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ORIGINAL RESEARCH

An optimized system for mobility evaluation in frailty phenotype assessment

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Abstract
The rapid ageing of society makes necessary the development of advanced technologies for the identification of frailty. In this paper, we present a system for mobility evaluation in frailty phenotype assessment. The system is equipped with wireless, small and non-invasive wearable sensors for an objective evaluation of mobility. The paper proposes an optimization of gait analysis algorithm using a dynamic threshold. The results obtained from a comparison with the gold standard show errors of 3.7% for double support, 5.1% for stride length, and 5.8% for stride speed. Moreover, a simple and automatic tool, which estimates postural and walking parameters to assist medical staff in assessing frailty, is developed.

Keywords Frailty phenotype · Inertial sensors · Gait analysis · Postural stability

1 Introduction

In recent years demographic changes in society are leaded to a significant increase of older people over 80 years old. One of the health states related to the ageing is frailty (Razjouyan et al. 2018). Frailty is a condition of increase in vulnerability caused by a cumulative decline in the physiologic systems resulting risk of disability, morbidity, psychological decline, hospitalization, and mortality (Ensrud et al. 2009). There are two major techniques to defining frailty: one is the deficit accumulation approach of Rockwood (Theou et al. 2015) that believe in co-occurring diseases as the major predictor of frailty (Bandeen-Roche et al. 2015). The other is the frailty phenotype (FP) of Fried associated with physical and mental energy decline (Alexander et al. 2011) and it is focused on five core clinical criteria for frailty evaluation: weight loss, exhaustion, weak grip strength, slow walking speed and low physical activity (Alexander et al. 2011). These phenotypic criteria represent the predictors of frailty classifying a subject as frail (3–5 criteria), pre-frail (1–2 criteria) or non-frail (no criterion). FP takes into consideration only five criteria that still provide a good groundwork for a standardized frailty evaluation screening. This frailty definition also allows to take into account the social and psychological condition which play an important role in the subject decline.

Given that the FP is defined by the study of Dasenbrock et al. (2016) as the most used and robust frailty definition, it is also implemented to determine the biological age of a person (Pierleoni et al. 2018). Biological age represents the age based on the biological quality and functioning of tissues, apparatus and organs of an individual. It is the real age of a person and it is fundamental for assisting medical staff in diagnosis and post-operational therapies.

In the FP evaluation, the ability to move or be moved freely and easily is a health critical aspect of an elderly person. This ability is generally verified by assessing the walking speed of the subject. Therefore, the mobility evaluation of an elderly subject plays a fundamental role in the FP assessment (Fried et al. 2001).

Numerous researchers have suggested that information technology (IT) and sensor technology, in particular wearable inertial sensors, are important to evaluate the mobility of an elderly. Sensor technology means the use of sensors to measure and control changes of biological or technical systems. Inertial sensors in this field are used to measure the translational and rotational acceleration of the body of a human being. In fact, the inertial sensors are increasingly being used in frailty (Pierleoni et al. 2019a), because they represent the ideal solution thanks to their

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small size, non-invasiveness, reduced weight and wireless transmission ability.

Among mobility test to determine FP, gait assessment is the most sensitive test. Schwenk et al. (2014) provided an overview of studies which used gait analysis to identify frailty. In this work stride length, stride speed and double support were used to best distinguish within frail, pre-frail and non-frail individuals.

There are several mobility evaluation methods in FP assessment and some of these include in addition to gait analysis the evaluation of postural stability. Nevertheless, researches based on postural stability for frailty evaluation are controversial (Dasenbrock et al. 2016). Schwenk et al. (2014) determined hip sway and mean center of mass sway as relevant balance parameters for the identification between non-frail and pre-frail condition, but no parameter has differentiated between pre-frail and frail. Also Thiede et al. (Glaviano et al. 2016) did not identify any significant difference in balance parameters. On the contrary, Martínez-Ramírez et al. (2011) have examined orientation and acceleration signals of a tri-axial inertial magnetic sensor during the quiet standing balance tests in a frail, a pre-frail and a healthy population. The frail group showed, during the closed eyes postural test, greater values in the sway area of the center of mass (COM) than the healthy group. The study of Galán-Mercant and Cuesta-Vargas (2014) measured and described the magnitude of accelerometry values in the Romberg test in two groups of frail and non-frail elderly people. They detected that peak acceleration value is the most important parameter to distinguish between frail and non-frail subjects.

