

LASSO Regression for Monitoring Patients Progress Following ACL Reconstruction via Motion Sensors: A Case Study

Salvatore Tedesco and Brendan O’Flynn

Tyndall National Institute, University College Cork

Lee Maltings, Prospect Row, Cork, T12R5CP, Ireland

E-mails: salvatore.tedesco@tyndall.ie, brendan.oflynn@tyndall.ie

Abstract — Inertial data can represent a rich source of clinically relevant information, which can provide details on motor assessment in subjects undertaking a rehabilitation process. Indeed, in clinical and sport settings, motor assessment is generally conducted through simple subjective measures such as a visual assessment or questionnaire given by caregivers. Thus, inertial sensor technology and associated data sets can help provide an objective and empirical measure of a patient’s progress. In this publication, several metrics in different domains have been considered and extrapolated from the three-dimensional accelerometer and angular rate data sets collected on an impaired subject with knee injury, via a wearable sensing system developed at the Tyndall National Institute. These data sets were collected for different activities performed across a number of sessions as the subject progressed through the rehabilitation process. Using these data sets and adopting a combination of techniques (LASSO, elastic net regularization, screening-based approaches, and leave-one-out cross-validation), an automated method has been defined in order to select the most suitable features which could provide accurate quantitative analysis of the improvement of the subject throughout their rehabilitation. The present work confirms that changes in motor ability can be objectively assessed via data-driven methods and that most of the alterations of interest occur on the sagittal plane and may be assessed by an accelerometer worn on the thigh.

Keywords — Regression; Feature Selection; Motor Assessment; Rehabilitation; Wearable.

I. INTRODUCTION

THIS paper is the extended presentation of [1], first published at HealthInfo 2018. While [1] illustrated an effective method for defining a single score indicator which could monitor the rehabilitation progress from features obtained by inertial sensors comparing impaired and unimpaired limb, this work analyses the same features with different data analytics techniques with the goal to investigate which combination of feature, limb, axis and sensor is the most sensitive and helpful to determine changes in motor capacity. Motor assessment is the aspect of biomechanics which studies the process by which the musculoskeletal system can create and control coordinated movements [2]. Voluntary movement requires the transmission of a message from the brain to the appropriate muscle which also controls the smoothness and

coordination of the movement. If motor function is intact, muscles can be commanded to move so as to allow symmetrical movements with significant strength levels. However, reduced motor function can occur as a result of injury or trauma to the central nervous system, muscles, ligaments, and so on. Thus, motor impairments can be associated with a number of disorders, such as Parkinson’s disease, stroke, cerebral palsy, or orthopaedic injuries, all of them requiring long rehabilitation periods. Therefore, it is essential to track accurately a patient’s progress as they proceed through the rehabilitative regimes prescribed to them by their care givers/clinicians, and consequently to tailor patient-specific rehabilitation programs, through the accurate assessment of human motion during the performance of clinically defined tasks, and the development of measured empirical data sets associated with their performance.

With particular reference to the treatment of patients with lower extremity injuries, literature has recently shown a paradigm shift, going from time-dependent concepts to function-based concepts [3], where qualitative and quantitative tests comparing affected and unaffected sides must be met before successfully accessing the following rehabilitation stage.

Qualitative and quantitative motor assessment is typically divided into clinimetrics, balance analysis, and gait analysis.

Indexes, rating scales, questionnaires, and observational forms represent the clinical standard for knee joint assessment, including, for instance, Knee Injury and Osteoarthritis Outcome Score (KOOS), Oxford Knee Score (OKS), Tegner Lysholm Knee Scoring Scale, International Knee Documentation Committee (IKDC), Western Ontario & McMaster Universities Osteoarthritis Index (WOMAC) [4]. However, these tools are subjective and, even when utilised by experienced clinicians, may not be adequate or sensitive enough.

Gold-standard technology adopted in gait analysis for quantitative movement analysis include camera-based motion analysis, instrumented treadmills, force platforms [5], and despite the achieved high performance, their application is constrained by costs, access to specialist motion labs, as well as practicality of application for larger patient/subject groups.

A viable alternative is represented by the adoption of small-size low-cost, wearable sensing units whose consideration for lower-limbs monitoring during rehabilitation, in order to provide objective performance of impaired subjects throughout

the process, has been growing lately. Indeed, inertial sensors, typically including accelerometers, gyroscopes, and magnetometers, have been used to derive gait parameters efficiently both in healthy and symptomatic subjects [6].

As a matter of fact, inertial sensors have been used in a great number of applications, such as navigation systems, activity classification, augmented reality systems, and so on [7][8], and biomechanics, in particular, has achieved significant progress from the adoption of this technology [9].

In the last years, researchers have investigated the possibility to define comprehensive indexes which could quantitatively define gait impairment, thus removing the subjective aspects from the assessment. Some examples are the Gait Deviation Index (GDI) [10], the Gait Profile Score (GPS) [11], and the Classifier Oriented Gait Score (COGS) with related sub-scores [12][13], which provide an indication of the deviation of a subject's conditions in comparison to healthy individuals by taking into account the full-body joint trajectories during walking tasks. However, it may be impractical to measure the full-body joint angles, and similar scores were obtained using limited number of inertial sensors. For instance, Wang et al. [14] defined the Gait Variability Index (GVI) from time-related features obtained by 4 sensors attached on the lower-limbs showing the possibility to monitor gait changes in people with neurodegenerative disorders in a 12 months' period. Likewise, [15] showed that one sensor attached on the lower-back can provide a score (defined as Multifeature Gait Score with related sub-scores considering temporal, symmetry, regularity, complexity, amplitude and distribution aspects) which can assess gait quality by testing the method against healthy adults, sedentary and active older adults. In this case, well-known gait temporal features and time-related acceleration features were adopted for the evaluation.

