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# A Brief Review on the Sensor Measurement Solutions for the Ten-Meter Walk Test

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**Abstract:** The wide-spread use of wearables and the adoption of the Internet of Things (IoT) paradigm provide an opportunity to use mobile-device sensors for medical applications. Sensors available in the commonly used devices may inspire innovative solutions for physiotherapy striving for accurate and early identification of various pathologies. An essential and reliable performance measure is the ten-meter walk test, which is employed to determine functional mobility, gait, and vestibular function. Sensor-based approaches can identify the various test phases and their segmented duration, among other parameters. The measurement parameter primarily used is related to the tests' duration, and after identifying patterns, a variety of physical treatments can be recommended. This paper reviews multiple studies focusing on automated measurements of the ten-meter walk test with different sensors. Most of the analyzed studies measure similar parameters as traditional methods, such as velocity, duration, and other involuntary and dangerous patients' movements after stroke. That provides an opportunity to measure different parameters that can be later fed into machine learning models for analyzing more complex patterns.

**Keywords:** ten-meter walk test; measurement; inertial sensors; physiotherapy; review

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## 1. Introduction

In recent years, mobile devices' evolution increased the hardware properties in terms of sensors, computing power, battery capacity, and improved software capabilities [1–3]. Mobile devices are being applied in non-traditional areas, such as medicine, physiotherapy, and informatics [4–7].

There are different life areas, e.g., high-performance sports areas, that use the sensed devices [8–12]. The medical subject also uses sensors that may increase the execution of different treatments and diagnoses [13–15]. These devices may improve the physiotherapy measurements by using the embedded sensors. Currently, physiotherapists are limited to using a stopwatch to measure the time that the various individuals took to do the different tests [16].

Creating different patterns with the sensors' signals allows the automatic measurement of various physical tests and other movements using low-cost sensors [17–19]. This data can also create different disease patterns for its automatic identification with artificial intelligence methods [20–22]. Various physical functional tests are commonly used in physical therapy, including the Timed-Up and Go test [22–27], the Heel-Rise test [28,29], the 30 s Chair Stand test [30,31], the Functional Reach test [32], etc.

This study aimed to review the various technologies that may help automate the ten-meter walk test measurement with mobile devices. The ten-meter walk test is in physiotherapy where the individual walks ten meters, and its typical duration in healthy individuals does not exceed 20 s [33,34]. This test is a performance measure used to assess walking speed in meters per second over a short distance. It can be employed to determine functional mobility, gait, and vestibular function.

This paper analyzed studies related to the ten-meter walk test measurement automation. As a result, we identified the sensors that can be used to improve the measurements, determine the extracted features, and analyze which methods are used to extract conclusions based on these parameters. After filtering the various databases, we analyzed several related papers devised until 21 October 2020.

The remainder of the paper is structured as follows. Section 2 describes research questions, inclusion criteria, search strategy, and study characteristics that were analyzed. Then, in Section 3, the results from the search are described, and the included articles are thoroughly analyzed. Section 4 discusses and summarizes the findings, and finally, Section 5 concludes the paper, pointing out future research directions.

## 2. Materials and Methods

### *2.1. Research Questions*

This systematic review was based on the following questions: (RQ1) Which sensors can improve the measurement of the ten-meter walk test results? (RQ2) Which features can be extracted from the sensors during the performance of the ten-meter walk test? (RQ3) Based on the methods used, which are the benefits of the implementation of the different methods?

### *2.2. Inclusion Criteria*

The study of the methods and the sensors for the measurement of the results of the ten meter walk test was performed with the following inclusion criteria: (1) studies that measure the parameters of the ten meter walk test with sensors; (2) studies that present various implementations of ten meter walk test; (3) studies that present the purpose of the study; (4) studies that clearly define the population of the study; (5) studies that show the results; (6) studies presenting original research; (7) studies that were published between 2009 and 2020; (8) studies written in English.