The world increase in the elderly population leads the scientific community to direct research on technological tools that evaluate a large number of subjects in a short time. In this sense, the decrease in costs, in times of test execution and data processing is the challenge that researchers have to face because medical staff needs efficient, fast and automatic instruments. In this study, we propose a mobility evaluation system for FP assessment. Using wearable inertial sensors, the proposed system is able to provide analysis of the walking parameters and the postural stability of a subject.

2 Material and method

The final aim of this work is to develop a mobility evaluation system which can be integrated in an e-health system for Frailty Phenotype assessment. We have adopted the method of Frailty Phenotype to calculate frailty. The FP assessment in addition to determining the physical state also takes into account the psychological well-being strictly correlated to physical frailty. In fact, psychological deficits lead to a worsening of physical frailty and, at the same time, physical frailty is a risk to a worsening of cognition or depression. For this reason, the mobility evaluation in addition to physical state indirectly gives information to the mental and psychological health of a subject. The 5 phenotypic criteria taken into consideration for FP assessment are: unintentional body weight loss (shrinking), maximum grip strength (weakness), the self-report exhaustion level (poor endurance and energy), physical mobility evaluation (mobility), and kilocalories expended per week (level of physical activity). The block diagram of the e-health system is shown in Fig. 1.

The proposed system has been created with the aim of making the mobility evaluation as much objective as possible, and of supplying a user-friendly and automatic system for walking and postural stability parameters estimation to the customers. Starting from the data acquired by two wearable sensors in specific motion tests, the medical staff is able to define if the subject is frail or non-frail for mobility. The developed system is based on two wearable devices consisting of a tri-axial accelerometer, a tri-axial gyroscope, and a tri-axial magnetometer realizing a Magnetic angular rate and gravity (MARG) sensor. Specifically the NGIMU (Next Generation Inertial Measurement Unit) devices from X-io Technologies are used. Raw data acquired by the MARG sensors can be stored in an on-board SD card and transmitted via WiFi to a PC or

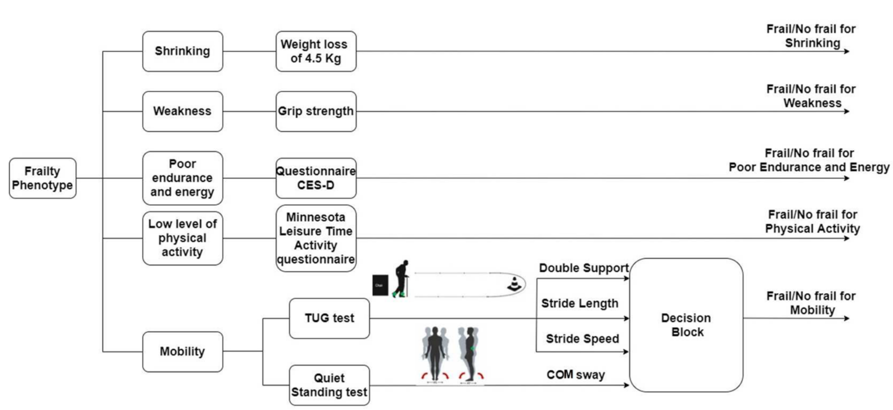

Fig. 1 Block diagram of the frailty phenotype assessment

a smartphone running specific Android Mobile Apps or custom software. In the proposed system, a stand-alone Matlab application is developed using the Matlab Compiler software package. The stand-alone application is able to receive raw data from each sensor and provide a complete and reliable measurement of the orientation of the body segment where it is positioned (Pierleoni et al. 2014). Moreover, in the stand-alone application a gait analysis algorithm together with a tool to estimate postural and walking parameters are also implemented.