However, all these examples present some limitation. First of all, these works only consider gait assessments, but do not evaluate additional exercises typically performed during rehabilitation. Moreover, [14][15] which adopted inertial sensors, considered an ageing population of interest and did not test the methods with subjects involved in lower-limbs rehabilitation. Finally, most of these studies considered well-known gait metrics and joint angles for their evaluation. Nevertheless, it has been reported in literature that a data-driven approach may be more beneficial to discriminate impaired from unimpaired subjects. As an example, van den Dikkenberg et al. in [16] observed that, in order to discriminate healthy subjects from Total Knee Replacement (TKR) patients, accelerations (which were significantly different in 213 cases out of 216) were more useful than angles (38 cases out of 52). Furthermore, Patterson et al. [17] studied that gyroscope features were able to discriminate healthy from Anterior Cruciate Ligament (ACL)-reconstructed individuals, which was not possible using spatial or temporal variables.

Most of the studies which apply wearable inertial sensors in lower-limbs rehabilitation generally considered the assessment of impaired subjects against a healthy control during a one-off assessment, or discriminate between correct and incorrect execution in specific rehabilitation exercises [18-21]. However, to date, only a small amount of studies considered the quantitative assessment of patients' performance via inertial sensors during rehabilitation following lower-extremity

injuries. This task can be particularly challenging as it consists of isolating the gradual changes in movements due to recovery and improvement despite the presence of a multitude of sources of variability. Indeed, sources of intra- and inter-variability are even more significant in patients following rehabilitation, due to different levels of pain, fatigue, and possible compensations.

Some examples are shown in [22-25]. The main limitations of those studies are related to the short period for data collection which have investigated only the initial part of the rehabilitative process (from 5 days to a maximum of 4 months in [23]). Moreover, the previous works do not evaluate the features extrapolated from the inertial data and their combination so as to show which of them can be the most beneficial and sensitive for clinicians when monitoring patients' movements performed during lower-limb rehabilitation exercises.

The present study analyzes through various data analytic techniques the data collected with the aim of investigating the relationships between inertial-based time-domain features and changes in clinical outcomes and motor performance of adults involved in lower-limb at-home rehabilitation following knee injuries. Besides establishing which of these features are the most sensitive and helpful to determine changes in motor capacity, aspects related to axis, limb, and sensor selection are also investigated, as they could be of relevant importance for reducing the problem dimensionality in the context of wearables where power consumption and computational complexity are of prime concern. The results could help clinicians and sport scientists to gain a comprehensive picture of patients' condition and provide more targeted medical feedback. This investigation is carried out by using a wearable inertial system [26-28] developed at the Tyndall National Institute, consisting of two sensors per limb, able to provide a complete biomechanics assessment for a series of scripted activities.

The present work is organized as follows. Hardware platform description and test protocol are described in Sections II and III, respectively. The features evaluated are illustrated in Section IV. The data analysis is instead performed in Section V. Discussion of the results is illustrated in Section VI. Finally, conclusions are drawn in the final section.

II. HARDWARE PLATFORM

The biomechanical monitoring system consists of two Tyndall Wireless Inertial Measurement Units (WIMUs) per leg [26-28]. The platform measures $44 \times 30 \times 8$ mm and 7.2 g without battery (Figure 1). The WIMU is equipped with a high-performance low-power ARM Cortex-M4 32-bit microprocessor operating at a frequency up to 168 MHz, part of the STM32F0407 family produced by STMicroelectronics. It also features a floating point unit, single precision, high-speed embedded memories (1 Mb of Flash memory, 192 + 4 Kb of SRAM), an extensive range of enhanced I/Os and peripherals, and standard and advanced communication interfaces.

Inertial sensors (three-dimensional accelerometer and gyroscope, MPU-9250 from Invensense) are the main sensing components on the platform and are wired to the microcontroller through the I2C communication. Sensor data can be:



Fig. 1. Tyndall Wireless Inertial Measurement Unit (WIMU).

- transmitted wirelessly via a communication Bluetooth Low-Energy (BLE)-complaint module (Broadcom BCM20737S), representing a single mode low-energy solution with integrated ARM CM3 microcontroller unit, radio frequency and embedded Bluetooth Smart Stack;
- or logged to a removable Micro SD card at 250 Hz.

For measurement of inertial data, the Invensense MPU-9250 was chosen for its low power consumption and the high range (16 g for accelerometer and 2000 deg/s for the gyroscope) with limited noise levels.

The platform also features a USB connector, battery charger, fuel gauge, external I/O connectors, three LEDs, and power switch. All the components were chosen for their specific fitness in mobile applications and, averagely, the overall power consumption in TX/RX mode is 100 mA, dropping to 40 mA (17 mA) for stand-by (sleep mode).

