

A scoping review about recognition of health conditions using inertial sensor signals

Uma revisão de escopo sobre reconhecimento de condições de saúde usando sinais de sensores inerciais

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Resumo: Esta revisão de escopo mapeou estudos acerca da identificação de condições de saúde por meio de sinais de marcha extraídos de sensores inerciais. Os estudos incluídos deveriam identificar condições de saúde usando sinais de sensores inerciais, disponíveis em português, espanhol ou inglês, de 2010 a 2023. A busca foi realizada nas bases de dados IEEE Xplore, PubMed, Scopus, Web of Science e Lilacs, além de busca na literatura cinzenta. Os dados foram analisados de forma descritiva e através da análise de conteúdo de Bardin. Foram incluídos 220 estudos. As principais condições de saúde identificadas usando sinais de marcha de sensores inerciais foram a Doença de Parkinson e a Esclerose Múltipla. Os dados foram capturados principalmente usando um sensor durante um percurso estimado e testes funcionais. Os principais sensores utilizados para capturar características de marcha e movimento foram acelerômetro, giroscópio e magnetômetro. Cerca de metade dos estudos (52,07%) usaram aprendizado de máquina. Os métodos e variáveis diferem bastante, e muitos carecem de descrições claras de precisão. Esta revisão identificou várias condições de saúde que podem ser identificadas por sinais de marcha de sensores inerciais, podendo promover o diagnóstico precoce, prevenindo seu aparecimento e progressão.

Palavras-chave: Sensor inercial. Condição de saúde. Marcha. Detecção precoce. Envelhecimento saudável.

Abstract: This scoping review mapped studies on the identification of health conditions through gait signals extracted from inertial sensors. Studies included should identify health conditions using inertial sensor signals, be available in Portuguese, Spanish or English from 2010 until 2023. The search was performed in the databases IEEE Xplore, PubMed, Scopus, Web of Science and Lilacs, in addition to gray literature search. Data were analyzed descriptively and through Bardin content analysis. 220 studies were included. The main health conditions identified using gait signals from inertial sensors were Parkinson's Disease and Multiple Sclerosis. Data were captured mainly using a sensor during an estimated path and functional tests. The main sensors used to capture gait and movement features were accelerometer, gyroscope, and magnetometer. About half of the studies (52.07%) used machine learning. The methods and variables differ greatly, and many lack clear accuracy descriptions. This review identified several health conditions that can be identified by gait signals from inertial sensors, which can promote early diagnosis, preventing its onset and progression.

Keywords: Inertial Sensor. Health Condition. Gait. Early Detection. Health Aging.

Introduction

According to the International Classification of Functioning, Disability and Health (ICF), "health conditions" describe diseases, disorders, injuries or traumas (WHO, 2001). Chronic

health conditions affect the older population include circulatory issues, neoplasms, diabetes, respiratory problems, musculoskeletal issues, postural instability, and falls (Moraes *et al.*, 2019; IBGE, 2020). Gait changes related to these conditions are widely studied, particularly

concerning postural instability, falls diabetes, and Parkinson's Disease (Lin *et al.*, 2019; Guedes *et al.*, 2019).

Gait evaluation is commonly done through observation, which is low-cost but subjective and unreliable. Technological instruments like inertial sensors have been developed for a more rigorous analysis. These sensors are low-cost, easy to use, and highly sensitive for detecting body position and orientation (Ghislieri *et al.*, 2019; Oliveira, 2022). They are increasingly used to assess various health conditions (Yang *et al.*, 2019).

Inertial sensors help identify health conditions such as Parkinson's Disease, multiple sclerosis, fatigue, balance changes, lumbar and lower limb movements, postural control, falls, breathing patterns, and cardiovascular monitoring (Baker; Gough; Gordon, 2021; Ibrahim *et al.*, 2022; Ullrich *et al.*, 2022). However, there are no guidelines or databases consolidating this information. A literature review can map the main inertial sensors and methods associated with identifying these conditions for both scientific and clinical use.

A preliminary search on Pubmed and Google Scholar found three relevant studies (Ghislieri *et al.*, 2019; Ponciano *et al.*, 2020; Acosta-Vargas *et al.*, 2023). These studies differ in focus, methodology, and language scope from the present review, which includes studies in English, Portuguese, and Spanish. This review is the first to verify health conditions identified by gait and movement signals from inertial sensors and the methodologies used in this process.