Using two of these simple devices it is possible to carry out the Timed Up and Go (TUG) test and the Quiet Standing Test. The TUG test is a simple motion task to measure the mobility level of a person who requires static and dynamic balancing skills. It is a standard method for mobility evaluation and is commonly used for the identification of subjects with motor problems, balance and at risk of falls. During the TUG test, the two devices are positioned on the feet of the subject and the system is able to automatically estimate the walking parameters such as double support, stride length and stride speed. The developed algorithm for the estimation of the walking parameters is described in paragraph 2.1.

Considering the loss of postural control is related to an increase in frailty, it is necessary to include the postural stability assessment in mobility. In fact, high oscillations of center of mass in a static position lead to a lack of balance, increase frailty and the risk of falling. In order to add the postural control monitoring to the mobility evaluation, the Quiet Standing Test has been introduced. In this test one wearable device is placed on the trunk of the subject who remains standing with arms outstretched. During the Quiet Standing Test, the subject invariably sway to maintain balance, and this motion is measured using the anterior-posterior (AP) and the medial-lateral (ML) components of the COM as described in our previous work (Pierleoni et al. 2019c). The remainder of this section presents the optimization of gait analysis algorithm and a simple and automatic tool to estimate postural and walking parameters.

2.1 Optimization of gait analysis algorithm

In our previous work, a gait analysis algorithm based on wearable devices was proposed (Pierleoni et al. 2019b). Despite the good results obtained, this algorithm is limited because it is based on a fixed threshold. In order to evaluate subjects with disabilities or diseases that influence walking, it is necessary to develop a dynamic threshold algorithm. One of the goals of this work is the optimization of gait analysis algorithm using a dynamic threshold which is adaptive to the subject.

Starting from the raw data acquired by each sensor, the orientation of the feet is calculated using the Attitude and Heading Reference System (AHRS) proposed by Madgwick et al. (2011). The quaternions derived from AHRS and the raw data acquired by the accelerometer are used to compute the acceleration rotated providing acceleration components in the Earth's reference system (Pierleoni et al. 2014).

An experimental method for detecting the stance and swing phases is implemented analyzing the angular speed and the inclination angle of the foot in the lateral axis. Starting from raw data acquired by the triaxial accelerometer, the acceleration magnitude is calculated. Then raw data of gyroscope in the lateral axis is filtered with a low-pass Butterworth filter with a cut-off frequency of 5 Hz, to eliminate high-frequency noise. The gyroscope signal is used to detect the most important points of the stride: the Mid Swing (MS), the Initial Contact (IC) and the Foot Off (FO), as we can see from Fig. 2. The MS is the midpoint of a swinging motion and it is recognizable because it is the only maximum of the gyroscope signal at each gait cycle. The IC is the instant when the heel begins to touch the ground and it is identified as the first minimum of the gyroscope signal. The FO is the instant when the toe detaches from the ground and it is identified as the second minimum. These 3 points are determined with a *findpeaks* Matlab function (Casamassima et al. 2014).

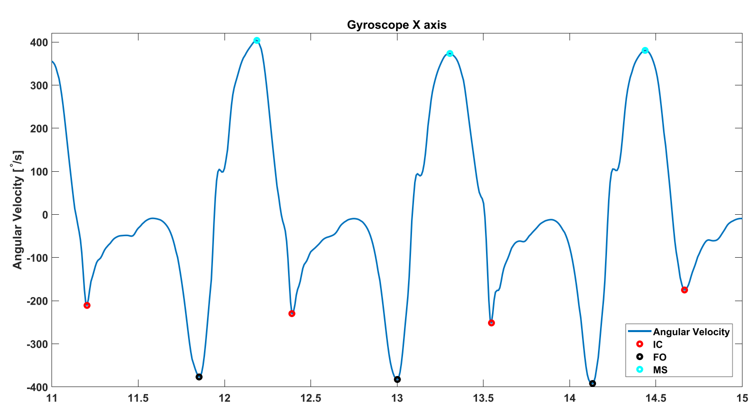

Fig. 2 Angular velocity of the lateral axis with the most important points of the stride: the IC which is circled in red, the FO in black and the MS in cyan