III. PROTOCOL FOR DATA COLLECTION

In conjunction with clinical partners [29], an experimental protocol for data collection was developed to evaluate patient progress. The rehabilitation tasks considered are walking (at defined speeds on a treadmill, e.g., 3, 4, 6 km/h), and exercises such as half-squat, hamstring curl, and flexion-extension, which are defined by physiotherapists as good indicators of rehabilitation progress.

The system has been tested with an impaired subject. The impaired subject is a female athlete, age: 44, height: 161 cm, and weight: 52 kg, with good general health status, with a history of knee injuries and surgery (reconstructed anterior cruciate ligament in the left leg following a sporting injury). The tests were carried out during the course of the rehabilitation program, e.g., starting 1 month before surgery and finishing 7 months after surgery. Overall, the subject has been evaluated in 8 sessions through three periods: once in pre-surgery conditions (e.g., 1 month before surgery), then 6 times in a range of 20 weeks starting one month after surgery (namely short-term post-surgery), and finally once 3 months after the last data capture (e.g., during long-term post-surgery period).

The participant was wearing four devices, two of them were attached to the anterior tibia, 10 cm below the tibial tuberosity, and the remaining two to the lateral thighs, 15 cm above the tibial tuberosity, using surgical adhesive tape.

A number of repetitions have been collected for each exercise, so as to provide an accurate picture of the overall conditions, and each exercise was repeated twice. Most of the exercises were performed during the majority of the data

captures. Hamstring curl, as well as walking at 3 and 4 km/h, were performed at every session. Similarly, flexion-extension was always recorded except in the pre-surgery session due to subject's impairment of movement. For the same reason, half-squat and walking at 6 km/h were not recorded in the first 2 sessions after surgery. The order of the exercises within a session was randomized. Prior to participation, the participant received a verbal and written explanation of the study protocol and written consent was obtained. The study received approval by the Clinical Research Ethics Committee at the University College Cork.

IV. FEATURES

The metrics considered for the patient's assessment are well-known statistical features extrapolated from the time-domain. Those variables are applied on every segmented walking stride/exercise repetition for both legs performed during the sessions. More details on the computation of the features are reported in [26]. The selected features are described below:

- Mean, standard deviation, variance, skewness, kurtosis, root mean square (RMS), signal magnitude area, and energy calculated over the acceleration and angular velocity magnitudes,
- Mean, minimum, maximum, median, standard deviation, coefficient of variation (CV), peak-to-peak (p-p) amplitude, and RMS over the x-, y-, and z-axis of the acceleration and angular rate signals.
- Autocorrelation on the x-, y-, and z-axis of the acceleration and angular rate signals measured taking into account all the repetitions/strides in a session as a whole.
- Regularity on the x-, y-, and z-axis of the acceleration and angular rate signals. It is calculated as the ratio between the unbiased autocorrelation coefficient at the first dominant period and the coefficient at the second dominant period, both measured taking into account all the repetitions in a session.

All those features are calculated for both thigh and shank for both legs. Overall, the number of features extracted is $p = 152$, which means that, in this scenario, the number of predictors is much larger than the number of observations n ($p \gg n$, $n = 8$).

The data analysis is implemented off-line over the data collected using a commercial software package (MATLAB R2017b, The MathWorks Inc., Natick, MA, 2017).

V. DATA ANALYSIS

Preliminary analysis described in [26][27] have highlighted that several parameters are seen to be potentially relevant to provide indications on patient's performance during rehabilitation. However, to support clinicians during their clinical practice, it is essential to understand which of those features are related to currently used clinical indexes.

An accurate assessment of a patient's performance requires the selection of the informative features, excluding those uninformative or redundant. Some features can be informative for some exercises and being redundant for others; thus, it is important to define an automatic method for selecting those

features. A common technique for feature selection is the Least Absolute Shrinkage and Selection Operator (LASSO) [24]. This regression tool requires to define an output in order to adjust the weights of a linear model which defines the features to be selected. However, this method may show some relevant limitations.

In the case of interest, with a number of predictors much larger than the number of observations n (also known as, “high dimensional small sample size” - HDSS), the LASSO can only select n variables at most; moreover, if a group of variables is highly correlated, then the LASSO will select only one variable from this group ignoring the others.

These limitations may be overcome with a dual-stage approach. Firstly, screening-based approaches [30][31], which are an effective and computationally efficient method which can reduce the $p \gg n$ problem to more acceptable dimensions, could be used to reduce the number of predictors. For example, the Sure Independence Screening (SIS) [32] is a simple method which preserves only those features whose correlation against the responses y_i is above a pre-defined threshold. Secondly, when the number of predictors is strongly reduced, elastic net regularization [33] is adopted to the LASSO, by adding an additional penalty term. The elastic net technique solves the following regularization problem:

$$\min_{\beta_0, \beta} \left(\frac{1}{2n} \sum_{i=1}^n (y_i - \beta_0 - x_i^T \beta)^2 + \theta P_\alpha(b) \right) \quad (1)$$

Where $P_\alpha(b) = \sum_{j=1}^p \left(\frac{1-\alpha}{2} \beta_j^2 + \alpha |\beta_j| \right)$, with y_i being the response at observation i , x_i is the p -dimensional data, θ is the regularization parameter which controls the strength of the shrinkage of the variables, β a vector of the resulting coefficients of the linear model, and α being the weight of the additional penalty term and included in the range [0-1]. For $\alpha = 0$ the elastic net approaches the ridge regression, while when $\alpha = 1$ it is equivalent to the naïve LASSO technique.