### *2.3. Search Strategy*

This systematic review consisted of the studies that follow the inclusion criteria in the following electronic databases: IEEE Xplore, ACM Digital Library, ScienceDirect, and PubMed with natural language processing (NLP)-based framework described in [35]. The following research terms were used to research this systematic review: “Ten-Meter Walk Test” AND “sensor”. Every study was independently evaluated by the authors, determining their suitability with the agreement of all reviewers. The studies were analyzed to identify the various methods for using sensors to measure the ten-meter walk test results. The research was performed on 21 October 2020.

### *2.4. Extraction of Study Characteristics*

Several parameters were extracted from the various studies. The extracted data from the different studies are presented in Table 1: year of publication, location, population of the study, purpose, sensors used, and diseases present in the population analyzed. In general, the source code of the implemented methods and the dataset used are not available in the various studies, and, consequently, it is not publicly shared. Thus, we contacted the corresponding authors of the analyzed studies to obtain more information about the research performed. It was verified that a small set of studies had been completed, and this subject needs more analysis.

**Table 1.** Study analysis.

| Study | Year of Publication | Location | Population | Purpose | Sensors Used | Type of Methods | Diseases |
|---|---|---|---|---|---|---|---|
| Held et al. [36] | 2020 | Switzerland | 1 patient | The study proposed a method for gait rehabilitation and a system to capture motions' data with sensors to provide feedback on gait performance. | Accelerometer<br>Gyroscope<br>Magnetometer | Statistical | Stroke |
| Harari et al. [37] | 2020 | United States of America | 50 participants | It presented a method to develop predictive models for ten meter walk test during inpatient rehabilitation. | Accelerometer<br>Gyroscope<br>Magnetometer | Machine learning | Stroke |
| Washabaugh et al. [38] | 2017 | United States of America | 39 subjects | This study aimed to validate and analyze the repeatability of spatiotemporal metrics. | Accelerometer<br>Gyroscope<br>Magnetometer | Statistical | Not applicable |
| Reissman et al. [39] | 2017 | United States of America | 12 individuals | The ten meter walk test was used for the assessment at self-selected velocity of gait. | Eight camera video system with reflective markers<br>Electromyography (EMG) sensors | Statistical | Stroke |
| Lonini et al. [40] | 2016 | United States of America | 11 subjects | The study proposed a method for the evaluation of walking skills with lower limb exoskeletons. | Accelerometer | Statistical | Not applicable |
| Ma et al. [41] | 2016 | United States of America | 19 persons | It presented a gait analysis approach to examine gait patterns. | Accelerometer<br>Gyroscope<br>Magnetometer | Machine learning | Glaucoma |
| Mudge et al. [42] | 2009 | New Zealand | 49 participants | It presented the analysis of four clinical measures of the walking ability and the results obtained. | StepWatch Activity Monitor | Statistical | Stroke |

## 3. Results

As presented in Figure 1, we identified 35 studies from the selected sources, of which two papers were duplicated. After analyzing each research article's metadata, i.e., title, abstract, and keywords, 16 studies were excluded from the analysis because they did not directly relate to evaluating the tten-meterwalk test with sensors. The full text of the remaining 17 articles was assessed considering the inclusion criteria, and consequently, ten articles were excluded. Finally, the remaining seven papers were examined and included in qualitative and quantitative syntheses.

