A Technological Solution for Supporting Fall Prevention Exercises at the Physiotherapy Clinic

Joana Silva
Fraunhofer Portugal AICOS
Porto, Portugal
joana.silva@fraunhofer.pt

Dinis Moreira
Fraunhofer Portugal AICOS
Porto, Portugal
dinis.moreira@fraunhofer.pt

João Madureira
Fraunhofer Portugal AICOS
Porto, Portugal
joao.madureira@fraunhofer.pt

Eduardo Pereira
Fraunhofer Portugal AICOS
Porto, Portugal
eduardo.pereira@fraunhofer.pt

André Dias
Sensing Future Technologies
Coimbra, Portugal
andredias@sensingfuture.pt

Inês Sousa
Fraunhofer Portugal AICOS
Porto, Portugal
ines.sousa@fraunhofer.pt

***Abstract*—Several fall risk factors contribute to a fall, being most of them related to the person physical capabilities as mobility, balance control, and muscle strength. Several fall prevention programs are reported to revert fall-related factors, however there is a lack of personalization in these solutions. This paper describes a technological solution to be used by physiotherapists, at the clinic, for an objective analysis of fall prevention exercises, personalized exercise prescription and progression assessment over time. The exercises are monitored with two wearable inertial sensors and a pressure platform for mobility, strength and balance assessment. In order to validate the system, a set of five exercises, from the Otago Exercise Program, were tested with a group of 16 elderly volunteers during several sessions. Spatial, temporal and balance metrics were extracted during the exercises, providing quantitative feedback during the exercise. The results indicate that inertial and pressure sensors are suitable for exercise tracking during fall prevention exercises. Range of motion, weight distribution and shifting, balance and cycle identification were successfully monitored for all exercises.**

***Index Terms*—Fall prevention exercises, Wearable inertial sensors, Pressure platform, Otago exercise program, Physiotherapy**

I. Introduction

The incidence of falls is higher in persons aged above 65 years old when compared to any other age group. Every year, one out of three elderly falls and the complications of the falls are reflected in a decrease of the quality of life, physical activity restriction, fear of falling, social isolation and ultimately cognitive decline. Moreover, falls are responsible for several institutionalizations and loss of independence in this population [1] [2]. Most factors underlying a fall are intrinsic to the person. These factors are related to mobility capabilities, balance control, muscle strength or other disorders that affect the sensory system [1]. Currently, there are a variety of tools, questionnaires and functional tests to evaluate one or more fall-related factors [1]. These fall risk factors are amendable and could be minimized or reverted when the elder follows a fall prevention program based on physical exercises for mobility, strength and balance retrain.

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Fall risk screening is crucial for triggering adequate fall prevention strategies. However, there is a need for integration between fall prevention solutions and fall risk assessment methodologies, which results in a lack of standardization and personalization of fall prevention programmes [1] [2]. Technological solutions could provide healthcare professionals with quantitative feedback on the exercises execution and patients' progression, when submitted to fall prevention programs.

This paper describes a technological solution for supporting fall prevention exercises at physiotherapy clinics. The outcome for the healthcare provider will be the delivery of personalized fall prevention exercises, analysis of exercise-related metrics extracted by inertial and pressure sensors and exercise progression analysis over time. For the elderly, the outcome will be an expected higher engagement during the program, provided by the continuous and interactive feedback during the exercises and awareness of preventive strategies to reduce falls.

The remainder of this paper is organized as follows. Section II describes several prior art technological solutions for fall preventions. Sections III to IV describe the proposed system, the exercise programme, along with the underlying methodology. Section V presents the validation results using the proposed system and Section VI summarizes final conclusions, main contributions and directions for future work.

