GRF increase.

C. Using wearable technologies to extract walking parameters to assess fatigue

In various articles, accelerometer sensors have been utilized to analyze gait characteristics [82–88]. In one study, Shang et al. investigated the maximum voluntary contraction of the knee joint muscles (MVC). In this article, the footwear soles functioned as pressure sensors (Fig. 3).

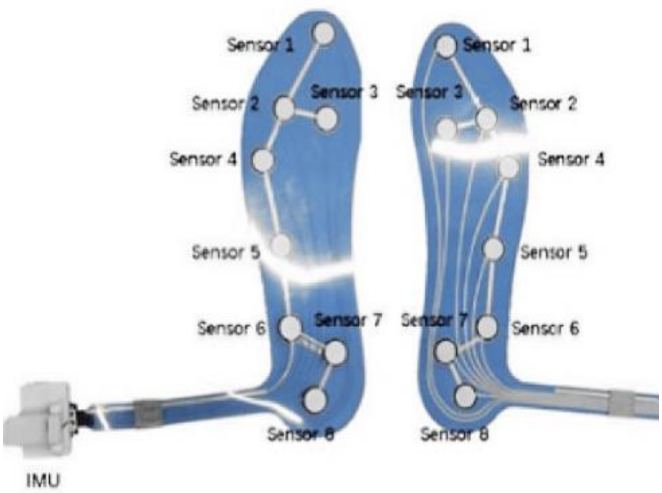

Fig. 3. The layout of the insole's pressure sensors [89]

This study involved six participants with right-leg dominance who wore sensors on their footwear. The researchers measured the changes in their gait after performing a squat exercise. A single gait cycle was defined as the unit of analysis, and the data were used to assess gait characteristics. The results showed that the MVC decreased under fatigue conditions, and a neural network model (Fig. 4) was applied to classify the fatigue level into four stages based on the MVC percentage obtained from the sensors [89].

Fig. 4. The neural network structure [89]

In a study, Guzhin et al. investigated fatigue by analyzing gait features using wearable sensors, that is, inertial measurement units (IMU) aligned on the back of shoes. In this research,18 elderly participants were recruited who walked on a treadmill for an hour. The data from the first, 30th, and 60th minutes were analyzed to identify the effects of fatigue on gait features. The results indicated that fatigue caused significant changes in the mean acceleration, angular velocity, and ankle rotation range. Moreover, this study corroborated the parameters obtained in previous studies [21,91-94] and revealed that fatigue increased the horizontal angle of ankle rotation, which impaired balance and caused heel pronation [90]. Zhenghui et al. evaluated the effectiveness of an anti-fatigue mat during prolonged standing by analyzing gait features using a neural network. They recruited 18 adults and adolescents who worked for four hours in front of a desk under the same conditions while wearing a wearable intelligence analyzer, an accelerometer, and a gyroscope.

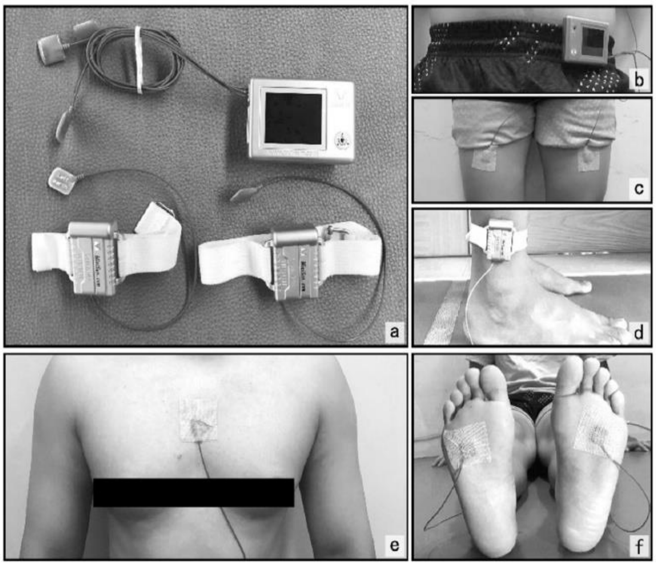

Fig. 5. The devices used in the research included accelerometers and a central processing unit (a), location of the main device (b), location of the thigh sensor (c), location of the ankle sensor (d), location of the sole sensor (f), location of the central sensor (e) [95]