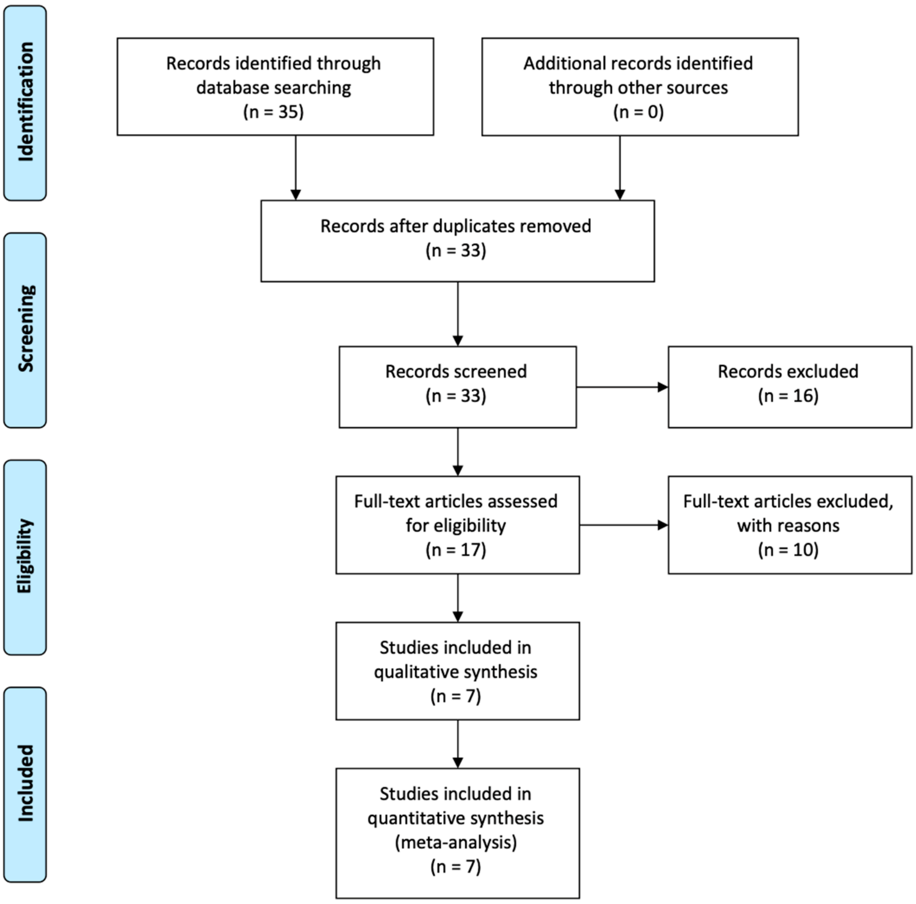

**Figure 1.** Flow diagram of the selection of the papers.

The studies were analyzed and selected, extracting the relevant information and metadata. The research performed in this study found research articles published between 2009 and 2020. As reported in Table 1, two studies (28.57%) were published in 2020, two studies (28.57%) were published in 2017, two studies (28.57%) were published in 2016, and one study (14.29%) was published in 2009. Following the sensors used, five studies (71.43%) used inertial or magnetic sensors, one study (14.29%) used the StepWatch Activity Monitor, and one study (14.29%) used an eight-camera video system with reflective markers and bi-polar surface Electromyography (EMG) sensors. Regarding the diseases of the studied population, four studies (57.14%) considered patients with stroke, one study (14.29%) considered patients with glaucoma, and two studies (28.57%) did not define the diseases of the participants. Most of the studies (71.43%) were performed in the United States of America, and the remaining studies were conducted in Switzerland (14.29%) and New Zealand (14.29%). Additionally, five studies (71.43%) considered solely statistical methods for analyzing the different variables, and only two studies (28.57%) used machine learning techniques for pattern classification.

In [36], the authors used the sensor-based motion capture system (Xsens MVN), which includes an accelerometer, a magnetometer, and gyroscope sensors to create a gait rehabilitation method in people that had a stroke to provide fine-grained feedback on gait performance. The study considered only one male aged 74 years old with a walking speed of 1.0 m/s and a step length of 0.56 m. It also intended to investigate the differences in the gait pattern of people with stroke based on virtual augmentation during overground walking and the system’s usability. The developed method was the Augmented Reality for gait Impairments after Stroke (ARISE) system, showing that it complemented the standard gait therapy. The system measured the time from a foot strike to the following release of the same foot and the time from a foot release to the same foot’s subsequent strike, reporting low differences. For the final analysis, the authors measured maximum and minimum values from a foot strike to the following release of the same foot and the period from a foot release to the subsequent strike of the same foot during the test's performance. The three sensors used compose the ARISE system that the patients said is comfortable. Still, it has a limited vertical field of view with 29 degrees of the HoloLens 2 that decreases the usability of the system. Moreover, it induces adverse movements, including neck pain or near-falls.