II. Related Work

There are several technological solutions for fall prevention, that rely on inertial sensors, pressure platforms or cameras for exercise monitoring, and to provide feedback to the user. Riablo system consists of a tablet with a keyboard, a pressure mat and 5 inertial sensors, which guide the user in every exercise, through a video game interface [3]. The solution includes 15 exercises for balance control, recover of the fluidity of motor gestures, and walk, providing real time feedback of flexion angle and target angle definition in the

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interface. VERA is a digital therapy platform that brings the guidance of a physical therapist into home, using the Kinect camera, that tracks 22 joints on the body [4]. The solution is delivered using video games with an avatar that guide the user movements through a virtual strength and balance exercise program. SWORD Phoenix is a rehabilitation platform, that provides assessment, prescription, exercise tailoring, training and progress evaluation, using wearable inertial sensors [5]. The solution could be used at home or at clinics and provides vibratory feedback on the major upper or lower limb joints, based on wearable 3D movement analysis. Rehametrics Physical Module includes 40 exercises with extensive personalization options which enables clinicians to prescribe therapy and monitoring using the Kinect and the Wii Balance Board [6]. The 3D Tutor uses a wearable sensor that could be placed in the head, trunk, upper and lower extremities [7]. The system gives movement-related instructions that prevent the development of undesired and compensatory joint movements, ensuring better performance of functional tasks. It could be used in physical and occupational therapy centers. BalanSens is a wearable sensor system for balance assessment, that uses wearable inertial sensors to estimate and report hip and ankle angles and center of mass related metrics. The system can be used at home or at clinics [8]. Most of the described systems are not designed for fall prevention, but for general physical rehabilitation, thus they may not incorporate the specificities of fall prevention exercise programs. The majority of the solutions rely only on wearable inertial sensors, for exercise monitoring, and lack a pressure platform for balance analysis and retraining. The combination of both sensor devices, has the advantage of enabling real time feedback of the plantar pressure distributions and center of pressure variations according to each movement phase, for each exercise. This real-time feedback allows the healthcare provider to promptly access and correct the elders' posture and weight distribution during all phases of the exercise. Moreover, few systems include a cloud platform dedicated to the healthcare provider for progression assessment and visualization of exercise-related metrics over time. This information is valuable to personalize each exercise parameters, allowing to retrain specific movements of each exercise, that are executed with more difficulty.

III. Technological Solution

A. *System Description*

The proposed technological solution aims to prevent falls by promoting physical exercise and reinforcing the correct execution of the exercises. The system was designed to allow its personalization for each user, by enabling the selection of individual exercise plans by the therapist, based on the user's profile and previous history. Moreover, the system provides an intuitive way to view instructions for each exercise and to monitor and evaluate each exercise performance over time.

The starting point was to create a platform that could easily be used to apply the Otago Exercise Programme (OEP), given that it has been validated to effectively reduce falls [9]. In order to provide physical exercise monitoring, the system was equipped with two inertial measurement units and a pressure platform. These sensors allow the system to monitor the user's movements in real time and to extract relevant exercise metrics, in order to provide feedback to the user. The real time feedback is provided at all times encompassing the current and target number of repetitions, an arrow pointing up and down for indicating the ascending and descending phases of the movement, respectively, and a heat map representing the different intensities for plantar pressure distributions (Fig. 1). These metrics are saved in a cloud database and could be used to track performance and assess overall progression over time.

Fig. 1. Healthcare provider and elder interaction with the Clinical Tool during the Knee Flexion exercise. Real-time exercise monitoring using an inertial sensor (A) and a pressure platform (B). Feedback is provided on the screen (C) during the entire exercise, with the current series information, number of performed repetitions, movement phases indication and plantar pressure distributions (heat map).

B. *Otago Exercise Programme for Fall Prevention*

The OEP is a set of leg muscle strengthening and balance retraining exercises, that has shown to be effective in reducing by 35% the number of falls [10]. The program is individually prescribed and delivered at home by trained instructors. A subset of exercises from the OEP were selected, aiming to provide subjects with support during the learning process of the OEP at the clinic and envisioning its extended use at home.

Strengthening exercises focus on major lower limb muscles: knee flexors, knee extensors, and hip abductors, ankle dorsiflexor and plantar flexor muscles. Progression in these exercises is achieved by increasing the number of repetitions to perform and/or by adding weights (strapping weighted bands around the ankles) to the exercise. *Knee flexion (KF)*: subject starts standing up and then bends the knee, bringing the foot toward the bottom and returning to the starting position. *Calf raises (CR)*: subject starts with the feet shoulder-width apart, come up onto the toes and then lower the heels to the ground.