A standard approach to define the regularization parameter when the sample size is small is through leave-one-out cross-validation (LOO CV). A description of this method is shown in [34]. LOO CV is repeated for different values of θ and α calculating, for each pair of coefficients, the related Mean Squared Error (MSE) and R-squared. The performance metrics associated to the minimum-plus-one standard error (1SE) point are then selected. The 1SE point is preferred over the minimum MSE point, as the former usually guarantees to build a model with fewer features. Finally, the optimal regularization parameters related to the models with the minimum MSE among the several models built considering the 1SE distribution are taken into account for feature selection and model generation.

Another aspect to solve in the LASSO approach is provided by the definition of the responses y_i . As shown in [24], this output was defined as linearly increasing from the first to the last test session, with this period ranging from 4 to 12 days. However, even though this assumption can be accepted for the

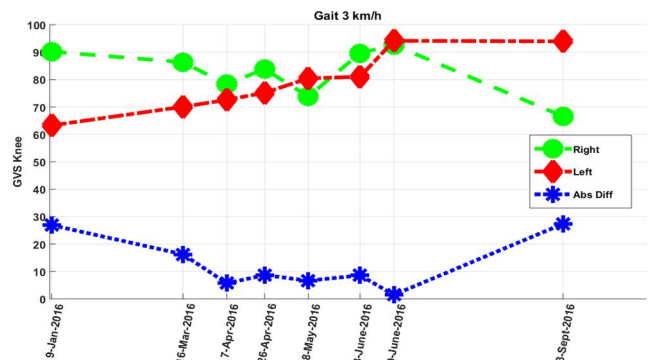


Fig. 2. GVS knee score. Gait 3 km/h.

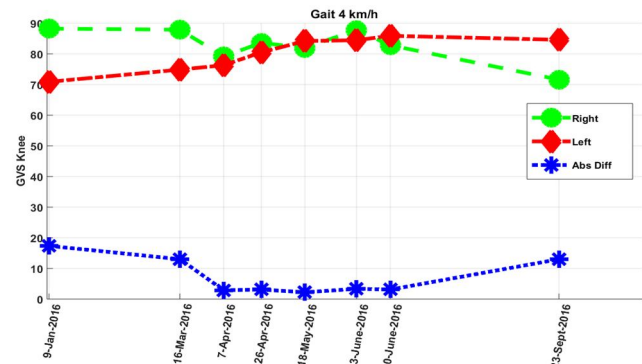


Fig. 3. GVS knee score. Gait 4 km/h.

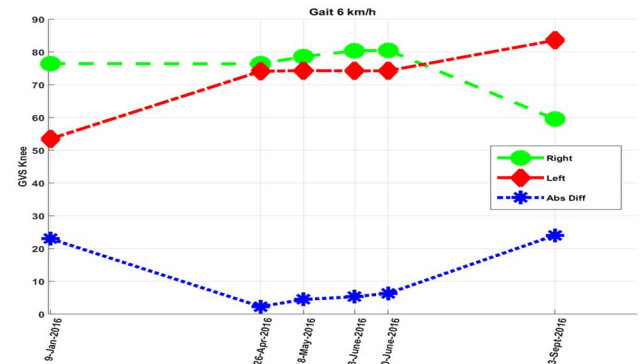


Fig. 4. GVS knee score. Gait 6 km/h.

short period of time immediately following surgery, it may be unrealistic when analyzing rehabilitation outcomes for a longer period post-surgery and also pre-surgery.

An alternative may be represented by the adoption of one of the gait indexes discussed in [10-13]; however, those indexes can be based on the joint angles collected from the full-body (as an example, GDI is obtained by taking into account pelvic and hip angles on all three axes, knee flex/extension, ankle dorsi/plantarflexion, and foot progression). Nevertheless, Baker et al. in [11] postulated that those nine variables could be taken individually to calculate a single gait variable, referred to as a Gait Variable Score (GVS), using the same mathematic approach described in [10]. Given that the knee flex/extension angle is obtained from the inertial sensors for all the sessions, the related GVS can be considered as a more accurate option to define the responses y_i . A similar approach, adopted using the Fugl-Meyer and the Wolf Motor Function Test scales in stroke

survivors was studied in [35]. The responses y_i are thus calculated as follows:

1. The knee angle time-normalised curves of all the subjects in a control group are averaged to define a template curve.
2. The natural logarithm of the Euclidean distance between the knee angle time-normalised curve for an individual subject in the control group and the template curve is obtained for all the control group participants, producing a $N_{control} \times 1$ vector, with $N_{control}$ being the number of subjects in the control group.
3. Mean and standard deviation of the distribution calculated at point 2 are defined.
4. The natural logarithm of the Euclidean distance between the knee angle time-normalised curve for the injured subject in the study and the template curve is obtained.
5. The value calculated at point 4 is standardized using the mean and standard deviation obtained at point 3.
6. The final score (which represents y_i at observation i) is calculated by subtracting from 100 the value calculated at point 5 multiplied by 10. As a result, scores of 100 or higher indicate the absence of gait pathologies, while to every 10 points that the score falls below 100 corresponds one standard deviation away from the control group mean.