Harari et al. [37] used wearable sensors for the development of predictive models during inpatient rehabilitation. The experiments were performed with 50 participants aged between 22 and 86 years old (57.5 ± 14.15), where 62% were male and 58% were female. It was performed between 3 and 181 days after stroke (18.8 ± 29.6). Regarding the ten meter walk test's velocity, the values reported were, on average, 0.47 m/s (male) and 0.76 m/s (female). The authors analyzed the gait speed during the rehabilitation, and the data were analyzed with Python version 3.7.3 to evaluate the normality of the data. After that, they applied different methods, including the Pearson product-moment coefficient, the point-biserial coefficient, and the Spearman's rank correlation coefficient. Finally, they developed predictive models with the cross-validated Lasso regression, and they applied the permutation importance analysis based on a random forest model. In conclusion, they reported a normalized error of 13–15% in different predictions. The different evaluated variables showed a high correlation with the results obtained by the accelerometer, the magnetometer, and the gyroscope sensors. The most reliable variables for the analysis of the test are stroke onset to rehabilitation admission, age, sex, body mass index, race, and diagnosis of dysphasia or speech impairment.

The authors of [38] used the APDM measurements (Mobility Lab v1, APDM, Inc., Portland, OR), which embed accelerometers, magnetometers, and gyroscopes to determine repeatability and validity of the spatiotemporal metrics, including stance percent, gait speed, git cycle time, swing percent, stride length, step duration, and cadence. The experiments were performed on 39 healthy individuals with an age between 23.8 ± 6.2 years old. Regarding the gender, 64% were male and 36% were female. For the ten meter walk test analysis, the gait speed was measured reporting high repeatability and validity. The analyses were performed with the SPSS for windows version 22 (SPSS Inc., Chicago, IL, USA) and R statistical software (version 3.1.3), establishing the Lin's concordance correlation coefficients, Pearson's correlations, intraclass correlations, minimally detectable change (MDC), standard error of measurement, and standard deviation of the measure. The detection of toe off events is difficult, showing poor accuracy in the identification of stance and swing times. Still, the errors can be minimized with the recalibration with the toe off detection algorithm. As it reports low accuracy in some detections, it reports reliable accuracies after calibration. Finally, the presented system is accurate and repeatable when measuring spatiotemporal gait parameters. However, it is more accurate with the use of inertial sensors placed at the foot rather than the ankle, providing an accurate and repeatable assessment with the measurement of asymmetric gait.

In [39], the authors assessed the velocity of 12 subjects (eight male and four female) during the ten-meter walk test's performance. The participants were between 43.3 and 67.0 years old (55.3 ± 8.7) and had suffered a stroke 74.9 ± 37.5 months ago. Compared with the previous studies, the authors assessed the gait speed. However, they used an eight-camera video system (Motion Analysis Corporation, Santa Rosa, CA) with reflective markers placed on the head, the lower limbs, the torso, and the pelvis. The bi-polar surface EMG sensors (Motion Lab Systems, Baton Rouge, LA) were utilized to record the bilateral muscle activity data from the adductor magnus, the gluteus medius, the vastus medialis, the rectus femoris, and the semitendinosus. For the statistical analysis, the NCSS software (v10, Kaysville, Utah) was used to assess the differences in flat walking kinematic joint angles (catch and washout), having reported reliable results with various tests, including the Kolmogorov–Smirnov test, analysis of variance (ANOVA), and Tukey-Kramer pairwise comparisons. In general, the values showed high correlation with the baseline, reporting a precision around 90%.

Lonini et al. [40] used the accelerometer to implement several methods, including step frequency, standard deviation of the frontal angle, approximated energy expenditure, number of steps, and Gaussian naïve Bayes surprise for the evaluation of gait speed. The tests were performed on eleven participants with age comprehended between 55.3 ± 8.7 years old, where five were female and six were male. With the assessment of gait speed, the individuals reported values between 0.178 and 0.48 m/s. The authors reported reliable results with the Gaussian naïve Bayes surprise and the Wilcoxon signed rank test. Still, more experiments should be performed with a large population to improve the results of the analyses. Finally, the trunk tilt and the acceleration counts were strongly correlated, where the featured independence simplified the model and prevented the overfitting of the distribution parameters to show reliable results without the presentation of the accuracy of the study.

