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Review

A systematic review of gait analysis methods based on inertial sensors and adaptive algorithms

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ABSTRACT

The conventional methods to assess human gait are either expensive or complex to be applied regularly in clinical practice. To reduce the cost and simplify the evaluation, inertial sensors and adaptive algorithms have been utilized, respectively. This paper aims to summarize studies that applied adaptive also called artificial intelligence (AI) algorithms to gait analysis based on inertial sensor data, verifying if they can support the clinical evaluation. Articles were identified through searches of the main databases, which were encompassed from 1968 to October 2016. We have identified 22 studies that met the inclusion criteria. The included papers were analyzed due to their data acquisition and processing methods with specific questionnaires. Concerning the data acquisition, the mean score is 6.1 ± 1.62, what implies that 13 of 22 papers failed to report relevant outcomes. The quality assessment of AI algorithms presents an above-average rating (8.2 ± 1.84). Therefore, AI algorithms seem to be able to support gait analysis based on inertial sensor data. Further research, however, is necessary to enhance and standardize the application in patients, since most of the studies used distinct methods to evaluate healthy subjects.

1. Introduction

Human gait corresponds to the physiological way of locomotion, which can be affected by several disorders [1]. Thus, gait analysis plays an important role in clinical practice, it provides information about subject's functional level and can be used for health monitoring to verify the efficiency of rehabilitation and to objectively evaluate surgeries' success [2]. The gold standard technologies for gait analysis are optoelectronic systems [3] that offer high accuracy in measuring kinematic features [4]. Unfortunately, such systems can only be used in large laboratories, as it is expensive and space consuming [5].

Regarding gait analysis, there are different nomenclatures for the classification of the events subdividing the gait cycle in distinct phases. Thus, we will start introducing the nomenclature used in this paper that is suggested by Perry and Burnfield [6]. As displayed in Fig. 1, one gait cycle can be divided into two phases, stance (ST) and swing (SW), which can be subdivided into five and three phases, respectively. Corresponding to the beginning of the ST phase, the initial contact (IC) describes the moment when one part of the foot, in physiologic gait the heel, touches the ground. The loading response (LR) starts with the IC and ends with the contralateral toe-off. Subsequently, the mid stance (MS) lasts until the heel-off of the reference leg. The MS is followed by the terminal stance (TS), which ends with the contralateral IC. The ST phase terminates with the pre-swing (PS), which ends with the toe-off of the reference leg. Considering the SW phase, the initial swing follows the PS and terminates when the ankle joint of the reference leg crosses the supporting leg. This phase is followed by the mid swing, which ends with the tibia of the reference leg being vertical to the ground. The gait cycle is concluded by the terminal swing, which ends with the initial contact of the reference leg.

There are several devices and methods to detect the aforementioned events [7]. Due to its practicality, wearable devices become more popular for providing people the possibility to measure bodily features constantly. Therefore, the request for such technology, which measures gait characteristics either for activity recognition or for gait event classification, has risen lately. The most cost-effective method uses either whole inertial measurement units (IMUs) consisting of gyroscopes, accelerometers, and magnetometers or parts of it to determine kinematic data [8]. The attempt of miniaturizing and mobilizing sensor technology [9] showed encouraging results [8]. These systems are used

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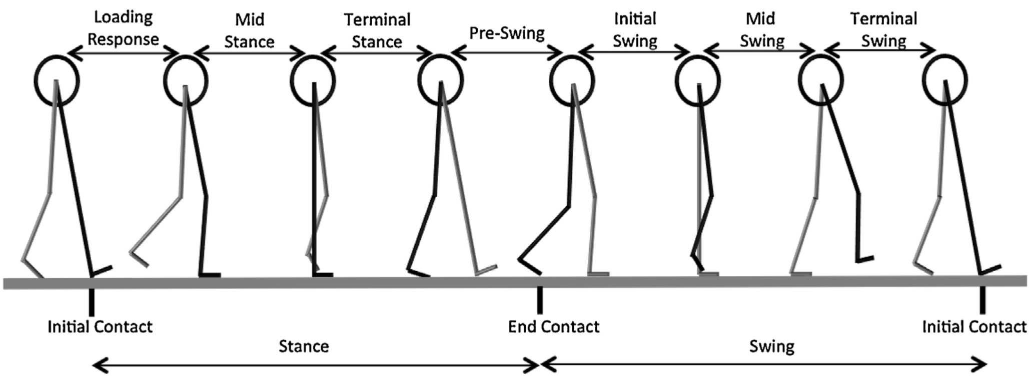

Fig. 1. Different nomenclatures for the gait phases is used in the literature. The terms of the RLAS are used in this review and displayed here.

to measure different kinds of kinematic gait data for diverse applications: functional electrical stimulation (FES) [9–11], gait initiation and termination [12], abnormal gait detection [13–18] and real-time applications [19–23].