Normative lower-limb angles data from a control group measured when walking at various speeds were available in [36]. Angles were time-normalised as a percentage of the gait cycle. Given that joint angle in gait is affected by age and gender [37], only data from female subjects with age between 21 and 35 were considered from [36]. As a result, overall 20 subjects were left from the original dataset, with average height equal to 166 cm and average weight of 62 Kg. For the walking speed of 3 km/h, the template curve was obtained from 13 subjects and 75 gait cycles in the speed range of 0.8-1.0 m/s. For the walking speed of 4 km/h, the template curve was obtained from 11 subjects and 61 gait cycles in the speed range of 1.0-1.2 m/s. For the walking speed of 6 km/h, the template curve was obtained from 11 subjects and 53 gait cycles in the speed range of 1.4-1.6 m/s.

It is worth noting that, while the dataset in [36] for the control group has been assembled using the gold-standard VICON as a reference, the knee angles from the injured subject were obtained with the hardware platform described in Section II. Even though this may be problematic, it has been demonstrated in [28] that this platform guarantees an average error in the estimation of the knee angle equal to -0.29, 1.54 and 1.58 deg at 3, 4, and 6 km/h, respectively (or 5.2, 7.4, and 11.3 deg if considering the RMS error), and thus it was deemed comparable with the gold-standard technology. The gait cycles were automatically segmented from the motion data using the procedure described in [38], while the joint angles were estimated via the algorithm in [39].

Examples of the knee angle-based GVS for left and right leg over the eight sessions for the various speeds are shown in

Figures 2-4, together with the related absolute differences.

From the figures, it is evident how the left leg shows an almost linear improvement in the GVS score over the different sessions. While the score increment stopped at the 7th session for walking at 3 and 4 km/h, it continued up to the 8th session for 6 km/h speed. On the other hand, for the first 7 sessions, the right leg tends to have a constant score, with limited variability at the increase of the speed. However, the last session shows a substantial drop in performance in the right leg, and this is evident on all the walking speeds. As a result, the absolute difference between the legs shows a linear almost monotonic trend tending towards zero, which confirms similar results in literature [40-42], with however a large value in the last session. Unfortunately, authors are not aware of a reasonable explanation for the shown behavior, which could be due to excessive training loads, fatigue, movement compensation dysfunction, etc. and since it occurs in the last session, it is not feasible to indicate it as an outlier or not. As a consequence, the GVS score reported is used as the responses y_i in the LASSO in two cases, with and without considering the last session.

In summary, the described data analysis includes the following steps:

1. From the collected raw motion data, each repetition/cycle is segmented and the related joint angle is estimated;
2. Using datasets available online with normative data, the GVS knee score for the walking tasks is defined for each session which corresponds to the responses y_i in the LASSO technique;
3. From the collected raw data, the features described in Section II are extrapolated for both legs, and the related absolute difference is obtained, which is afterwards standardized considering all the observations;
4. Relying on the SIS method, the features with a correlation against y_i lower than 0.7 are discarded;
5. Using the LOO CV approach, the LASSO problem is solved defining the best θ and α coefficients, and thus the related selected features and β vectors.

VI. RESULTS

In each session, each exercise was divided in two separate tests (both logged for 60 sec), and in each of the two tests a series of repetitions have been carried out by the subject. The overall number of repetitions recorded for all the sessions was: 184 hamstring curls (92 left / 92 right), 134 flexion/extensions (67 left / 67 right), 66 half squats, 478 strides for both legs when walking at 3 km/h, and similarly 544 strides when walking at 4 km/h, and 512 strides when walking at 6 km/h.

For each test, the features described in Section IV, were extrapolated and compared among the different sessions after applying the data analysis defined in Section V.

Owing to technical issues with system hardware during data recording, data from the right leg in the hamstring curl exercise on the first session are not available.

WIMUs have been attached to the anterior tibia, 10 cm

below the tibial tuberosity, and to the lateral thigh, 15 cm above the tibial tuberosity using surgical adhesive tape.

Finally, in order to have the same reference system for both WIMUs worn on the same leg, the method proposed by Seel et al. [43] has been adopted to virtually rotate around an axis the raw inertial data recorded on the shank. As a result, for all the WIMUs involved, the x-axis represents the mediolateral axis, the y-axis is the anteroposterior one, while the z-axis is the vertical axis. Thus, the plane y-z represents the sagittal plane. Results for all the exercises are described below.

A. Gait 3 km/h

Considering the gait task at 3 km/h, the resulting selected features are summarized in Table I.

As expected, when considering the responses y_i without the last session, better results in terms of MSE and R squared are achieved (MSE = 12.62 and $R^2 = 0.98$ vs. MSE = 16.82 and $R^2 = 0.92$ if the last session is kept). As a consequence, the model built without removing the 8th observation is simpler as fewer features show this particular behaviour. This model consists of 3 features versus 9 features for the model without the possible outlier. However, 2 out of the 3 features are in common between the two models. The number of features kept after applying SIS was 9 and 15, respectively.

B. Gait 4 km/h

Considering the gait task at 4 km/h, the resulting selected features are summarized in Table II.