The Foot Flat (FF) is a fundamental event of the gait cycle. It is the phase when the foot is completely resting on the ground. The identification of this phase is important because it allows to limit the acceleration integration window (Gujarathi and Bhole 2019). The FF event is calculated using the angle of inclination of the foot in the lateral axis (roll angle). The roll is the angle between the foot in the transverse plane and the ground. In order to calculate the FF event, it is necessary to identify two important points of the roll angle the low peak (LP) and the high peak (HP). The LP is the instant when the foot passes from plantarflexion to dorsiflexion and it corresponds to the minimum of the roll angle. The HP is the instant when the foot passes from dorsiflexion to plantarflexion and it represents the maximum of the roll angle. The *findpeaks* Matlab function is used to detect LP and HP points. The start point of FF phase (FFstart) is detected when the roll signal is constant and close to zero, which corresponds to the average between the HP and LP points. Figure 3 presents the angle of inclination of the foot in the lateral axis.

Once these parameters are calculated, a dynamic threshold can be determined. The stance phase is detected if two conditions are met: the signal is between FFstart and FO points and the acceleration magnitude is close to zero. Then, threshold detection speed and displacement is determined by double integration of the acceleration rotated following our previous study (Pierleoni et al. 2019b). Through the experimental method described above, the output value of the proposed algorithm: displacement, velocity, IC, FO and FFstart are used to derive the fundamental walking parameters as double support, stride length and stride speed.

2.2 Mobility evaluation tool

In this paper, we also develop a tool able to provide a mobility evaluation of the subject.

In fact, it is possible to improve the mobility accuracy introducing new parameters thanks to the use of wearable sensors capable of providing further information on the subject's health state. In order to provide a mobility evaluation tool, a stand-alone Matlab application is developed to objective evaluation of this criteria. Therefore, the data acquired by the wearable sensors during the TUG test are processed by the evaluation tool that obtains the most important mobility parameters, applying the algorithm described in Sect. 2.1. As shown in Fig. 4, the parameters calculated by the evaluation tool are reported in the graphic user interface, displaying double support, stride length and stride speed.

In addition to walking parameters, we add parameters related to postural stability assessed through the Quiet Standing Test. Postural parameters allow to understand if the subject is able or not to walk without losing balance. These parameters are calculated by the evaluation tool applying the algorithm described in Pierleoni et al. (2019c). As reported in Fig. 5 the Quiet Standing Test is made with open eyes (OE) and closed eyes (CE).

By clicking on the OE button, the OE analysis starts and all the parameters of the test are summarized on the interface, vice versa by clicking on the CE button. Romberg test button run the comparison between CE and OE test. Using the evaluation tool, the user can display a lot of parameters as mean COM position, mean distance in ML and AP direction, mean speed in ML and AP direction, AP and ML displacement. Furthermore, there is also the possibility to access the graph of the stabilogram, statokinesigram, and frequency analysis. By means of the graphical interface which shows the individual parameters and the graphs as those in Fig. 6, the medical staff can estimate if the subject has postural problems. The fundamental parameter, which distinguishes from fail and non-frail, is the COM sway in CE test (Martínez-Ramírez et al. 2015). Integrating this parameter with gait analysis parameters the doctor is able to evaluate if the subject is frail or non-frail for mobility. Moreover, using the developed stand-alone application, the parameters related to mobility and postural stability can be uploaded into the cloud application, proposed in our previous work (Pierleoni et al. 2019a), for frailty evaluation respect to the mobility criterion.