Thus, it is essential to review existing studies to identify or assist in the treatment of these conditions through signals from inertial sensors. Given the broad objective, a scoping review was conducted to map studies on identifying health conditions through gait and movement signals from inertial sensors.

Materials and methods

A scoping review was performed as per the recommendations of the Joanna Briggs Institute review manual (Peters *et al.*, 2020), following the PRISMA extension for scoping reviews (Tricco *et al.*, 2018). The review was registered in the Open Science Framework (DOI: 10.17605/OSF.IO/XDZT3). The research questions were: (RQ1) Which health conditions are identified through gait and movement signals extracted from inertial sensors, (RQ2) Which inertial sensors are used to identify or recognize health conditions, and (RQ3) How are inertial sensors used to identify or recognize health conditions.

The eligibility criteria were to have used inertial sensors and have identified a health condition. The criteria for inclusion in the studies were to identify health conditions through gait and movement signals extracted from inertial sensors and to have individuals over 18 years of age as participants in the study. Technical reports, policy documents, and articles whose full-text copies could not be obtained after attempts

to contact the authors were excluded. Regarding gait, the studies that were included contained one of the following terms: locomotion, walking, balance, or postural control. The included studies had data from any type of inertial sensors, such as accelerometers, gyroscopes, and magnetometers.

A search was performed on Pubmed and Google Scholar, to verify descriptors and terms about this review. From this search, the following descriptors were defined: inertial sensors, health conditions, gait, and signal processing, in addition to their related terms. All these descriptors and related terms are present in the search strategies, which were investigated in titles, abstracts, or keywords, in English, Portuguese, or Spanish. The search strategy was adapted according to the databases, with the addition of MESH terms and Boolean operators when necessary. The search strategy for the Scopus database is described below.

Search strategy: TITLE-ABS-KEY("inertial sensors" OR "inertial sensor" OR acceleromet* OR gyroscope OR magnetometer OR wearable) AND TITLE-ABS-KEY("health conditions" OR "health condition" OR "health problems" OR "health problem" OR disease* OR comorbidit* OR "chronic conditions" OR "chronic condition" OR "health disorders" OR "health outcomes") AND TITLE-ABS-KEY(locomotion OR walk OR gait OR balance OR "postural control") AND TITLE-ABS-KEY("signal processing" OR "features extraction" OR "machine learning" OR "automatic identification" OR recognition OR "gait analysis" OR screening).

The search was carried out in the databases IEEE Xplore, PubMed, Scopus, Web of Science and Lilacs, according to the determined search strategy. The titles of the articles were written in the same language to remove duplicates. As an additional strategy, a search was carried out in Google Scholar to also include gray literature (unpublished) studies, in which the first 150 studies were verified according to Google's relevance algorithm.

The selection of studies was carried out in five stages to identify the studies according to the defined search strategy. In the first step, all generated records were exported to the Microsoft Excel 2016 program, to remove duplicates. Three reviewers checked the titles of the studies found in the search in alphabetical order to verify that all duplicates were removed. The second step was to carry out a pilot test, in which two reviewers analyzed the titles and abstracts of 25 random studies found in the bibliographic search. Through this pilot test, it was possible to identify whether the established criteria were well-defined. The pilot test had 88% agreement among reviewers, so the selection continued.

In the third stage, all titles, abstracts, and keywords of the studies found in the database search were screened by two reviewers, independently, according to the eligibility criteria. In the fourth step, the two reviewers independently read the full texts of the studies that were selected in the previous step, so that the articles were included according to the inclusion criteria. In these two stages, disagreements were

resolved by a third reviewer.

The fifth step was the implementation of additional strategies, which consisted of searching the Google Scholar database in which the first 150 studies were verified according to Google's relevance algorithm. For this additional strategy, the same processes reported in the second and third steps were performed.

The data from the studies included in the scoping review were extracted into individual tables for each study. The extraction form was developed based on the recommendations of the JBI reviews manual (Peters *et al.*, 2020), in addition to other information that was also included. The form included study details (title, year, location, objective, methodology), sample characteristics (size, age, sex), inertial sensors used (type, sampling, body location), identified health conditions, gait and movement capture methods (e.g., functional tests, daily activities), and methods for recognizing or assessing health conditions. Two reviewers tested the extraction form in two studies to ensure that all relevant results were extracted.