In addition to the simultaneous acquisition of information from different joints involved in the movement pattern, the system must be able to deal with the complexity of processing such data in short time. In this context, artificial intelligence (AI), also called adaptive, algorithms have been applied to evaluate gait data, which was acquired either based on optoelectronic systems or inertial sensors [2,24]. Such algorithms are able to adapt their decision-making process based on the input data, despite its variability. Most importantly, adaptive algorithms can simplify the walking evaluation.

Our overarching goal in this article is to summarize those studies that applied adaptive algorithms to gait analysis based on inertial sensors data, to verify whether these algorithms are able to support the evaluation of different kinematic gait parameters. Therefore, the accuracy in determining gait phases, spatiotemporal features and joint angles of former published studies is stated and compared. Furthermore, by systematically reviewing the literature, we intend to proof the following hypotheses: (i) IMU systems are able to acquire gait kinematic parameters such as walking phases, spatiotemporal features and joint angles; (ii) adaptive algorithms can accurately classify gait events; (iii) the classification performed by the AI algorithms is relevant to the clinical practice.

2. Methods

2.1. Study identification and selection

A systematic literature search was conducted to find related works to the research hypotheses posed here. The review process was divided into four phases as shown in Fig. 2. As this review is related to engineering and medicine, an automated search in the main databases available, namely, Web of Science, ScienceDirect, IEEE, PubMed/MEDLINE, SCOPUS, CINAHL and Cochrane Library was undertaken to identify relevant publications. The search terms used were defined as *(gait OR walking OR locomotion) AND (analysis OR evaluation OR assessment) AND (inertial sensor OR inertial measurement unit (IMU) OR accelerometer OR gyroscope OR smart phone) AND (artificial intelligence OR machine learning OR adaptive algorithm OR intelligent algorithm)*. Publications in English, German, Portuguese and Spanish were considered. The publication period investigated was from 1968 to October 2016. Studies evaluating kinematic gait parameters – joint angles, gait phases or spatiotemporal features – of healthy or impaired subjects were only included if they used artificial intelligence for processing data which was acquired using inertial measurement units, accelerometers or gyroscopes. In the second phase, titles and abstracts were screened and publications, which did not meet the aforementioned criteria, were excluded. In the third phase, the full texts of the remaining publications were assessed and those that were ineligible, for not covering the set criteria, were excluded. In the fourth phase, all remaining publications were evaluated and the references checked for further publications, which could be included in this review.

2.2. Type of studies

Journal papers comparing the results using inertial sensors and artificial intelligences to any kind of generally accepted measurement system are the basis of this review. Book chapters, review papers and conference proceedings were excluded. Furthermore, studies which did not use IMUs exclusively or which used algorithms that could not be considered adaptive were excluded.

2.3. Data extraction

Two independent researchers performed the data extraction and the results were compared afterwards. Disagreements were discussed and solved in light of strict observance of the set criteria. In exceptional cases they disagree, a third researcher was consulted. Considering the methodological quality, the two reviewers focused on the following topics: sample; description of the study; type of sensor; sensor placement on the body; generally accepted measurement system used.

2.4. Quality assessment

The quality assessment of the included studies was divided into two different topics. Using the Critical Appraisal Skills Program (CASP) for Diagnostic Test Studies [25], the quality of data acquisition of the studies was individually assessed. To assess the quality of the adaptive algorithm used, the questionnaire developed by Wen et al. [26] was adopted. Both questionnaires comprise ten questions and each question has only three optional answers: “Yes”, “No” and “Partly”, in case there was not enough information. These three answers are scored as follows: “Yes” = 1.0, “Partly” = 0.5, and “No” = 0.0. As this review combines the fields of medicine and engineering, both quality assessment tools are not used as exclusion criteria, but as possibilities to objectively compare the different publications considering the relevant aspects of the topics examined.

3. Results

This section was divided into three parts. The first subsection deals with the results gathered from the CASP and the second subsection provides information about the analysis and rating of the adaptive algorithms used. The third one summarizes the gait parameters evaluated in the different studies and provides information about the sensor placement, sensor type, and measurement accuracy. The literature search yielded 22 journal papers that met the inclusion criteria (Fig. 2).