The authors of [41] used three-axis wearable sensors in a shoe-integrated sensing system for the gait analysis with machine learning approaches to examine gait patterns in glaucoma patients. The ten-meter walk test was assessed with the walking speed and other gait parameters, implementing a decision tree method with 10-fold cross-validation, reporting 80.8% accuracy in the test's assessment. Thereupon, the nearest neighbor algorithm was also implemented, and it presented an accuracy between 78.36% and 82.46% with spatiotemporal feature instances. The features were also tested with an ANOVA test to evaluate glaucoma patients' differences and healthy people. There were nine people with glaucoma (four males and five females) and ten healthy individuals (three males and seven females) aged between 55.13 and 72.27 years old. The features used were minimum, mean, median, and range, reporting high correlation values. The features showed prominent results in the detection of yield and significant differences between glaucoma patients and healthy controls. However, the accuracy of the study was not presented.

In [42], the authors used a StepWatch Activity Monitor in patients with stroke to measure the walking ability, implementing stepwise linear regression models, regression coefficients, $R^2$, $R^2$ change, P adjusted, and $R^2$ constant, which reported a correlation coefficient between 0.41 and 0.71 in the measurement of the gait speed. The population was 49 people (29 men and 20 women) aged 67.4 ± 12.5 years old, who had suffered a chronic stroke, later reporting that the ten-meter walk test is a reliable mean to assess walking performance. The StepWatch data were high correlated, and the study retrieved accurate data on usual performance. Unfortunately, the accuracy was not clearly presented.

## 4. Discussion

Only a small number of studies present the ten-meter walk test's implementation with the off-the-shelf mobile devices' sensors. The various treatments can be evaluated with this test without the physicians' constant intervention, and results can be obtained remotely.

Between the seven studies analyzed, as presented in Figure 2, it was possible to verify that the disease most present in the various studies is stroke (57%). The other illness analyzed in one study was glaucoma (14%), and the remaining studies did not relate to a specific disease (29%).

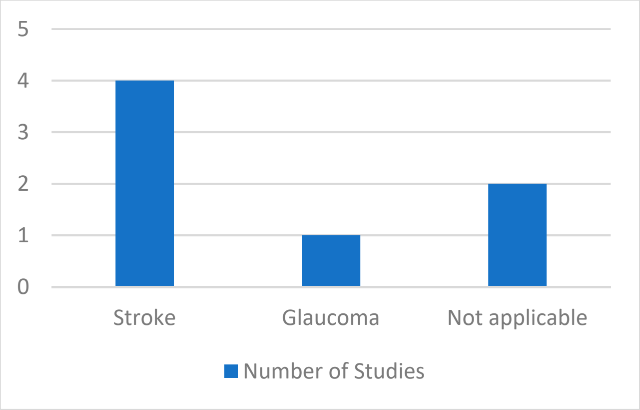

**Figure 2.** Distribution of the various diseases by the studies.

Regarding the sensors used in the various studies, 57% of these considered three inertial/magnetic sensors, i.e., accelerometer, magnetometer, and gyroscope, representing two studies (29%) related to stroke disease. Among the remaining studies, one study (14%) only used the accelerometer of undifferentiated illnesses, whereas another one (14%) used the StepWatch Activity Monitor, and the remaining study (14%) considered the use of an eight-camera video system with reflective markers and EMG sensors.

As to the countries of the various studies presented in Figure 3, five studies (71%) were performed in the United States of America, one study (14%) was conducted in Switzerland, and the remaining study (14%) was performed in New Zealand.

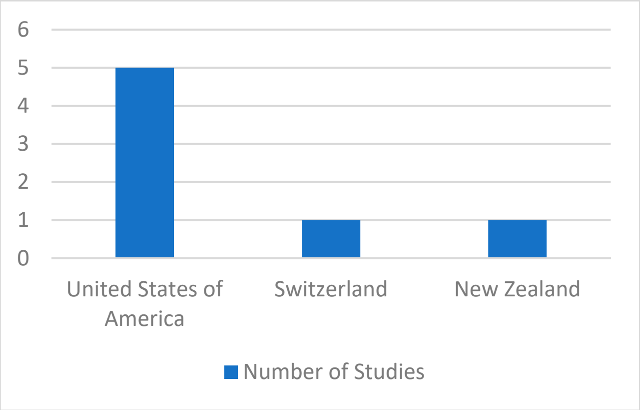

**Figure 3.** Distribution of the studies by different countries.

Concerning the different age ranges of the various studies, Figure 4 presents the distribution. It was possible to verify that the most relevant age ranges corresponded to five studies of people comprehended between 55 and 64 years old. Additionally, four studies comprehended people between 65 and 67 years old.