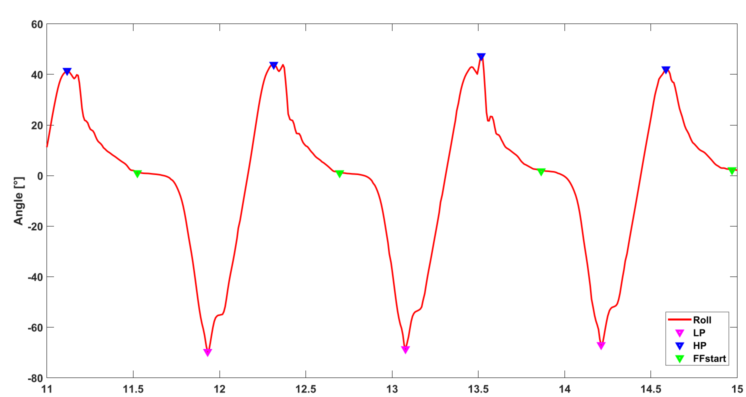

Fig. 3 Inclination angle of the foot in the lateral axis with HP, FFstart and LP points

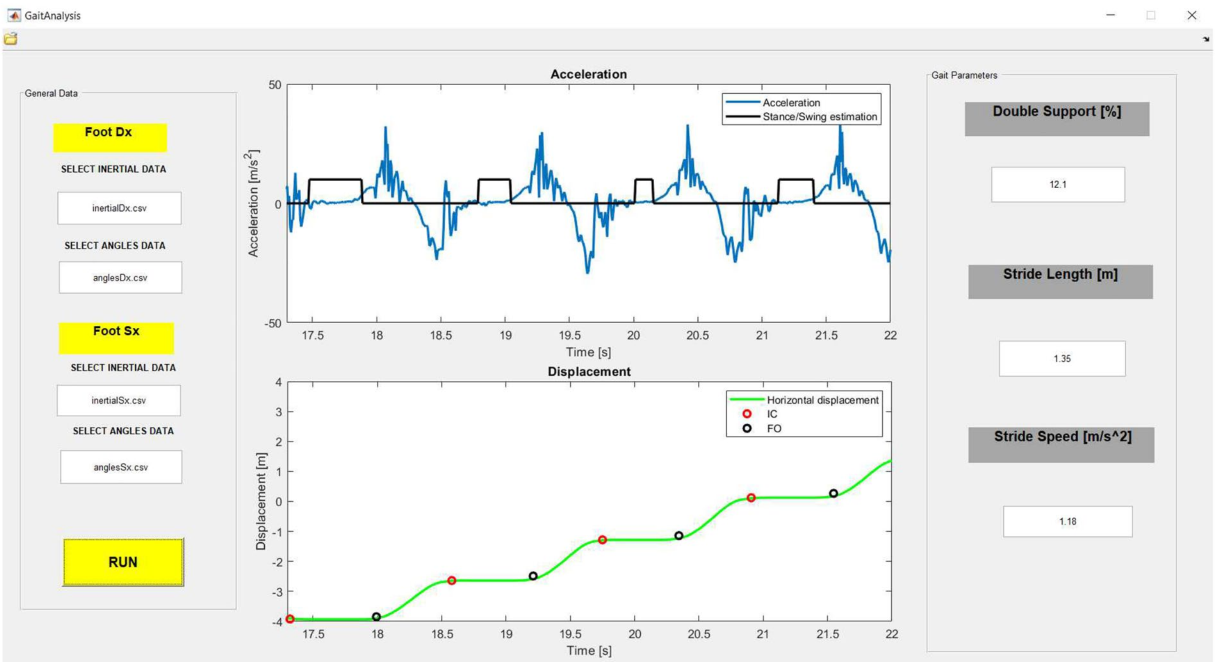

Fig. 4 The gait analysis interface displays in the first graph the acceleration signal along the walking direction and the square wave which estimates the stance and swing phases, in the second graph the horizontal displacement with IC and FO points and the parameters of double support, stride length and stride speed are shown