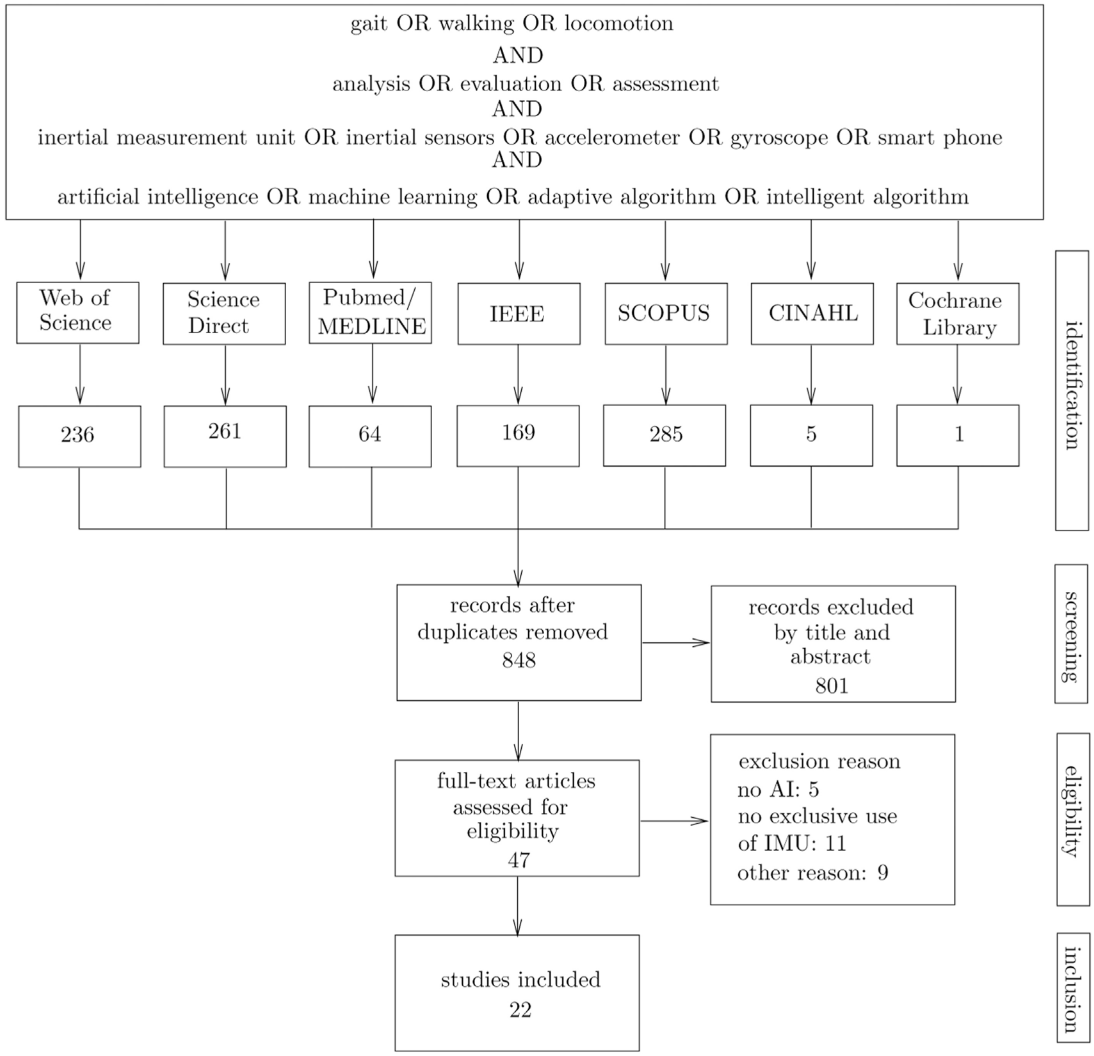

Fig. 2. Scheme of the four phases of the literature search process.

3.1. CASP quality assessment

The methodological quality, regarding the data acquisition by inertial sensors, was rated using the CASP (Table 1). There were no irresolvable disagreements between the researchers. The studies included in this review shared common threats to validity as most of them score negatively in the same areas. Most studies do not provide likelihood ratios and did not blind the evaluation. Thirteen of 22 papers were rated under 70%, the mean score was 6.1 ± 1.62.

Seven studies compared the measurement of inertial sensors to optoelectronic systems, such as Vicon, Qualisys, Motion Analysis or OptoTrack, which is considered the gold standard for gait analysis [15,16,20,27–30]. Force plates were used in eight studies as comparison method [10,11,15,19,21,23,31,32]. Additionally, infrared systems [14], functional assessment [17], counted number of steps [33], and stopwatch time linked to foot prints [18,22,34,35] were used to compare gait patterns. In ten studies a detailed description of the sample was absent [20–22,27–31,34,35] and, besides in Dobkin et al. [18], all research groups failed to blind the evaluation.