Unlike the previous case, considering the last session achieves a model with better performance metrics in terms of MSE and R-squared despite having twice the number of metrics. Interestingly, all the features in the model built without the last session are included in the model built considering all the sessions. The number of features kept after applying SIS was 18 and 25, respectively.

C. Gait 6 km/h

Considering the gait task at 6 km/h, the resulting selected features are summarized in Table III.

Again, considering all the sessions provides the best performance metrics in terms of MSE (6.18) and R-squared (0.96) selecting 29 features instead of the 44 chosen by the model that does not consider the last session. 21 out of the 29 features are included in both models. The number of features kept after applying SIS was 29 and 44, respectively.

D. Other Tasks

To the best of authors' knowledge, clinical indexes and ratings are available in literature only for gait tasks. Addressing these aspects also for general exercises in a rehabilitation process would be an important aspect in order to empower clinicians in their clinical practice. Given that the GVS score for the knee joint was similar at every speed, an average of those scores has been considered as an indication of the responses y_i when analyzing other non-walking tasks/exercises, as a better alternative than simply using a linear model.

For the flexion/extension exercise, the resulting selected features are summarized in Table IV.

Interestingly, in the model built without the last session, no features were selected with the best performance provided by a simple constant linear model; however, considering all the sessions suggested a more interesting model with good MSE/R-squared performance consisting of a limited number of features due to the chosen naïve LASSO approach. The number of features kept after applying SIS was 20 and 38, respectively.

For the hamstring curl exercise, the resulting selected features are summarized in Table V.

Again, the model built without the last session selected no features while the model considering all the sessions suggested to select 14 features. The number of features kept after applying SIS was 14 and 20, respectively.

For the half-squat exercise, the resulting selected features are summarized in Table VI.

The model built considering all the sessions provide the best results in terms of MSE and R-squared (7.51 and 0.98, respectively), together with a reduced number of features selected compared to the other model. Interestingly, 23 out of the 28 overlap between the two models. The number of features kept after applying SIS was 28 and 44, respectively.

E. Discussion

ACL injuries are common and functionally disabling. The biomechanical effects of ACL injuries are well-known in literature; however, few studies have followed individuals throughout the whole rehabilitation and treatment period. As shown in [44], alterations in frontal- and sagittal-plane walking kinematics and kinetics observed early (< 12 months) after surgery persisted in the following period (12-36 months). Despite clearance to return to physical activity, these gait patterns do not appear to normalize over time, which may indicate that the current approach to rehabilitation and assessment before return to activity is not adequately identifying individuals with dysfunctional movement patterns. This was also confirmed in [45], where biomechanical differences between limbs were observed 9 months after reconstruction across jump/landing tasks, and in [42] where joint kinematics differences were observed up to 6 years following reconstruction.

Therefore, a data-driven approach may be more suitable in order to identify those dysfunctional movement patterns during the rehabilitation process. Inertial sensors can then bring a huge impact on clinical practice.

This work analyzed the body-worn inertial data collected from a patient over the course of rehabilitation adopting a combination of techniques (LASSO, elastic net regularization, SIS, LOO CV, and quantitative clinical indexes) for the definition of an automated method which could select a number of features for better understanding and monitoring patient's progress in several test and, thus, predict the clinical outcome.

The resulting performance, for models considering all the therapeutic sessions, shows good values in terms of both MSE (average result 10.8) and R-squared (going from 0.9025 to 0.98). A summary of the features selected is shown in Table VII.

From the table, it is evident that accelerometer and gyroscope-derived features have the same importance in a

TABLE I. GAIT 3 KM/H

	<i>Features selected</i>	<i>MSE</i>	<i>R²</i>	<i>α</i>
With all sessions	<u>Accelerometer thigh (1)</u> : Mean Y-axis, <u>Gyroscope thigh (1)</u> : Mean Z-axis, <u>Gyroscope shank (1)</u> : Maximum Y-axis	16.82	0.928	1
Without the last session	<u>Accelerometer thigh (3)</u> : Mean Y-axis, Median Y-axis, CV X-axis <u>Gyroscope thigh (1)</u> : Mean Z-axis <u>Gyroscope shank (5)</u> : RMS magnitude, Mean X-axis, Minimum Y-axis, CV Y-axis, p-p amplitude Y-axis	12.62	0.984	0.8

TABLE II. GAIT 4 KM/H

	<i>Features selected</i>	<i>MSE</i>	<i>R²</i>	<i>α</i>
With all sessions	<u>Accelerometer thigh (2)</u> : Mean Y-axis, Median Y-axis <u>Accelerometer shank (3)</u> : RMS magnitude, RMS X-axis, Regularity Z-axis <u>Gyroscope thigh (3)</u> : Maximum X-axis, st_dev X-axis, p-p amplitude X-axis <u>Gyroscope shank (2)</u> : Maximum X-axis, RMS X-axis	11.26	0.9025	0.7
Without the last session	<u>Accelerometer thigh (2)</u> : Mean Y-axis, Median Y-axis <u>Gyroscope thigh (2)</u> : Maximum X-axis, St_dev X-axis <u>Gyroscope shank (1)</u> : Maximum X-axis	15.78	0.717	0.9