Balance retraining exercises focus on reinforcing body balance recovery using lower body exercises. Progression is ensured by removing support (e.g. stable structure) or increasing the number of repetitions to perform. *Knee bends (KB)*: subject starts with the feet shoulder-width apart, then squat down half way, bending the knees. *Sit to stand (STS)*:

subject starts seated on a chair, placing the feet behind the knees. Then, he leans forward over the knees, pushing off with both hands to stand up. *Tandem stance (TS)*: subject places one foot directly in front of the other foot, so the feet form a straight line and holds this position for 10 seconds. Then, he changes the foot behind and holds this position for 10 seconds.

IV. Exercises Monitoring

Exercise monitoring is provided by two inertial sensors located in the lower limbs and a pressure platform placed on the ground. All exercises performed in the same place are evaluated using both sensors. The monitoring algorithms use both sensor sources to extract exercise metrics. Identification of the exercise repetitions, duration and ROM are provided by the inertial sensors while balance information is given by the pressure platform.

A. Inertial Sensors

1) Specifications: A wearable device, Pandlet (Fraunhofer Portugal AICOS), equipped with an inertial measurement unit (IMU), composed by a tri-axial accelerometer, a tri-axial gyroscope and a tri-axial magnetometer, was used to acquire inertial data during the exercises at 50Hz [11]. Data was transmitted using BLE wireless technology to a main computer where the processing occurs.

2) Data analysis: IMU's measures acceleration, angular velocity and magnetic field direction, being widely used to estimate position and 3D orientation. Due to their ability to sense environment properties, a sensor fusion strategy was employed to estimate the attitude of the device relative to a fixed coordinate system (north-east-down) [12]–[14]. This was achieved by fusing relevant information from each sensor with a second order complementary filter [12], [13]. The relative orientation of the device over time was estimated for all time instants and represented by means of a quaternion [14].

The sensor fusion algorithm combines the long-term reference to the gravity direction provided by the accelerometer with the short-term accuracy of the gyroscope for measuring angular rotation. Magnetometer data were not considered, so no reference to the true North was available, being the fixed coordinate frame composed of a vertical axis (down axis - aligned with the gravity) and two arbitrary horizontal axis which would not necessarily point to the North and East directions. Nevertheless, relative changes in orientation can be calculated using this method.

Orientation quaternions derived from the complementary filter were used to convert readings from the sensor frame to the reference frame mentioned above [14]. Using this approach, an average of the first accelerometer readings and the estimated quaternions was calculated during a 5 seconds window, that corresponds to each exercise initial stance. Moreover, this initial stance characterization was only performed when the subject was not moving, corresponding to the stance of the subject when he initiated the movement. After the initial stance calculation, each new estimated quaternion was used to track orientation changes of the moving limb relatively to its initial stance. This relative joint angle estimation was obtained using the dot product operation between the initial stance accelerometer vector and a rotated version of it (given by the current quaternion), in order to map the current limb orientation relatively to its initial orientation.

This strategy was employed due to its simplicity and mainly because it does not require any specific calibration procedure neither a specific sensor orientation placement (device orientation is arbitrary). However, this approach outputs unsigned angles, which do not allow a fully characterization of the movement executed in all planes of movement, i.e., the direction of the movement is unknown. Most of the Otago exercises are cyclic and relatively simple to perform involving movement in only one plane (e.g. KF exercise - bending the knee back and forth) which can accurately be monitored with the proposed method. Simplicity on the sensors setup over additional movement detail was chosen for this system in order to keep it easy to use (either at clinics or at home) and functional. Pandlets' placement on the body was optimally chosen for each exercise, in order to be coincident with the direction of the required movement and to ensure the best possible estimation of the ROM. For the KF exercise, two Pandlets were placed laterally in each person's right and left ankles, respectively. For the CR exercise, each Pandlet was placed on the instep of the right and left foot, respectively. For the KB and STS exercises, one Pandlet was placed on the right ankle (laterally) and the other one on the middle of the thigh (laterally for the KB and centrally for STS). The Pandlets were not used for TS exercise monitoring. Estimated joint angles were used to identify each repetition of each exercise and correspondent phase.