All studies, besides Guenterberg et al. [34], Rueterbories et al. [10] and Williamson and Anderson [11], reported their experimental methods clearly. The calculation of likelihood ratios and reproducibility were missing in all studies except for four [15,17,19,21]. Eight of the 22 selected studies scored five or less than five [11,16,18,22,23,31,33,34]. Thus, their conclusions must be considered with some caution, especially because of missing neutrality in reporting results.

The sampling rate used to acquire motion data ranged from 22 to 320 Hz, 100 Hz was used in nine of the 22 studies [11,14,17,20,23,27–29,35]. Two studies did not state this rate [30,31]. The sensor size ranged from 20 mm × 15 mm × 7 mm for the smallest sensor to 78 mm × 37 mm × 10 mm for the largest one. All sensors are portable, either wireless or with wire attachment. However, the sensor's weight is a relevant consideration depending on the anatomical region investigated, since the sensors' placement may influence movement patterns. Sensors' weight varied from 30 g, a commercial device [19], to 125 g, a self-developed system [22].

3.2. AI quality assessment

We used the second questionnaire (Table 2) to evaluate the adaptive algorithms quantitatively. The results are displayed in Table 3. Compared to the rating of the methodological quality (Table 1), the rating of the adaptive algorithms is higher, with a mean score of 8.2 ± 1.84.

All studies, besides Dobkin et al. [18], adequately presented the research goals as well as the estimation context the algorithms were applied to. However, seven studies did not define their methods precisely [11,18,22,23,27,31,33], which compromises the understandability of the experimental design and, consequently, the possibility to indicate whether their designs are appropriate.

The experimental data sets are used to verify the accuracy of the

Table 1
CASP methodological quality assessment of studies. (1) Gold standard; (2) description of the sample; (3) description of the experiment; (4) evaluation blinded; (5) neutrality in the results; (6) likelihood ratios; (7) accuracy of the results; (8) reproducibility of the test; (9) validity of the test; (10) influence of the results.

Authors	1	2	3	4	5	6	7	8	9	10	Score
Aung et al. [27]	1.0	0.5	1.0	0.0	1.0	0.0	1.0	0.0	1.0	1.0	6.5
Bejarano et al. [19]	0.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	8.0
Chalmers et al. [16]	1.0	1.0	1.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	5.0
Dobkin et al. [18]	0.0	1.0	1.0	1.0	0.0	0.0	1.0	0.0	1.0	0.0	5.0
Findlow et al. [28]	1.0	0.5	1.0	0.0	1.0	0.0	1.0	1.0	1.0	1.0	7.5
Gonzalez et al. [23]	0.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	5.0
Goulermas et al. [30]	1.0	0.5	1.0	0.0	1.0	0.0	1.0	1.0	1.0	1.0	7.5
Guenterberg et al. [34]	0.0	0.5	0.5	0.0	1.0	1.0	1.0	0.0	0.0	0.0	4.0
López-Nava et al. [32]	0.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	1.0	1.0	6.0
Mannini et al. [29]	1.0	0.5	1.0	0.0	1.0	1.0	1.0	0.0	1.0	1.0	7.5
Mannini et al. [20]	1.0	0.5	1.0	0.0	1.0	1.0	1.0	0.0	1.0	1.0	6.5
Mannini(a) et al. [35]	0.0	0.5	1.0	0.0	1.0	0.0	1.0	0.0	1.0	1.0	5.5
Mannini et al. [13]	0.0	1.0	1.0	0.0	1.0	0.0	1.0	1.0	1.0	1.0	7.0
Mijailović et al. [31]	0.0	0.5	1.0	0.0	0.0	0.0	1.0	0.0	1.0	0.0	3.5
Rueterbories et al. [10]	0.0	1.0	0.5	0.0	1.0	1.0	1.0	0.0	1.0	1.0	6.5
Samà et al. [22]	0.0	0.5	1.0	0.0	1.0	0.0	1.0	0.0	1.0	0.0	4.5
Santhiranayagam et al. [14]	0.0	1.0	1.0	0.0	1.0	0.0	1.0	1.0	1.0	1.0	7.0
Taborri et al. [21]	0.0	0.5	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	7.5
Williamson et al. [11]	0.0	1.0	0.5	0.0	0.0	0.0	1.0	0.0	1.0	0.0	3.5
Yang et al. [17]	0.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	8.0
Yuwono et al. [33]	0.0	1.0	1.0	0.0	1.0	0.0	1.0	0.0	0.0	0.0	4.0
Zhang et al. [15]	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	9.0

Table 2
AI methodological quality assessment of studies – questions.