Results were presented by listing studies numerically and discussing their data, including the number and main reasons for excluding studies, the number and general characteristics of included studies, study design, participant demographics, sensors used, identified health conditions, and methods for recognizing these conditions. The data were counted in the form of relative and absolute frequency, through tables and text. Bardin's content analysis was used to group the various variables into three categories.

Results

A total of 3,706 studies were identified (3,556 from databases and 150 from Google Scholar), of which 220 were included. Among the reasons for exclusion, the most prevalent were 1) not having identified any health condition; 2) not having identified any health condition through gait or movement signals extracted from inertial sensors; 3) being a literature review. Review studies, despite being included in the initial search, were excluded in the full-text phase because they did not present data related to the research questions of this study. Protocols were excluded because they did not show results. Four studies were excluded due to difficulties in accessing their full texts, despite attempts to contact authors. Supplemental File 1 presents the PRISMA flowchart (available in DOI 10.17605/OSF.IO/G8CHU).

The included studies were carried out in 37 different countries, the main ones being the United States (18.64%), China (10.90%), the United Kingdom (9.55%), Italy (9.09%), and Germany (7.27%). We observed a growth in the number of publications over the years and among the years of publication, the most prevalent were 2020, 2022, and 2018.

The most prevalent design is the cross-sectional one (80.90%). In addition, regarding the sample, 44.55% had between 2 and 50 research subjects, most studies were

composed of both female and male genders (80.00%), and approximately half of the studies had adults and older people in the sample (48.64%). Most studies did not report whether the sample was probabilistic or non-probabilistic.

About research question 1 (RQ1), 41 health conditions were identified in the studies, the most prevalent being Parkinson's Disease (50.91%) and Multiple Sclerosis (10.00%), followed by Alzheimer's (5.91%), Falls (4.55%), Huntington's disease (4.55%). We also noted that other conditions, to a lesser extent, such as Glaucoma, Chronic Obstructive Pulmonary Disease (COPD), Sarcopenia, Chronic Cough, and Osteopenia were identified. Some studies identified more than one health condition. All identified health conditions are described in Table 1. All authors, years of publication, titles and health conditions identified by the sensors of all included studies are described in Supplemental File 2 (available in DOI 10.17605/OSF.IO/G8CHU).

Tabela 1. Health conditions identified through gait signals extracted from inertial sensors in the included studies.

Health Condition	n	Health Condition	n	Health Condition	n
Parkinson's Disease	112	COP	3	Herniated disk	1
Multiple sclerosis	22	Peripheral neuropathy	2	LSS	1
Alzheimer	13	Schizophrenia	2	Glaucoma	1
Fall/Faller	10	Phlebopathy	2	Goarthritis	1
Huntington's disease	10	Vestibular pathologies	2	Atrial fibrillation	1
MCI	9	Rheumatoid arthritis	1	Parkin mutation	1
Frailty	8	Asthma	1	PSP	1
OA	8	Cancer	1	Flat foot	1
Stroke	7	HV	1	CRPS	1
Dementia	6	MMA	1	Chronic cough	1
Cognitive Decline	4	PAD	1	Sleep disorder	1
Ataxy	4	FD	1	BPPV	1
Chronic pain	4	Osteopenia	1	ALS	1
Sarcopenia	4	Backache	1		

Note: COP: Chronic obstructive pulmonary MCI: Mild cognitive impairment. OA: Osteoarthritis. HV: Hallux valgus. MMA: Myotonic muscular dystrophy. PAD: Peripheral Artery Disease. FD: Fabry disease. LSS: Lumbar spinal stenosis. PSP: Progressive Supranuclear Palsy (PSP). CRPS: Complex Regional Pain Syndrome. BPPV: Benign Paroxysmal Positional Vertigo. ALS: Amyotrophic lateral sclerosis. Source: Developed by the authors.