For exercises with multiple repetitions, spatial and temporal metrics were extracted, for each repetition and for each movement phase, such as the number of cycles, joint angles, ascending and descending phases duration and exercise duration. A full cycle/exercise repetition was considered when the subject reaches the minimum pre-established target angle, previously defined with a group of physiotherapists for each exercise, and then returns to the initial position. Ascending phase duration was defined as the elapsed time since the initialization of each cycle movement and the moment when the correspondent target angle is reached. Descending phase duration was defined as the elapsed time since the moment when the target angle was reached until the moment it returns to the correspondent initial position. Cycle duration was defined as the sum of the ascending and descending durations. The exercise duration was defined as the elapsed time since the beginning of the exercise until the defined number of repetitions is reached.

B. Pressure Platform

1) Specifications: PhysioSensing platform (Sensing Future Technologies, Lda) measures pressure distribution at 50Hz. It comprises 1600 pressure sensors (10mm by 10mm) with maximum value of 100N/sensor. The size of the active area of the pressure platform is a square matrix of 40cm x 40cm. Voltage data are converted with an 8-bit A/D converter and is transmitted via USB (Universal Serial Bus) [15] to the main computer. It is possible to receive raw data of each pressure sensor, in a scale from 0 to 255, as well as raw center of pressure coordinates (CoP) in centimeters (*cm*).

2) Data analysis: Several balance metrics are retrieved during the exercise execution. For exercises with multiple repetitions, the balance metrics are extracted for each repetition and for each movement phase, i.e., ascending and descending phases, priorly identified by the inertial sensors. Balance metrics were extracted as described in [15]. From the CoP, several metrics were retrieved as the 95% confidence ellipse area, sum of oscillation, standard deviation of oscillation and sway range (difference between the maximum and minimum oscillation). From the matrix of pressure distribution, each foot weight was retrieved. Each foot pressure data were divided taking into consideration half of the matrix. For each half of the matrix, the sum of the active cells was calculated, that represents the pressure applied by each foot on the platform. Given the weight of the subject and the sum of the right and left foot active cells, the mean cell unit weight was calculated. For each foot, the sum of active cells was multiplied by the unit cell weight to give each foot weight.

C. Validation Tests

A group of 16 elderly (12 females) with mean age of 74.1 $\pm$ 10.1 years old was recruited to perform several sessions using the system. Although the OEP is designed to be implemented at home, the prescription and initial validation tests were conducted in a physiotherapy clinic. The tests were monitored by a healthcare professional in order to ensure compliance, proper exercise execution and monitoring during the whole session. In average, each subject participated in 8 sessions.

V. Results & Discussion

A. Identification of each exercise repetition

In order to evaluate the system capability to identify each exercise repetition, a manual inspection of the each exercise joint angle signal was conducted. Each subject participated in approximately 8 different sessions overtime, which resulted in a large number of signals eligible for manual inspection. Thus, only each subject's last session manual inspection was performed, encompassing joint angle data from KF, CR, KB, STS exercises, yielding 65 signals for analysis. Moreover, monitored joint angle data was available for all time instants providing the necessary means for the identification and validation of each exercise repetition, according to the pre-established exercise criteria. The positive condition was to detect a repetition, while the negative condition was to not detect it. The ground truth was provided by the physiotherapist annotations. Performance metrics such as precision or positive predictive value (PPV), recall or true positive rate (TPR), false negative rate (FNR) and false discovery rate (FDR) were used to evaluate the proposed system performance (Table I) [16].

As it can be seen in the Table I, the results from the overall system performance indicate that the system can be suitable for exercise monitoring purposes, especially for KF and CR exercises. These exercises obtained a recall and precision above 90%, with almost no false detected cycles neither missing cycles (FNR and FDR < 0.1).