N°	Question
Q1	Are the aims of the research clearly defined?
Q2	Is the estimation context adequately described?
Q3	Are the estimation methods well defined and deliberate?
Q4	Is the experimental design appropriate and justifiable?
Q5	Is the experiment applied on sufficient project data sets?
Q6	Is the estimation accuracy measured and reported?
Q7	Is the proposed estimation method compared with other methods?
Q8	Are the findings of the study clearly stated and supported by reporting results?
Q9	Are the limitations of the study analyzed explicitly?
Q10	Does the study add value to academia or clinical community?

adaptive algorithms. Most of the studies employed more than one set to perform the tests but seven works used one database only [11,21,29,31,33,35]. Therefore, their accuracy is limited and they were not fully rated for this question. Excluding Dobkin et al. [18], all studies measured and stated the performance of the algorithms. Ten studies report cross-validation coefficients and seven of these used the Leave-One-Subject-Out (LOSO) method to validate the estimation of the algorithms [13,14,20,21,27,29,35].

In order to decide on the relevance of the studies for enhancing the state-of-art, we analyzed if the results were clearly stated and the limitations of the studies were explicitly explored. Additionally, it was analyzed if the researchers compared their results to other techniques. Nine studies did not compare their results to any other algorithm [10,13,14,18,23,28,31–33]. Ten of 13, which applied more than one algorithm, performed statistical tests to validate their results [15–17,19–21,29,30,34,35]. We also found that five of the included studies [11,16,18,31,33] did not provide additional value to academia or to the clinical community, thus their conclusions also should be

Table 3
AI methodological quality assessment of studies.

Authors	Q1	Q2	Q3	Q4	Q5	Q6	Q7	Q8	Q9	Q10	Score
Aung et al. [27]	1.0	1.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	9.0
Bejarano et al. [19]	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	10.0
Chalmers et al. [16]	1.0	1.0	1.0	0.0	1.0	1.0	1.0	0.0	1.0	0.0	7.0
Dobkin et al. [18]	1.0	0.0	0.0	0.0	1.0	0.0	0.0	0.0	1.0	0.0	3.0
Findlow et al. [28]	1.0	1.0	1.0	1.0	0.5	1.0	0.0	1.0	1.0	1.0	8.5
Gonzalez et al. [23]	1.0	1.0	0.0	1.0	1.0	1.0	0.0	1.0	0.0	1.0	7.0
Goulermas et al. [30]	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	10.0
Guenterberg et al. [34]	1.0	1.0	1.0	0.0	1.0	1.0	1.0	1.0	0.0	1.0	8.0
López-Nava et al. [32]	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	9.0
Mannini et al. [29]	1.0	1.0	1.0	1.0	0.5	1.0	1.0	1.0	1.0	1.0	9.5
Mannini et al. [20]	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	9.0
Mannini(a) et al. [35]	1.0	1.0	1.0	1.0	0.5	1.0	1.0	1.0	0.0	1.0	8.5
Mannini et al. [13]	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	9.0
Mijailović et al. [31]	1.0	1.0	0.0	1.0	0.5	1.0	0.0	0.0	0.0	0.0	4.5
Rueterbories et al. [10]	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	9.0
Samà et al. [22]	1.0	1.0	0.0	0.0	1.0	1.0	1.0	1.0	1.0	1.0	8.0
Santhiranayagam et al. [14]	1.0	1.0	1.0	1.0	1.0	1.0	0.0	1.0	1.0	1.0	9.0
Taborri et al. [21]	1.0	1.0	1.0	1.0	0.5	1.0	1.0	1.0	1.0	1.0	9.5
Williamson et al. [11]	1.0	1.0	0.0	0.0	0.5	1.0	1.0	1.0	0.0	0.0	5.5
Yang et al. [17]	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	10.0
Yuwono et al. [33]	1.0	1.0	0.0	1.0	0.5	1.0	0.0	1.0	1.0	0.0	6.5
Zhang et al. [15]	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	1.0	10.0

analyzed with caution due to failure in the aforementioned categories.

In summary, there is no standard method to report the application and performance of adaptive algorithms. Due to this lack in standardization, the comparability of results from different studies is difficult.