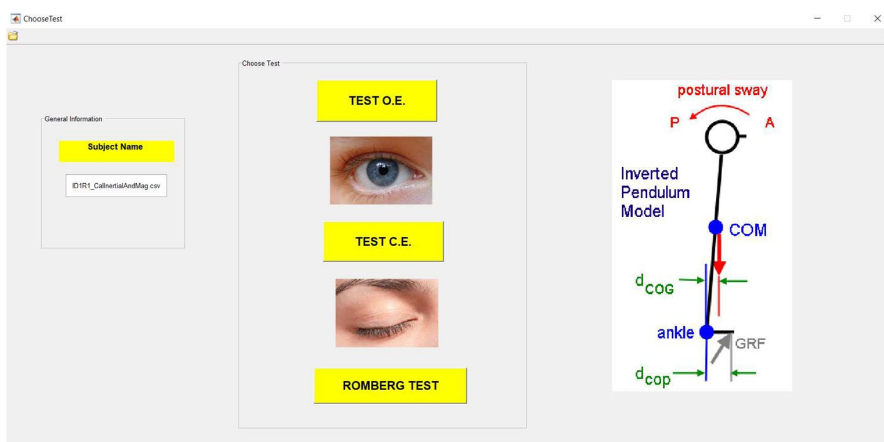

Fig. 5 The postural stability interface displays 2 stability test, the open eyes (OE) and the closed eyes (CE) test. The analysis starts by clicking the relative button. Romberg test button run the comparison between CE and OE test

3 Experimental results

In order to validate the algorithm described in the previous section, the most important parameters of walking obtained by the proposed system were compared with those determined by an optoelectronic system taken as a reference. 5 healthy subjects, 2 female and 3 male, aged between 26 and 35, were involved in this validation test. Each subject performs 3 repetitions of the path, for a total of 15 trials (Pierleoni et al. 2020). The validation test results are illustrated in Table 1 where for all trials the values of double support, stride length and stride speed are shown. In particular, the table shows the values obtained from the Wearable System (WS) and the Gold Standard (GS) and the error between them. Moreover, on the last row of the table, the percentage error between the two systems is highlighted, showing the obtained average values.

The average absolute error (E_A) of the percentage of double support, for all trials, is 3.7 ± 1.9%. The average relative error (E_r) of stride length is 5.1 ± 1.5% and the average relative error of stride speed is 5.8 ± 1.2%. Results show that the