TABLE III. GAIT 6 KM/H

	<i>Features selected</i>	<i>MSE</i>	<i>R²</i>	<i>α</i>
With all sessions	<u>Accelerometer thigh (14)</u> : St_dev/Variance/Skewness magnitude, Mean X-Y-Z-axis, Minimum Y-Z-axis, Maximum Y-axis, Median X-Y-Z axis, autocorrelation Y-axis, Regularity Y-axis <u>Accelerometer shank (2)</u> : CV X-axis, p-p amplitude Y-axis <u>Gyroscope thigh (10)</u> : Mean/Skewness/RMS/Area/Energy magnitude, Maximum Z-axis, Median Z-axis, St_dev X-axis, p-p amplitude Y-Z-axis, <u>Gyroscope shank (3)</u> : Median Y-axis, St_dev Z-axis, p-p amplitude Z-axis	6.19	0.96	0.3
Without the last session	<u>Accelerometer thigh (17)</u> : St_dev/Variance magnitude, Mean X-Y-axis, Minimum X-Y-axis, Maximum Y-axis, Median X-Y-Z-axis, St_dev Z-axis, CV X-Y-Z-axis, RMS X-axis, autocorrelation Y-axis, Regularity Y-axis <u>Accelerometer shank (4)</u> : Maximum X-axis, CV X-axis, p-p amplitude X-Y-axis <u>Gyroscope thigh (14)</u> : Mean/Skewness/Area/Energy magnitude, Mean Z-axis, Maximum X-Z-axis, Median Z-axis, St_dev X-axis, CV X-Y-axis, p-p amplitude X-axis, RMS X-axis, autocorrelation Z-axis	63.7	0.53	0.2

	<i>Features selected</i>	<i>MSE</i>	<i>R²</i>	<i>α</i>
	<u>Gyroscope shank (9)</u> : Mean X-Z-axis, Minimum X-axis, Maximum X-axis, Median Y-axis, St_dev X-axis, p-p amplitude X-axis, autocorrelation Z-axis, Regularity Z-axis			

TABLE IV. FLEXION/EXTENSION TASK

	<i>Features selected</i>	<i>MSE</i>	<i>R²</i>	<i>α</i>
With all sessions	<u>Accelerometer thigh (1)</u> : Mean Y-axis <u>Gyroscope shank (1)</u> : Mean Z-axis	6.04	0.95	1
Without the last session	N/A	21.35	0	0.9

TABLE V. HAMSTRING CURL TASK

	<i>Features selected</i>	<i>MSE</i>	<i>R²</i>	<i>α</i>
With all sessions	<u>Accelerometer thigh (7)</u> : Mean Y-axis, Minimum Y-axis, Maximum Y-axis, Median Y-Z-axis, RMS Y-axis, Regularity Y-axis <u>Accelerometer shank (5)</u> : Skewness/Area/Energy magnitude, autocorrelation Z-axis, Regularity X-axis <u>Gyroscope thigh (1)</u> : RMS Y-axis <u>Gyroscope shank (1)</u> : Mean Y-axis	16.98	0.93	0.1
Without the last session	N/A	21.28	0	0.9

TABLE VI. HALF-SQUAT TASK

	<i>Features selected</i>	<i>MSE</i>	<i>R²</i>	<i>α</i>
With all sessions	<u>Accelerometer thigh (18)</u> : Variance magnitude, Mean X-Y-Z-axis, Minimum X-Y-Z-axis, Maximum Z-axis, Median X-Y-Z-axis, St_dev Z-axis, CV Y-Z-axis, p-p amplitude Z-axis, RMS Y-Z-axis, Regularity Z-axis <u>Accelerometer shank (4)</u> : Maximum X-axis, p-p amplitude X-Y-axis, autocorrelation Z-axis <u>Gyroscope thigh (4)</u> : Median X-axis, RMS Y-Z-axis, autocorrelation X-axis <u>Gyroscope shank (2)</u> : RMS magnitude, CV Z-axis	7.51	0.98	0.1
Without the last session	<u>Accelerometer thigh (20)</u> : Mean X-Y-Z-axis, Minimum X-Y-Z-axis, Maximum X-Y-Z-axis, Median X-Y-Z-axis, St_dev Z-axis, CV Y-Z-axis, p-p amplitude Z-axis, RMS Y-Z-axis, Regularity Y-Z-axis <u>Accelerometer shank (6)</u> : Mean/Skewness/Area magnitude, Maximum X-axis, p-p amplitude Y-axis, Regularity Z-axis <u>Gyroscope thigh (5)</u> : Maximum X-Y-axis, RMS Y-Z-axis, autocorrelation Z-axis <u>Gyroscope shank (8)</u> : Mean/Skewness/RMS/Area/Energy magnitude, Maximum X-axis, CV X-Z-axis	77.69	0.65	0.3