3.3. Measurement of gait parameters

The examined studies are divided into groups according to their topic: determining (i) joint angles [16,28,30], (ii) gait phases [10,11,19–21,23,27,29,31,33,34] and (iii) spatiotemporal parameters [14,18,20,22,32,33,35]. Other three studies were discussed (iv), whose primary outcomes are not gait parameters in particular, but which use AI algorithms for clustering subjects into different groups based on their gait characteristics [13,15,17].

- *(i) Joint angles.* Different joint angles were determined by Chalmers et al., Goulermas et al. and Findlow et al. [16,28,30]. Chalmers et al. focused on the ankle angle, using a triaxial accelerometer placed on the dorsal part of one shoe. They were able to achieve an RMS error of 4.9° in normal walking and 6.5° in a walk containing toe walking with fuzzy c-means clustering. Goulermas et al. and Findlow et al. measured ankle, knee and hip angles with IMUs placed on the foot and shank. Using a general regression neural network (GRNN), both studies achieved high intrasubject predictions, but lower inter-subject predictions compared to an optoelectronic measurement system.

  AI algorithms are rarely used to evaluate joint angles. Three studies were found, but two of them [28,30] belong to one research group. Their algorithm showed a good possibility of measuring joint angles even for inter-subject predictions.
- *(ii) Gait events.* The number of correctly classified gait events as well as the detection delay was stated in different studies. Especially for real-time applications, the detection delay is important. While some

Table 4
Gait phases detection, (IC) initial contact; (LR) loading response; (MS) mid stance; (TS) terminal stance; (PS) pre-swing; (EC) end contact; (SW) swing.

Authors	IC	LR	MS	TS	PS	EC	SW
Aung et al. [27]	X					X	
Bejarano et al. [19]	X					X	
González et al. [23]	X					X	
Mijailović et al. [31]	X					X	
Yuwono et al. [33]	X					X	
Guenterberg et al. [34]	X		X			X	X
Mannini et al. [29]	X	X		X		X	
Mannini et al. [20]	X	X		X		X	
Rueterbories et al. [10]		X	X		X		X
Taborri et al. [21]	X	X		X		X	
Williamson et al. [11]		X	X	X	X		X

research groups determined the most common gait events, initial and end contact [19,23,27,31,33], others focused on additional events [10,11,20,21,29,34] (Table 4).

Yuwono et al. [33] used a waist-worn IMU and a Bayes filter to evaluate IC. They showed, that the IC could be determined using gyroscopic data only with an accuracy of about 90% while using additional acceleration data can improve this result to more than 97%. Mijailović et al. [31] developed an artificial neural network to determine IC and EC using six accelerometers placed along the legs. The relative error for event detection was 11% for intrasubject estimation and 14% for inter-subject estimation. Using a Gaussian mixture model, Aung et al. [27] dealt with the detection of IC and EC during inclining and declining gait as well as walking on different terrains with accelerometers placed on feet and ankles. They achieved detection accuracy for all conditions larger than 90%. The sensor on the foot showed a slightly better performance.

With an accelerometer placed close to the L3 vertebra, González et al. [23] evaluated IC and EC in real-time. The proposed algorithm was able to detect all gait events with a mean detection delay of 117 ms for the initial contact and 34 ms for the end contact. Bejarano et al. [19] tested a real-time state machine algorithm on healthy subjects at three different continuous walking speeds, changing walking speeds, and on stroke patients with IMUs placed at the subjects' shanks. All ICs and ECs were detected in healthy walking, for patients with severe disabilities it was decreased to 99.3% for IC and 87% for EC. The detection delay was increased from 13.66 ms to up to 52.37 ms.

Williamson and Anderson [11] used a uniaxial accelerometer placed on the shank to determine different gait events (Table 4) with the help of two different supervised machine learning algorithms. The detection of TS proofed to be most difficult while LR and SW showed the best results. Rueterbories et al. [10] investigated different gait events (Table 4) in healthy and hemiparetic subjects with accelerometers placed on the foot using a state machine algorithm. A high accuracy could be shown for the healthy subjects while the detection accuracy for the hemiparetic subjects was heavily reduced. Additionally, the detection delay increased for the hemiparetic subjects.

Mannini et al. [20] developed a real-time algorithm based on a hidden Markov model (HMM) to determine gait events using a foot-mounted gyroscope. They achieved a detection accuracy of 100% and a mean detection delay of less than 43 ms. For IC and EC the detection delay was even reduced. Earlier, Mannini and Sabatini [29] achieved slightly worse results using another HMM. Guenterberg et al. [34] used a HMM to classify gait events with the help of eight IMUs placed on the arm, forearm, thigh and ankle to investigate which sensor position and type offers the highest accuracy. They found the sensor placed on the thigh and using all sensors of the IMU to lead to the best result. Taborri et al. [21] also used a real-time algorithm based on a HMM to process data from triaxial gyroscopes placed on feet, shanks and thighs to investigate the best sensor position. They found the sensor on the foot to give the best results when using a single sensor. Using more than one sensor the accuracy could be improved. The mean detection delay for all gait phases was shorter than 60 ms.