TABLE III.
Summary of Studies using Wearable Technologies to Extract Walking Parameters

Study	Objective	Methods	Key Findings
Fatigue Level Prediction of Lower Extremity Knee Flexor and Extensor Muscles using Neural Network.	To investigate fatigue effects on gait using pressure sensors in footwear soles.	Pressure sensors in soles; squat exercises for fatigue; neural networks for classification.	MVC decreased with fatigue; fatigue classified into four stages.
Identifying fatigue indicators using gait variability measures: A longitudinal study on elderly brisk walking.	To study the effects of fatigue on gait in the elderly using IMUs.	IMUs on shoes; treadmill walking for 1 hour; data at 1st, 30th, 60th minutes analyzed.	Fatigue caused changes in mean acceleration, angular velocity, and ankle rotation range; increased horizontal angle of ankle rotation impaired balance.
Gait characteristics and fatigue profiles when standing on surfaces with different hardness: Gait analysis and machine learning algorithms.	To evaluate the effectiveness of anti-fatigue mats using wearable sensors during prolonged standing.	Accelerometers and gyroscopes; 4-hour standing test with/without anti-fatigue mat.	Walking speed decreased with fatigue; women had higher stride length before fatigue; the anti-fatigue mat had more benefits for women; men were less prone to fatigue from standing.

The participants performed the test twice, either on an anti-fatigue mat or on the ground. The researchers compared several gait parameters on both surfaces before and after each test. They found that walking speed was slower on the anti-fatigue mat than on the ground, and both were slower than before fatigue. Thus, walking speed decreased with fatigue. Women had higher stride length before fatigue, but there was no significant difference between the two surfaces. Single support/double support, which reflects balance, was highest before fatigue and lowest on the mat. The next parameter, swing work, which measures the leg swing during walking, was highest before fatigue and lowest on the mat. Finally, leg strength decreased the most after standing on the ground. This difference was more pronounced in women than in men. This study revealed that using a mat had more benefits for women than men. Men walked faster and with longer strides than women, and they were less prone to fatigue from standing for long periods. The authors suggested that gait parameters were useful indicators of fatigue caused by standing and that using an anti-fatigue mat could reduce fatigue from prolonged standing. Research has shown that females are more vulnerable to fatigue-induced gait changes, particularly in stride length and leg falling strength, when standing for long periods, compared to males who show higher resistance. This supports our finding that women benefited more from using an anti-fatigue mat [95]. The summary of these studies is included in Table III.

D. Using Image processing to extract walking parameters to assess fatigue

Many studies have evaluated gait features using image processing, specifically by recruiting depth sensors like the Kinect sensor [96–100].

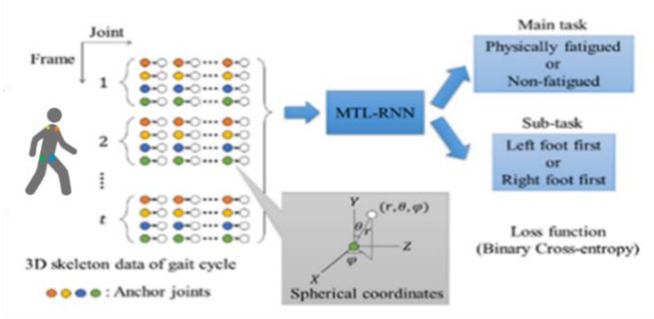

Fig. 6. A summary of the suggested method [101]

Kota et al. conducted a study using the Kinect sensor and deep learning techniques to assess the fatigue level. The overview of the proposed method is depicted in Figure 6. The method utilizes a recurrent neural network (RNN) that outputs the probabilities of fatigue and non-fatigue states based on a walking cycle of 3D joint positions. The data analysis required determining the participants' resting heart rates before walking four times for five minutes, with one-minute breaks between each walk. The intensive activity stage involved repeated box climbing until fatigue onset. Heart rate indicated extreme exhaustion. The participant walked for 10 minutes and reported their fatigue level again. Finally, the data collected by Kinect at each stage underwent analysis and training. The figure below (Fig. 7) shows the sensor setup.