Regarding people´s gender, all studies had, on average, 15.29 male individuals and 10.57 female individuals.

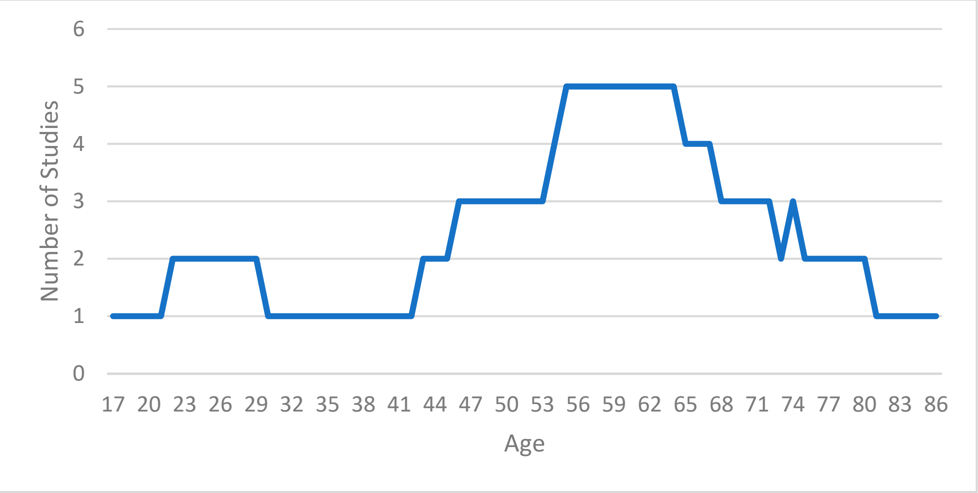

**Figure 4.** Distribution of the studies by different age ranges.

The most used features in the different studies consisted in spatiotemporal features, including velocity and distance. For the different analysis, the statistical methods implemented were diverse, where the ANOVA method was the most used. There are many statistical methods that can be explored in the future, e.g., student t-test. The integration of the measurements of the different studies in other studies or feature work was not presented, and the authors mainly analyzed the walking manners of the people. However, the inertial sensors were tested as embedded in different kinds of devices, including smartphones, smartwatches, and the StepWatch, among others. Unfortunately, it is a topic that is not very well studied, and only one study presented the accuracy of the study. However, this study is relevant in clinical practice to promote the creation of a solution for patient empowerment for physical therapy with remote treatments. Thus, we intend to create a personal digital life coach for physicians and patients to monitor various diseases' evolution. Thus, during the pandemic time, it will help people to continue the treatments remotely.

## 5. Conclusions

This article performed a systematic review on the use of sensors and automated approaches for measuring the ten-meter walk test. Only seven articles were considered relevant per the inclusion criteria, which means that this area may be an attractive field for future research. In line with this, mobile devices and mobile applications allow measurement of the ten-meter walk test. Furthermore, specialized mobile applications may be developed to self-assess their walking performance and report this to their physicians.

From the seven studies identified with this review, the main findings are the following:

- (RQ1) Which sensors can improve the measurement of the ten-meter walk test results? The sensors that can improve the measurement of the different outcomes are not identified. Still, the most used sensors are the inertial sensors available in mobile devices.
- (RQ2) Which features can be extracted from the sensors during the performance of the ten-meter walk test? As this test is related to the ten-meter walk test, the most extracted feature is the test's speed.
- (RQ3) Based on the methods used, which are the benefits of the implementation of the different methods? The tests used for the analysis were mostly statistical tests to perform the comparison of the other people that completed the experiments.

There is a lack of studies related to developing a method for analyzing the ten meter walk test with sensors. However, the sensors may increase the reliability of the measurements of the test's performance, and it empowers various diagnostics in health.

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