Sensor type and placement varied between the research groups. Some groups used single accelerometers [10,11,23,27,31] or gyroscopes [20,21,29] other groups used complete IMUs consisting of accelerometers, gyroscopes and magnetometers [19,33,34]. The choice of sensor neither showed a correlation to the parameters evaluated nor to the application. The detection accuracy for IMU and gyroscope based algorithms was higher than for algorithms based on accelerometers only. Most commonly, sensors were placed on the lower extremities. Taborri et al. [21] found the best placement for a gyroscope only to be on the foot while Bejarano et al. [19] reached the same accuracy with an IMU placed on the shank. Although there is no standard for sensor placement, the most commonly used sensor positions, independent of the type of sensor used, are foot and shank [10,11,20,27,29], leading to the highest detection accuracy and the shortest detection delay. Guenterberg et al. [34] also achieved an accuracy of 100% using an IMU mounted on the thigh, but Mijailović et al. [31], who placed three accelerometers along the leg, only achieved an accuracy of less than 90%. Both studies did not evaluate the detection delay.

Sensors placed on the waist [23,33] were only used for evaluating both IC and EC. One algorithm [23] was able to detect all IC and EC gait events, but showed a comparatively long detection delay. Yuwono et al. [33] only published information on the accuracy of detecting EC and no further statistical values. Only Rueterbories et al.[10] and Bejarano et al.[19] tested their algorithms on non-healthy subjects, namely hemiparetic or post-stroke patients. Both algorithms showed clearly decreased detection accuracy and an increased detection delay, depending on the severity of the injury. However, the system of Bejarano et al. outperforms the accelerometer-based one of Rueterbories et al.

- *(iii) Spatiotemporal parameters.* Table 5 displays an overview of the spatiotemporal parameters most commonly measured. Besides classifying the different gait phases, Mannini et al. [20] compared over-ground and treadmill walking. Although they could not produce reference data, the trend shows no difference for the evaluated parameters (Table 5). In another study [35], they used the same parameters to compare the performance of two different algorithms for the determination of gait velocity and walking distance in healthy people and stroke patients using foot-mounted IMUs. For three different self-selected walking speeds the proposed algorithms' estimation accuracy was between 91% and 96%. Dobkin et al. [18] estimated the outdoor walking speed also of post-stroke patients,

Table 5
Spatio-temporal parameters.

Authors	Stride Time	Step time	Stance time	Gait velocity	Cadence	Stride symmetry
Dobkin et al. (2011)				X		
López-Nava et al. [32]	X	X	X		X	
Mannini et al. (2014)	X		X		X	
Mannini(a) et al. (2014)				X		
Yuwono et al. (2014)					X	X

using a triaxial accelerometer placed on the shank. The correlation coefficient with the stopwatch-time was 0.98 (p = 0.001). Both, Mannini and Sabatini [35] and Dobkin et al. [18], achieved high estimation accuracies and correlations compared to alternative measurement systems although they used diversified sensor types and placements.

Yuwono et al. [33] deduced cadence and stride symmetry from the IC, which they determined to get further information about temporal gait parameters.

López-Nava et al. [32] measured temporal gait parameters of young and older healthy adults with a triaxial accelerometer placed on the ankle. With a Bayesian model, they determined the parameters displayed in Table 5, as well as IC, EC, number of strides, number of steps and swing time. IC, EC and the number of steps and strides could be estimated with an accuracy of 100%. Only for stance and swing phase time the relative estimation error was higher than 5%. Compared to a force plate system (GaitRite), the weakest correlation was found for the swing phase time with 74%. Additionally, they classified single support and double support time. Samà et al. [22] estimated step length and gait velocity from a single waist worn IMU. The relative velocity error was 15.3% for one kernel and 21.3% for the other kernel, the length error was 18.6% and 22.2%, respectively. Santhiranayagam et al. [14] estimated the minimum toe clearance of healthy young and older subjects using a foot-mounted IMU. This gait parameter describes the minimum height of the toe during mid swing and is used as a predictor for fall risks. Using a GRNN they achieved an RMSE of 7 mm, which was within one standard deviation of the group mean.