Regarding research questions 2 and 3 (RQ2 and RQ3), it was identified among the included studies that the main types of inertial sensors used were accelerometers (75.45%), gyroscopes (48.18%), and magnetometers (15.45%). Other inertial sensors have not had their types reported. Regarding the location of the body where the sensors were attached, according to the locations mentioned in the articles, the most

prevalent was the foot (29.55%), followed by the region of the vertebra (L3, L4, or L5) (15.91%), ankle (10.45%), shin (10.00%), thigh (10.00%), wrist (9.09%), and waist (8.64%). Other places appeared in smaller quantities of studies, such as the tibia and elbows (Chopra; Moerenhout; Crevoisier, 2015; Tîrnăucă *et al.*, 2022). In some studies, more than one type of sensor was used and in more than one location on the body. Regarding the sampling values, in Hertz, identified in the studies, most used inertial sensors at a frequency of 100 Hertz (Hz) (36.82%), followed by 101 to 150 Hz (16.82%) and 5 to 30 Hz (8.18%), with some studies not reporting the frequency used and some using more than one value.

Regarding the mode of gait capture, 58.18% of the included studies used paths (which consist of certain tasks proposed by the study researchers, involving walking a certain established distance, with or without obstacles), 33.18% used functional tests (such as Timed Up-and-Go - TUG, 6-Minute Walk Test - 6MWT and 10-MWT Walk Test - 10-mWT) and 12.73% activity of daily living (using the sensor in your home to perform your daily tasks). Some studies used more than one capture mode.

Several methods were used to analyze gait and movement variables extracted from inertial sensors, with most studies using machine learning methods (54.55%). The 96 studies that used statistical methods had a wide variety, the main ones being Analysis of Variance (ANOVA) (28.64%), T-student test (22.73%), Mann-Whitney U test (17.73%), Pearson's correlation test (14.55%), and Chi-Square test (14.09%). Among the 220 studies, about 41.36% presented accuracy data.

Among the 120 studies that used machine learning methods, the most used methods were Support Vector Machine (SVM) (47.50%), Regression (39.17%), Random Forest (35.83%), K-Fold Cross-validation (22.50%), K-Nearest Neighbor (KNN) (20.83%), Decision Tree (17.50%), Naive Bayes (14.17%). In the other item, several other methods used in a few studies are included, such as Deep convolutional neural network (DCNN) and Deep learning models that were not specified.

The variables used to screen health conditions add up to more than a thousand variations and types. Considering the inductive analysis, three categories emerged as the main results: 1) General Parameters, analysis of the main gait and movement components derived from sensor data, such as angle, speed, step, cadence, and length, among others. 2) Time-frequency features: time and frequency variables derived from raw accelerometry data and transformed into variables 3) Variability: variables derived from variance measures of the variables (Coefficient of variation (CV) of stride time, coefficient of variation in step time).

Discussion

A total of 220 studies identified health conditions using gait signals and movement extracted from inertial sensors, being the most used sensors were accelerometers, gyroscopes, and

magnetometers and the main attachment places of the body were feet, vertebra, ankle, and shin. Gait was verified mainly via paths established by the researchers and functional tests. The main health conditions identified were Parkinson's Disease, Multiple Sclerosis, Alzheimer's, Fallers, and Huntington's Disease, and the main data analysis methods used were statistical tests such as Analysis of Variance (ANOVA), T-student test, Mann-Whitney U test, Pearson's correlation test, and Chi-Square test, or machine learning methods, such as Support Vector Machine, Regression, Random Forest, and K-Fold Cross-validation.

Greater use of inertial sensors for early detection of health conditions is observed due to their ease of use. These sensors can be easily taken to the patients since they are small, inexpensive, and can be found in some equipment that is widely used in everyday life, such as smartphones and smartwatches. Furthermore, the sensors maintain patient privacy as they are less invasive than cameras, for example. Therefore, its use for the diagnosis of health conditions can be more advantageous compared to diagnostic equipment present in hospitals, since these are usually more expensive and more difficult to use (Haghi *et al.*, 2022).

Parkinson's disease and Multiple Sclerosis were the most frequently tracked health conditions in the studies identified. According to Ponciano *et al.* (2020), Parkinson's disease is the most reliably detectable condition through sensors such as accelerometers. Other conditions that were identified less frequently in our review were also identified only once by the author, such as lumbar radiculopathy, epilepsy disease, bipolar disorder, arrhythmia, and sleep apnea. The identification of falls/fallers was also identified as one of the most frequent, although well below the number of articles with Parkinson's disease. However, this condition is one of the most studied in the literature, due to its great association with human movement and human gait (38,39). The same is being seen with Frailty, where there has been increased interest in exploring how wearable sensors have been used to identify frailty (Vavasour *et al.*, 2021).