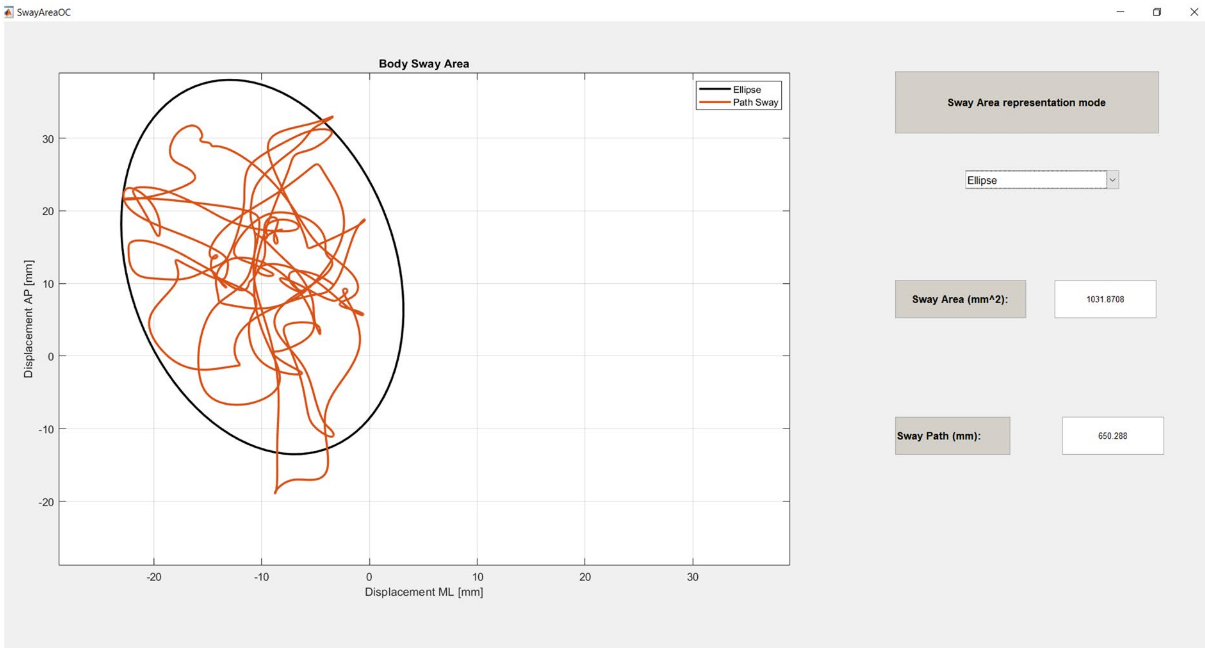

Fig. 6 The postural stability interface shows the most important parameter for mobility evaluation, the COM sway in CE test. The tool displays in the graph the path sway of the COM with the confidence ellipse and the value of the sway path and sway area

Table 1 Values of double support, stride length and stride speed obtained from the wearable system (WS) and the gold standard (GS) and the error between them

Trial	Double support [%]		E_A [%]	Stride length [m]		E_r [%]	Stride speed [m/s]		E_r [%]
	WS (m±sd)	GS (m±sd)	(m±sd)	WS (m±sd)	GS (m±sd)	(m±sd)	WS (m±sd)	GS (m±sd)	(m±sd)
1	15.3 ± 3.0	19.3 ± 3.2	4.7 ± 1.2	1.18 ± 0.02	1.25 ± 0.01	4.5 ± 1.2	0.79 ± 0.02	0.85 ± 0.02	7.0 ± 0.2
2	13.5 ± 3.0	12.9 ± 3.2	1.8 ± 2.2	1.21 ± 0.06	1.29 ± 0.01	5.7 ± 2.8	0.85 ± 0.02	0.94 ± 0.007	8.4 ± 2.5
3	10.5 ± 3.0	14.7 ± 3.2	4.2 ± 3.1	1.14 ± 0.02	1.19 ± 0.05	4.2 ± 1.6	0.84 ± 0.01	0.88 ± 0.01	4.5 ± 2.2
4	13.0 ± 1.5	15.3 ± 3.3	3.3 ± 2.2	1.19 ± 0.03	1.23 ± 0.01	3.2 ± 1.9	0.95 ± 0.03	1.01 ± 0.01	5.8 ± 0.2
5	18.1 ± 2.2	12.2 ± 3.3	5.9 ± 1.1	1.11 ± 0.01	1.20 ± 0.04	7.5 ± 3.1	0.91 ± 0.02	0.96 ± 0.01	5.2 ± 1.0
6	17.5 ± 2.2	18.8 ± 3.3	2.1 ± 2.1	1.41 ± 0.01	1.46 ± 0.03	4.0 ± 1.8	1.17 ± 0.01	1.25 ± 0.01	6.3 ± 0.4
7	19.2 ± 3.3	14.8 ± 3.9	5.4 ± 3.2	1.18 ± 0.05	1.25 ± 0.01	5.4 ± 2.3	0.94 ± 0.03	1.03 ± 0.01	8.5 ± 3.0
8	11.2 ± 3.3	8.9 ± 2.9	2.3 ± 2.0	1.44 ± 0.02	1.47 ± 0.05	2.1 ± 0.1	0.90 ± 0.1	0.94 ± 0.1	5.0 ± 1.0
9	10.5 ± 3.0	11.4 ± 2.9	3.9 ± 2.3	1.39 ± 0.01	1.48 ± 0.01	6.4 ± 0.4	1.15 ± 0.01	1.21 ± 0.01	4.8 ± 0.2
10	15.5 ± 2.0	17.5 ± 2.2	3.2 ± 2.1	1.42 ± 0.04	1.55 ± 0.02	8.3 ± 1.5	1.10 ± 0.04	1.22 ± 0.01	9.8 ± 1.0
11	14.0 ± 2.1	13.5 ± 2.2	2.3 ± 1.1	1.46 ± 0.04	1.57 ± 0.01	6.5 ± 1.2	1.16 ± 0.02	1.25 ± 0.01	7.2 ± 1.3
12	19.3 ± 2.3	14.1 ± 2.2	6.1 ± 2.2	1.43 ± 0.02	1.53 ± 0.03	5.6 ± 0.7	1.11 ± 0.04	1.20 ± 0.03	7.4 ± 0.8
13	12.1 ± 1.2	10.7 ± 2.8	3.5 ± 1.0	1.35 ± 0.02	1.39 ± 0.03	4.1 ± 2.2	1.18 ± 0.01	1.19 ± 0.02	2.5 ± 1.0
14	16.8 ± 2.4	14.1 ± 2.8	2.8 ± 1.1	1.39 ± 0.1	1.42 ± 0.02	5.3 ± 1.3	1.19 ± 0.06	1.21 ± 0.01	2.0 ± 1.8
15	14.2 ± 2.0	16.4 ± 2.8	3.1 ± 1.2	1.37 ± 0.01	1.42 ± 0.01	3.5 1.0	1.22 ± 0.1	1.25 ± 0.1	2.0 ± 2.0
Average	14.7 ± 2.5	14.3 ± 3.1	3.7 ± 1.9	1.31 ± 0.03	1.36 ± 0.02	5.1 ± 1.5	1.03 ± 0.02	1.11 ± 0.03	5.8 ± 1.2