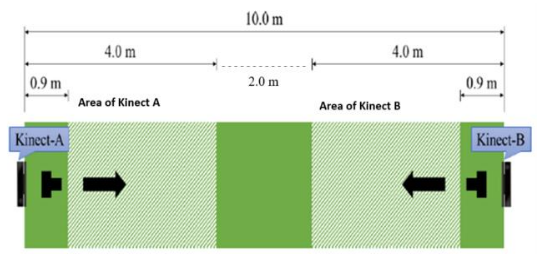

Fig. 7. The gait captures space from a top perspective. Kinect sensors are located at both ends of the route. A T-shaped marker signifies the start position, and an arrow marker signifies the walk direction [101]

In this research, the supporting foot is used as the neural network's input. Since this foot is static during a step, the ankle joint is considered as the support, and the neural network identifies fatigue by processing its features [3].

Another study using image processing aimed to investigate the effects of carrying a load on fatigue and gait characteristics. This was done using reflective spherical markers and an eight-camera motion capture system to monitor whole-body kinematics in three dimensions at a frequency of 100 Hz. The study included three test levels: no load, 7.5 kg, and 15 kg, during which participants walked on a treadmill at their preferred speed.

Following three pre-fatigue trials, participants underwent fatigue training to induce fatigue. During this training, they were instructed to run on the treadmill at a speed of 8 mph, a pace determined from observations made in a pilot study. Fig. 8 and 9 illustrate the participant setup and the placement of the markers on the body, respectively. In the pilot study, all healthy male participants reached fatigue within 2 to 10 minutes of running at this speed. The Borg Rating of Perceived Exertion (RPE) scale was employed to assess fatigue levels, specifically the Borg 6-20 scale, where "6" indicates “no effort at all” and “20” signifies “maximum effort.”

Fig. 8. Participant and test setup [102]

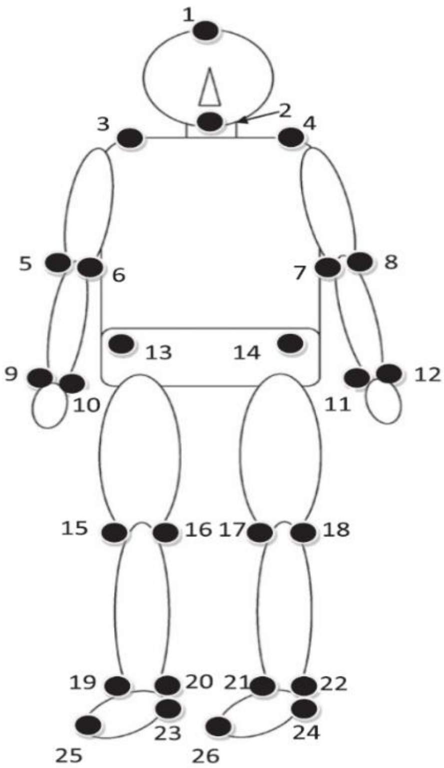

Fig. 9. Placement of markers on the body [102]

At each 30-second interval during the fatigue exercise, participants rated their fatigue level using the RPE scale. The exercise was halted when a participant first rated their RPE at or above 17, indicating “very intense, and you are very tired” on the Borg scale. Measures of gait variability included stride length variability and stride width variability. Stride length was defined as the anterior-posterior distance between consecutive left and right heel strikes, while stride width was the medial-lateral distance between these strikes.

Additionally, the dynamic range of motion (ROM) for the knee, hip, and trunk in the sagittal plane was calculated as the difference between the maximum and minimum joint angles during a gait cycle. The ankle and knee joint centers were determined as the midpoints of markers located on the corresponding lateral and medial bony landmarks. The study found that fatigue significantly impacted the variability of stride width, hip ROM, and trunk ROM. Specifically, after fatigue was induced, stride width variability, hip ROM, and trunk ROM all increased compared to the pre-fatigue condition. Furthermore, the post-fatigue condition was associated with a trend towards greater knee ROM, as the difference in knee ROM between the post-fatigue and pre-fatigue conditions approached significance. [102] Table IV summarizes the objectives, methods, and key findings of these studies.