However, the use of inertial sensors despite being advantageous for analyzing some health conditions may not be advantageous for other conditions. The present review verified a study by Ma, Fallahzadeh and Ghasemzadeh (2016) that identified glaucoma through gait inertial sensors signals, however, there are equipment and tests that are more specific and adequate for the screening of this health condition, thus, the identification of this condition through inertial sensors may not be as suitable. We noticed, by the huge number of studies found and the growth in the number of publications over time, that there is a race in search of analyzing the data coming from these sensors for different health conditions. Despite the great contribution of these data coming from sensors, many conditions are multifactorial and multicausal, with little contribution from the gait movement itself, compared to other body structures and even the environmental context.

It was identified that the inertial sensors used in the included studies were used in different parts of the body, the main feet, vertebrae, ankle, and shin. A study by Madcor, Adel, and Gomaa (2021) that analyzed which body location sensors were used, which generated data from a gait pattern, found that movements in different parts of the body can be used in the treatment of different conditions. Thus, the great variability of the location on the body of the sensors identified in the studies of this review and the diversity of health conditions verified are justified. On the other hand, it is difficult to standardize a test without a clear fixation of the sensor in the place of the body for more confidence and accuracy, which could bring more reliable cutoff scores and aligned procedure models.

In relation to the features used to screen health conditions, three main categories were identified: General Parameters, such as angle, speed, step, cadence and length, among others; Time-frequency characteristics; Variability variables, such as stride time coefficient of variation (CV) and stride time coefficient of variation. This wide variety of features may be due to the fact that, according to Ruiz-Ruiz *et al.* (2021), the most significant parameters that discriminate groups of patients vary according to the condition studied. For frailty, the author identified that the most significant parameters are double support time, gait speed, stride time, stride time and number of steps/day or percentage of walking/day. As for falls, the significant parameters were those related to stability or trunk movements. Time-frequency variables have already been successfully explored in several works to identify fallers (Ponti *et al.*, 2017; Bet; Castro; Ponti, 2021).

It was observed that more than half of the analyzed studies used Machine Learning to analyze gait, with the most used algorithms being Support Vector Machine, Regression, Random Forest, and K-Fold Cross-validation. However, this type of technique and analysis depends on the quality of the characteristics collected, a large data set, and a high processing capacity to ensure its generalization (Ponciano *et al.*, 2020; Mello; Ponti, 2018). According to Ponciano *et al.* (2020), due to the complexity of this analysis, the authors prefer to use only simpler statistical methods, such as the comparison of variables, than to implement machine learning and artificial intelligence techniques in their studies.

To analyze gait and movement, it was identified that there are some capture modes most used, such as paths established by the researchers, functional tests, and activities of daily living. A study that compared the use of inertial sensors to analyze gait (Andrenacci *et al.*, 2021) used functional tests and paths to capture gait, as well as a study by Chen *et al.* (2019), who analyzed the participants' gait for seven days while they carried out their activities of daily living. It is then verified that these are the most used gait capture modes, however, using a path established by the researchers themselves ends up making it difficult to reproduce in future studies because it is not known, for sure,

which materials and methods were used to develop this path.

This scoping review is the first to map all health conditions identifiable through inertial sensor gait signals. Searches were conducted in five databases and the gray literature. Studies in English, Portuguese, and Spanish were included. Also, two reviewers independently evaluated all titles, abstracts, and full texts. A limitation was the inability to access four full papers despite three attempts to contact the authors, affecting their inclusion. Future studies should conduct a systematic review with meta-analysis to assess the quality of studies identifying health conditions through inertial sensors, as most do not detail their sampling methods.

Conclusion

The main health conditions identified through gait and movement signals extracted from inertial sensors were Parkinson's Disease and Multiple Sclerosis, and the main inertial sensors used were accelerometers, mainly placed on the feet while the research subjects performed a predetermined path through the researchers. It is possible to identify health conditions through gait and movement analysis using inertial sensors. This allows a possible screening and treatment of conditions at an early stage, being able to collaborate for health promotion and prevention through access to e-health.

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