TABLE I
System performance results for identification of each exercise repetition.

Exercise	*PPV*	*TPR*	*FNR*	*FDR*
Knee Flexion	1.0	0.98	0.02	0
Calf Raises	0.96	0.93	0.07	0.04
Knee Bends	1.0	0.75	0.25	0
Sit to Stand	1.0	0.77	0.23	0

For the KB and STS exercises, the results are similar, however a higher number of missing cycles was obtained. These higher values of FNR can be related to the more challenging nature of these type of exercises, suggesting that exercise target angle (target ROM) should be re-adjusted and personalized for each user in order to achieve a more cost effective solution by matching the individual needs and difficulties of each subject. Despite the latter fact, the remaining performance metrics were within acceptable values (FNR ≤ 0.25 and Recall ≥ 0.75) suggesting that these two exercises can be monitored with the proposed solution.

Although no direct comparison can be performed, due to different sample sizes and subjects' age distributions, the obtained results are in line with the ones obtained in previous work [17]. Both studies concluded that previous knowledge of some exercise-related parameters (e.g. expected ROM) are essential to validate each repetition. The work of [17] accomplished this by using a ”Teach-in Mode”, where a reference model for each exercise was built and used as a tailor-made gold standard, acquired according to the user's capabilities. On the other hand, in the work of [18], a target ROM was previously defined for each exercise and reached in all repetitions since their primary focus was to validate the angular measurements and sensors misplacements rather than counting exercise repetitions. Yet, they concluded that an user-oriented exercise prescription and analysis will not only encourage the users to keep exercising as well as continuously improving their exercise skills over time.

B. Exercise metrics extraction

Inertial and pressure platform metrics were extracted for all subjects, all sessions and all repetitions. Samples with null metrics were removed, as well as, sessions with errors. The exercises were grouped by type, i.e., unilateral and bilateral exercises. Unilateral exercises use each limb at a time, as the KF and TS exercises, while bilateral exercises require the use of both limbs together, as the CR, KB and STS exercises. For the unilateral exercises, the metrics were extracted for each leg, while for the bilateral exercises, the metrics were extracted for each movement phase, ascending and descending.

For the TS, it was considered that the feet were placed diagonally in the pressure platform, so the weight was calculated for the upper left triangle and for the lower right triangle. The exercise is performed firstly with the right leg in the front and secondly with the left leg in the front. For the CR exercise, only the ascending phase of the movement was analyzed with the pressure platform. For the KB exercise, the ascending phase was considered when the person stretches the legs and the descending phase was considered when the person bends the knee. For the STS, it was considered the standing as the ascending phase and the sitting as the descending phase.

The approach used for relative joint angle estimation was previously proved to be capable of measuring joint angles with an acceptable accuracy (averaged error $\leq 9°$ when compared to Kinect or video analysis systems) [13]. This error was similar to the one obtained when using traditional goniometer measurements at clinics (errors of 6 or 7°) [12], [13], but higher than the error obtained by [18] (error of 5°).

C. Statistical analysis

A statistical analysis of the inertial and pressure platform metrics was conducted to compare right and left leg movement execution (unilateral exercises) and to compare different movement phases, i.e. ascending and descending (bilateral exercises). A two-tailed t-test was used to evaluate statistical significance of all metrics with 95% confidence interval. The average and standard deviation of all inertial and pressure platform metrics are displayed for the unilateral exercises in the Table II and for bilateral exercises in the Table III.

TABLE II
INERTIAL SENSORS AND PRESSURE PLATFORM METRICS FOR THE UNILATERAL EXERCISES: KF AND TS. VALUES ARE THE MEAN (STANDARD DEVIATION), ACROSS ALL SUBJECTS, SESSIONS AND REPETITIONS.