TABLE IV
Summary of Studies using Image Processing to Extract Walking Parameters

Study	Objective	Methods	Key Findings
Physical Fatigue Detection from Gait Cycles via a Multi-Task Recurrent Neural Network	To assess fatigue levels using the Kinect sensor and deep learning techniques.	Kinect sensor; RNN with 3D joint positions; walking cycles (4x5 min with breaks) followed by box climbing for fatigue; heart rate monitoring.	RNN output probabilities of fatigue vs. non-fatigue states; ankle joint features indicated fatigue levels.
Effects of load carriage and fatigue on gait characteristics.	To investigate the effects of load carrying on fatigue and gait characteristics using motion capture.	8-camera system with reflective markers; treadmill walking at preferred speed with loads (0, 7.5, 15 kg); fatigue induced by running at 8 mph; Borg RPE scale (stopped at ≥17).	Post-fatigue: increased stride width variability, hip ROM, trunk ROM; trend toward greater knee ROM.

IV. Discussion

A. Critical Analysis of Gait Parameters Under Fatigue

The analysis of fatigue detection through gait parameters reveals both convergent and divergent findings across different measurement modalities, highlighting the complexity of fatigue-induced biomechanical changes and the methodological challenges inherent in this research domain.

B. Contradictory Findings and Methodological Implications

A critical examination reveals significant contradictions in reported gait parameters under fatigue conditions. Force plate studies by Barbieri et al. [42] demonstrated increased stride length with fatigue, while wearable sensor research by Helbostad et al. [41] reported unchanged stride length despite other significant gait modifications. Zhang et al., using machine learning and inertial sensors, found consistent stride length reductions [21], whereas other studies showed variable patterns dependent on fatigue progression stages [90].

These contradictions likely stem from fundamental methodological differences rather than conflicting physiological responses. The variations in experimental designs, fatigue induction methods (physical exercise vs. mental tasks), measurement techniques, and participant characteristics contribute to these inconsistencies, suggesting that standardized protocols are essential for reliable comparison of findings.

C. Methodological Quality and Evidence Synthesis

Each measurement modality presents distinct advantages and limitations that influence detection accuracy and practical applicability:

Force plates provide high measurement precision but suffer from limited ecological validity due to laboratory confinement and expensive infrastructure requirements [71,72]. Wearable sensors offer superior real-world applicability but exhibit variable accuracy rates (67-75%) and require sophisticated signal processing [103]. Image processing approaches show promise for detailed kinematic analysis but remain computationally intensive and environmentally sensitive [5,71].

The heterogeneity in study design and fatigue induction protocols presents significant challenges for evidence synthesis. Studies employing different fatigue induction methods demonstrate varying gait parameter responses, suggesting that the mechanism of fatigue induction critically influences observed biomechanical changes [12].

D. Population-Specific Responses and Research Gaps

Despite methodological variations, specific gait parameters demonstrate consistent fatigue-induced changes across studies. Step width variability and mediolateral trunk acceleration represent robust indicators of fatigue-induced biomechanical changes [41,42]. Helbostad et al. [41] demonstrated significant increases in step width and variability with fatigue, findings confirmed by other studies [21,104,90].

The literature reveals significant gaps in population-specific responses, with older adults demonstrating more pronounced gait alterations under fatigue conditions [12,59-61]. Gender-based differences indicate that women exhibit greater knee joint flexion reductions under fatigue [105], suggesting detection algorithms may require population-specific calibration.

E. Technological Integration and Future Directions

Recent advances in machine learning applications show promise for enhancing detection accuracy by identifying complex parameter interactions [106,107]. The development of personalized fatigue detection models that account for individual differences in gait patterns represents a critical advancement need. This personalized approach could enhance generalizability and reliability across diverse populations, enabling tailored interventions in healthcare and occupational safety. Studies have demonstrated that walking rhythms can effectively reveal work fatigue patterns among young adults [108], while research on specific populations shows that fatigue effects on knee kinematics and kinetics during walking vary significantly, particularly in individuals with flat feet [109].

Integrating microelectromechanical systems (MEMS) accelerometers with neuromorphic computing enables real-time gait pattern identification with high accuracy and low power consumption [110]. Machine learning algorithms, such as Bidirectional Long Short Term Memory Networks (BD-LSTM), have been successfully applied to estimate ground reaction force waveforms from inertial measurement unit data [111].