developed algorithm increases the accuracy of the estimation of gait analysis parameters because the errors obtained are lower than those obtained in our previous work (Pierleoni et al. 2019b).

A usability test for the mobility evaluation tool was also performed by a series of users. Each user answered a series of 15 questions on the most critical issues encountered during the assigned duties. These questions primarily related to the user-friendliness of the interface and the effectiveness of the tool in performing the planned activities. The answers, which were provided in closed form, range from 1 (very poor) to 5 (excellent). The usability test administered to users is presented in

Fig. 7 Questions submitted to the examiners of the tool

N°	Questions	1	2	3	4	5
1	I think that I would like to use this system					
2	I find the system unnecessary complex					
3	I think the system was easy to use					
4	I think that I would need the support of a technician to be able to use the system					
5	I find the various functions in the system well integrated					
6	I think there was too much inconsistency in the system					
7	I would imagine that most people would lear to use this system quickly					
8	I find the system very cumbersome to use					
9	I feel very confident using the system					
10	The texts in the software modules is clear					
11	The buttons are well visible					
12	The software is slow, there are an await or some breaks during operation					
13	I am able to upload an excel file, run it, display analysis results					
14	I am able to display and understand the figures					
15	I am able to modify results					

Fig. 7. The test results show that more than 96% of the 30 users gave a total score between 4 and 5 points. The interface achieved a mean score of 4.3, a median of 4, an standard deviation of 0.64.

4 Conclusion

This paper proposes an optimized system for mobility evaluation in frailty phenotype assessment. The system is equipped with wireless wearable sensors and it is able to provide an objective analysis of mobility. One of the aims of this study was to present an optimization of gait analysis algorithm. In particular, we focused on the detection of a dynamic threshold to improve the accuracy of the results. In order to validate the algorithm, the parameters of double support, stride length and stride speed were compared with those determined by a reference system. The results obtained showed errors of 3.7% for double support, 5.1% for stride length, and 5.8% for stride speed which represent an accuracy increase in gait analysis parameters estimation. Considering that the balance and walking analysis is fundamental, to better evaluate the mobility and to prevent the falls, a test to evaluate balance has been added to the proposed system. Moreover, a simple and automatic tool to estimate postural and walking parameters has been integrated in order to improve the frailty assessment. In future developments, with the aim to improve the present work, an extensive acquisition campaign will be planned in order to improve the performance of the developed algorithm. Further acquisition campaigns will be conducted performing a comparison between the proposed mobility evaluation tool and the traditional methodologies for the mobility evaluation in the Frailty Phenotype assessment.

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