	Metric	***KF***	***TS***
Right Leg	Angle (degrees)	37.7 (7.1)*	–
	Asc. Duration (sec)	0.98 (0.32)	–
	Desc. Duration (sec)	2.4 (0.44)*	–
	Cycle Duration (sec)	3.5 (0.48)*	–
	Ellipse Area (cm)	2.45 (3.28)*	1.62 (1.36)
	Stdev Oscillation (cm)	0.26 (0.20)*	0.13 (0.06)
	Sum Oscillation (cm)	2.56 (1.70)*	13.32 (6.43)
	Sway range (cm)	0.99 (0.76)*	0.65 (0.30)
	Lower Weight (kg)	–	47.89 (7.82)*
	Upper Weight (kg)	–	16.29 (6.99) *
Left Leg	Angle (degrees)	39.36 (8.55)*	–
	Asc. Duration (sec)	0.99 (0.23)	–
	Desc. Duration (sec)	2.82 (0.68)*	–
	Cycle Duration (sec)	3.81 (0.64)*	–
	Ellipse Area (cm)	4.91 (7.19)*	1.65 (1.20)
	Stdev Oscillation (cm)	0.39 (0.30)*	0.13 (0.06)
	Sum Oscillation (cm)	3.65 (2.63)*	13.85 (6.29)
	Sway range (cm)	1.48 (1.16)*	0.66 (0.29)
	Lower Weight (kg)	–	49.94 (9.80) *
	Upper Weight (kg)	–	18.34 (7.94) *
Total	Number cycles	19.37 (2.43)	–
	Duration (min)	3.66 (0.81)	0.97 (0.23)

(*) Statistical significance between legs (p-value$\leq$0.05)

1) *Unilateral exercises:*

Considering the KF exercise, it was verified that differences between the platform metrics for the right and the left legs were all statistically significant ($p \leq 0.05$). On the other hand, statistically significant differences for the *Angle*, *Descending Duration* and *Cycle Duration* inertial metrics were found between the right and left legs. Observed differences between legs could be related to an injury, muscle imbalance or the fact that each person has a dominant leg, that will grant more control of the whole leg movement over the non-dominant leg. However a more detailed analysis must be performed in order to correlate these findings. These findings showed that differences in movement execution between different legs can be identified and monitored with this system, enabling exercise personalization throughout sessions, when needed. For example, muscular weakness after a knee surgery, muscular imbalances and asymmetries can be tackled using this type of analysis by customizing exercise parameters and sessions until no differences in exercise execution between different legs can be observed.

For the TS exercise, the differences between the platform metrics with the right leg in the front and with the left leg in the front were not statistically significant ($p > 0.05$), except for the *Upper Foot Weight* and *Lower Foot Weight*. These differences are due to the fact that the person may apply higher weight in the back leg in order to maintain balance during the tandem position. The CoP variations are explained by the compensatory oscillations of the person to retrain a stable position.

TABLE III
INERTIAL SENSORS AND PRESSURE PLATFORM METRICS FOR THE BILATERAL EXERCISES: KB, STS AND CR. VALUES ARE THE MEAN (STANDARD DEVIATION) ACROSS ALL SUBJECTS, SESSIONS AND REPETITIONS.

	Metric	***KB***	***STS***	***CR***
Ascending	Duration (sec)	2.56 (1.4)*	1.51 (0.39)*	0.89 (0.28)*
	Ellipse Area(cm)	3.05 (3.73)	43.21 (64.52)	5.10 (4.05)
	Stdev Oscil.(cm)	0.15 (0.09)	0.66 (0.56)	0.26 (0.11)
	Sum Oscil.(cm)	4.67 (1.87)*	13.23 (6.82)*	13.97 (4.96)
	Sway Range(cm)	0.56 (0.32)*	2.86 (2.67)*	1.45 (0.84)
	Left Weight(kg)	33.67 (7.42)	34.08 (11.0)	31.24 (6.93)
	Right Weight(kg)	32.64 (5.01)	32.32 (9.90)	34.48 (5.32)
Descending	Duration (sec)	1.41 (0.38)*	3.59 (1.63)*	2.73 (0.51)*
	Ellipse Area(cm)	3.08 (4.74)	49.41 (96.75)	–
	Stdev Oscil.(cm)	0.14 (0.08)	0.66 (0.71)	–
	Sum Oscil.(cm)	7.73 (3.98)*	24.38 (16.64)*	–
	Sway Range(cm)	0.63 (0.37)*	3.87 (4.74)*	–
	Left Weight(kg)	33.79 (7.47)	34.19 (11.0)	–
	Right Weight(kg)	32.66 (5.03)	32.38 (10.0)	–
Total	Angle(degrees)	27.83 (8.99)	–	14.24 (4.1)
	Number cycles	13.30 (4.26)	11.37 (4.89)	19.93 (0.29)
	Duration(min)	2.69 (0.83)	2.80 (1.24)	3.71 (0.41)