Based on the gaps identified in this review, several specific research priorities emerge that require immediate attention. Researchers should prioritize developing standardized protocols for fatigue induction, measurement procedures, and parameter definitions to enable meaningful meta-analyses and systematic comparisons across studies. Longitudinal studies tracking fatigue progression over weeks to months are critically needed, particularly in real-world occupational settings among healthcare workers, construction personnel, and transportation operators, rather than relying on acute fatigue induction protocols.

Population-specific algorithm development represents another crucial priority, requiring dedicated studies with adequate sample sizes from older adults, individuals with chronic conditions, and high-risk occupational groups to establish population-specific detection thresholds. The investigation of hybrid measurement approaches that integrate force plate precision with wearable sensor practicality should be pursued to leverage the strengths of each measurement modality while mitigating individual limitations.

For practitioners and technology developers, evidence-based clinical implementation guidelines are essential for integrating gait-based fatigue detection into existing healthcare workflows. Priority applications include developing workplace-specific fatigue monitoring systems for shift workers, long-haul drivers, and construction workers, with systems designed to trigger intervention protocols before safety-critical performance degradation occurs. Technology developers should focus on creating user-friendly interfaces incorporating machine learning algorithms, adapting to individual baseline patterns, and providing personalized fatigue thresholds rather than universal detection criteria.

Research should also identify the minimum set of gait parameters required for accurate fatigue detection across different populations and fatigue types, including determining optimal sensor placement configurations and sampling frequencies for wearable devices. Studies investigating the optimal timing for fatigue-based interventions by establishing the relationship between gait parameter changes and performance degradation are needed to determine when interventions become most effective. Finally, economic evaluation studies should assess the cost-effectiveness of different fatigue detection approaches in healthcare monitoring, occupational safety, and sports performance optimization applications.

F. Limitations and Quality Assessment

- *Literature Limitations*

The heterogeneity in study designs, sample sizes, and outcome measures across included studies prevents meaningful meta-analysis and limits evidence synthesis. The predominance of cross-sectional studies over longitudinal designs restricts understanding of fatigue progression patterns over time. Additionally, methodological inconsistencies exist across studies, including variations in fatigue induction methods and measurement protocols, contributing to the contradictory findings observed in specific gait parameters.

Limited research on specific occupational or clinical populations restricts the generalizability of findings to real-world applications. The absence of standardized fatigue detection thresholds across studies also impedes the development of universal detection algorithms.

- *Review Process Limitations*

Our systematic review was limited to English-language publications and conducted at a single time point in

September 2024. The categorization of studies into three measurement modalities, while providing organizational clarity, may not capture the full complexity of hybrid approaches that combine multiple measurement techniques. Additionally, the subjective nature of study selection and data extraction introduces potential for reviewer bias despite following systematic protocols.

V. CONCLUSION

This systematic review examined fatigue detection methods through gait analysis, categorizing approaches into three primary methodologies: force plates, wearable sensors, and image processing techniques. The comprehensive analysis of 111 studies revealed that both physical and mental fatigue induce significant gait parameter changes, with monitoring these features providing a promising approach to fatigue assessment.

Several gait parameters demonstrate consistent variations across studies, including step width, gait speed, and knee joint angles, representing reliable indicators of fatigue-induced biomechanical changes. However, substantial discrepancies exist in how specific parameters are reported to change with fatigue, particularly stride length measurements, highlighting the need for standardized protocols.

The findings indicate substantial potential for developing more precise and reliable detection techniques. Future research should prioritize refining measurement methodologies, exploring novel gait features, and addressing current inconsistencies. Integrating advanced technologies, particularly machine learning with wearable sensors, presents significant opportunities for creating real-time, user-friendly tools deployable across clinical, occupational, and everyday settings.

The development of personalized fatigue detection models accounting for individual differences represents a critical advancement need. The systematic classification and analysis presented provide a foundation for developing next-generation fatigue detection technologies while addressing identified methodological challenges, ultimately contributing to better health outcomes and injury prevention through accurate, accessible, and reliable fatigue detection systems.

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