- *(iv) Other approaches.* Mannini et al. [13] used a HMM and a support vector machine (SVM) to classify different pathological gaits by IMUs placed on the shank. Therefore, they detected IC and EC from post-stroke patients, Huntington's disease patients and healthy subjects. They achieved an overall classification accuracy of 90.5%. All misclassification occurred between the two different impaired populations. Zhang et al. [15] used a SVM to classify fatigue and non-fatigue gait of healthy subjects. The IMUs were placed at the right shank and the sternum. The parameters measured were step length and width, heel contact velocity and single stance time. The intrasubject classification accuracy was 97%, the inter-subject classification accuracy was 90%. Yang et al. [17] clustered complex regional pain syndrome patients and healthy subjects into groups. They investigated amongst others the parameters step time and cadence with an accelerometer placed at the lower back. They compared the performance of five supervised machine learning methods and achieved classification accuracy up to 99.38%.

4. Discussion

The purpose of this systematic review is to verify whether adaptive algorithms can support gait analysis based on inertial sensors data. Quality assessment is originally used as the basis for weighting quantitative data in a meta-analysis, which is an important data synthesis strategy [26]. However, the retrieved data in this review was produced by diversified experimental designs, which leads to distinct data. A meta-analysis, therefore, would be inappropriate. For this reason, we did not use the quality assessment results to weight the retrieved data, but only to guide the interpretation of review findings and to indicate the strength of inferences.

Although the evaluation of joint angles shows good results, there is only a limited amount of studies that deal with these variables. One of those, Chalmers et al. [16], is rated below average in both quality assessment tools. Therefore, it needs to be considered with reservation. Hence, only results of one research group are available and no further conclusions can be made.

Using IMUs and gyroscopes placed on the foot and shank, the best results could be achieved. Guenterberg et al. [34] and Mijailović [31] found the thigh to be the best for sensor placement, but both studies are low rated in methodological quality assessment. The same problem exists for the results of Dobkin et al. [18]. They need to be considered with reservation due to its rating on the CASP and on the AI quality assessment. Unfortunately, no research group that determined spatio-temporal parameters stated likelihood ratios or values for reproducibility [18,22,32,33,35]. Additionally, one study showed a lack of validity [33]. For these reasons, it is impossible to compare the results reasonably.

Regarding the clustering of different gaits into groups [13,15,17], the results prove the capability of adaptive algorithms in this field since most of the studies show an above-average rating in experimental quality and AI assessment. Among the adaptive methods, artificial neural networks (ANN) [11,14,17,28,31,34] and hidden Markov models (HMM) [13,20,21,29,33,35] were more often applied in the included papers. Six studies applied each technique with equivalent qualities, according to our assessment. Nonetheless, a single group performed four of six publications with HMM, what indicates that ANN is the most disseminated method for performing this kind of clustering.

In general, the outcomes of this systematic review show an extensive lack of standardization in reporting methodology and especially results of evaluation undertaken using adaptive algorithms. There is only a limited amount of studies in this field, especially the performance of adaptive algorithms on the determination of joint angles needs to be evaluated due to the encouraging results of the discussed papers. Gait phase discrimination can be done using different adaptive algorithms. The evaluation of IC and EC is most commonly done and also applied to real-time applications. Therefore, the first step towards feedback systems is made.

5. Conclusions

After screening the literature, we realized that some of the included studies failed to report expected information in diagnostic test studies and did not cater for some indispensable methodological procedures. Even though, we found that inertial measurement units could acquire the kinematic features of the human gait, considering the high-rated papers. Especially, gait events such as initial and end contact can be recognized reliably.

Nonetheless, there is a lack of standardization to perform such evaluation, as well as to report the results. The current review revealed encouraging results regarding the application of adaptive algorithms on IMU-based data to support the gait analysis. Such methods provide easily understandable data representations for healthcare professionals, even who are not used to such approach.

Due to these reasons, the application of IMUs analyzed in this paper has a great unexplored potential to support physicians. We highlight the application in real time when this evaluation becomes such a valuable tool that works as feedback during the treatment. Thereby, it could also help in rehabilitation, providing information either to patients or to healthcare professionals.

In summary, the research papers retrieved in this systematic review suggest that the adaptive algorithms are able to support gait analysis based on inertial sensor data. Since most of the studies evaluated healthy subjects, further research is necessary to enhance the application in patients, providing standardization for the method. Obviously, a more thorough investigation should be carried out prior using Inertial Sensors and Adaptive Algorithms as a clinical tool.

Conflict of interest

We hereby certify that there is no conflict of interest, and that this paper content has not been published or submitted elsewhere.

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