(*) Statistical significance between phases (p-value$\leq$0.05)

2) *Bilateral exercises:*

Considering the bilateral exercises group, statistically significant differences were observed for the *Duration* metric between the ascending and descending phases, for all evaluated exercises ($p \leq 0.05$). These findings indicate that each exercise ascending and descending movements could not be performed uniformly, suggesting that a higher degree of difficulty was experienced when performing one of these two movements, although a more thorough analysis must be performed to validate these time differences.

However, as mentioned for unilateral exercises, this type of information could support the physiotherapist to personalize each exercise by targeting and work more the movement phase in which each subject reveals more difficulties. This type of approach might be valuable to either clinicians or elderly, for effectively improve strength and coordination.

For KB and STS exercise, the differences between ascending and descending platform metrics were not statistically significant ($p > 0.05$), except for the *Sum Oscillation* and *Sway Range* metrics. This exercise also obtained the highest values in the platform metrics due to the higher variation in the center of pressure during the exercise, while sitting and standing transitions. For CR exercise, any comparison between phases was made because only the ascending phase was analyzed.

VI. Conclusions

The goal of this system was to provide a technological solution for supporting falls prevention at physiotherapy clinics, based on the clinically validated OEP. The solution should enable the prescription of personalized exercise plans based on individual needs, provide real-time feedback during exercises and generate detailed progression reports. Strength and balance retraining during the exercises was monitored using a pair of wearable sensors together with a pressure platform. Thus, relatively to other fall prevention based technological solutions on the market, it grants the advantage of providing movement characterization, balance information and pressure distributions simultaneously, on every movement.

Overall, the system works effectively for exercise monitoring purposes not only by providing an accurate exercise repetition detection, but also by extracting relevant exercise information (spatial, temporal and balance metrics) for all tested exercises. Moreover, real time feedback of the number of repetitions, plantar pressure distributions, center of pressure variations and exercise time-related instructions were provided to both elderlies and healthcare providers. All extracted metrics during the exercises were stored in a cloud database constituting a web health record platform, specially designed for the healthcare providers. This platform allows exercise data visualization overtime enabling the tracking of each subject evolution and performance results between sessions.

The obtained results for all tested exercises were promising, constituting a valuable source of information for clinical practice or even for home-based rehabilitation solutions. The proposed Clinical Tool could constitute a complete solution for elderly mobility assessment and evaluation over time, since it combines simultaneously inertial and pressure data (which was not present in other studies) and exercise tailoring, by enabling the sustainable increased in terms of difficulty in each exercise, without discarding proper balance control and weight distributions during the exercises.

Future improvements include a systematization of the overall process involved in fall prevention strategies by enabling the implementation of more physical exercise programmes, by providing automatic exercise plan recommendation based on the user history and allowing its personalization for each exercise. By adjusting the exercise plan and settings, each individual will have the possibility to work on a particular physical limitation that may exist and to continuously evolve over time. Moreover, the web health record platform will also have the possibility to generate individual exercise reports with the most meaningful information, recommend new exercises or suggest an increase in difficulty and allow specific exercise parameters adjustment (target ROM, number of repetitions, etc). Finally, clinical trials for validating the effectiveness of this solution for reducing the fall risk are needed and will be crucial for validating a technological solution based on a fall prevention programme.

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