TABLE VII. FEATURES SELECTED - SUMMARY

		<i>Gait 3 km/h</i>	<i>Gait 4 km/h</i>	<i>Gait 6 km/h</i>	<i>Flex/Extension</i>	<i>Hamstring Curl</i>	<i>Half-Squat</i>	<i>Total</i>
Thigh	Accelerometer magnitude			3			1	4
	Accelerometer X-axis			2			3	5
	Accelerometer Y-axis	1	2	6	1	6	5	21
	Accelerometer Z-axis			3		1	9	13
	Gyroscope magnitude			5				5
	Gyroscope X-axis		3	1			2	6
	Gyroscope Y-axis			1		1	1	3
	Gyroscope Z-axis	1		3			1	5
Shank	Accelerometer magnitude		1			3		4
	Accelerometer X-axis		1	1		1	2	5
	Accelerometer Y-axis			1			1	2
	Accelerometer Z-axis		1			1	1	3
	Gyroscope magnitude						1	1
	Gyroscope X-axis		2					2
	Gyroscope Y-axis	1		1		1		3
	Gyroscope Z-axis			2	1		1	4
	Total	3	10	29	2	14	28	86
Sensors	Accelerometer	1	5	16	1	12	22	57
	Gyroscope	2	5	13	1	2	6	29
Limbs	Thigh	2	5	24	1	8	22	62
	Shank	1	5	5	1	6	6	24

number of tasks, such as walking at different speeds and flexion/extension. However, this is not shown for other exercises, e.g., hamstring curl and half-squat, where features selected from the accelerometer are present in a larger number. This may indicate that accelerometry may be sufficient to detect incorrect movement patterns, and this can be even more important in battery-powered devices, considering the gyroscope power consumption is typically larger than the accelerometer's (almost 7 times larger in the platform built in Section II). Secondly, features obtained from thigh and shank limbs have similar distributions in a number of tasks (walking at 3-4 km/h, flexion/extension, and hamstring curl), except for gait at 6 km/h and half-squat, where thigh-derived features are more prominent. This can be explained by the fact that those two exercises are more physically demanding for the subjects, and ACL tears causes a decrement in the quadriceps and hamstring muscles, with the decrease in quadriceps strength being 3-fold greater [46]. Thus, a limited strength in the thigh muscles can limit the control of the knee and lower limbs during complex and demanding activities in the rehabilitation phase. This aspect may be further investigated by adding electromyography (EMG) sensors in future analysis. Finally, when taking into account the individual features, it is evident how features extrapolated from the accelerometer over the anteroposterior axis on the thigh are the only features present in every task. Features from the other axis, sensors, and limbs are uniformly distributed across the different exercises, with no

preference of one over the other, except for the accelerometer-based features extrapolated from the vertical axis of the thigh, which are found in walking at 6 km/h and half-squat tasks. Over 24% of the overall features selected in all the tasks is obtained from the anteroposterior axis of the accelerometer located on the thigh, and 15% of the overall features are from the vertical axis. These findings confirm the results discussed in [44], with most of the alterations of interest taking place in the sagittal plane.

Regarding the application of the SIS method, the number of features kept after using this method was included between 9 and 29 (when considering all the therapeutic sessions), and between 15 and 44 when not considering the last session. In percentage, the kept features represent a fraction of the originally considered features in the range of 5.9-19% (with all sessions), and 9.8-28.9% (without the last session). This confirms the effectiveness of the SIS method in reducing $p \gg n$ problems to more acceptable dimensions. Another interesting aspect is that the number of features kept with SIS in the model built with all the sessions is lower than the number of features kept without considering the last session for all the exercises. This was expected since the last session introduces an unexpected behavior in the responses y_i which is more unlikely to be reproduced in the analyzed features.

Finally, it is also worth investigating that not always all the features kept using SIS are then adopted to build a model with the following LASSO/elastic net regularization. In fact,

exercises such as walking at 6 km/h, hamstring curl, and squat, show a model defined with the exact number of features filtered with SIS; this was expected as in those models the parameter α in the elastic net regularization approach is between 0.1 and 0.3, thus approaching a ridge regression which does not have the ability to further reduce the number of features. On the other side, exercises such as walking at 3 and 4 km/h and flexion/extension, show a model defined using between 10 and 55% of the features filtered with SIS; this occurs as in those models the parameter a is included between 0.7 and 1, thus approaching the naïve LASSO technique which has the ability to further reduce the number of features.

This study only considered well-known time-domain statistical features for this analysis, extrapolated from acceleration and angular rate signals of the shank and thigh, proving their sensitivity for a number of exercises. However, as only a single subject was available for the present study, an enhanced number of athletes, with homogeneous characteristics, will also be tested to have a more robust base and further validate the drawn conclusions.

VII. CONCLUSION

This work presented a combination of wearable inertial-based system and data analytics techniques for an objective assessment of lower-limbs in patients over the course of rehabilitation. The hardware platform adopted for the system realization and the data analytics involving inertial data collected from thighs and shanks have been described.

The studied techniques are able to indicate which features are more informative regarding patients' performance and could be easily taken into account by clinicians during their analysis. Results analysis confirmed that changes in motor ability can be objectively assessed via data-driven methods and that most of the alterations of interest occur on the sagittal plane and may be assessed by an accelerometer worn on the thigh. Future work should further assess the system capability to differentiate injured and non-injured subjects collecting larger datasets by recruiting a greater amount of participants and involving more exercise types. Moreover, datasets could be enriched by including additional sensing technologies, e.g., EMG, galvanic skin response, heart rate. Despite the availability of a number of public datasets, a rehabilitation dataset including the described characteristics is not yet available in literature and would further develop this area. Therefore, additional clinical trials are currently being planned in order to further validate the developed model in statistical terms. Moreover, the development of personalized models could be further investigated also adopting different data analytics methods, such as deep learning techniques.

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