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Spectral and Time-Frequency Domains Features for Quantitative Lower-Limb Rehabilitation Monitoring via Wearable Inertial Sensors

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***Abstract*—Inertial data represent a rich source of clinically relevant information which can provide details on motor assessment in subjects involved in a rehabilitation process. Thus, a number of metrics in the spectral and time-frequency domain has been considered to be reliable for measuring and quantifying patient progress and has been applied on the 3D accelerometer and angular rate signals collected on one impaired subject with knee injury through a wearable wireless inertial sensing system developed at the Tyndall National Institute. The subject has performed different activities evaluated across several sessions over time. Data show that most of the studied features can provide a quantitative analysis of the improvement of the subject along rehabilitation, and differentiate between impaired and unimpaired limb motor performance. The work proves that the studied features can be taken into account by clinicians and sport scientists to study the overall patients' condition and provide accurate clinical feedback as to their rehabilitative progress. The work is ongoing and additional clinical trials are currently being planned with an enhanced number of injured subjects to provide a more robust statistical analysis of the data in the study.**

Keywords—Inertial Sensors; Spectral Analysis, Time-Frequency Domain Features; Rehabilitation Monitoring.

I. INTRODUCTION

Biomechanics analysis is frequently used in both clinical and sporting practice by clinicians and plays a crucial role in athletes' effective rehabilitation by tracking patient progress through the assessment of human motion during the performance of clinically defined tasks.

Gold-standard technologies [1] (e.g., VICON, force platforms, etc.), can provide quantitative movement information during formal gait analysis achieving high performance, in terms of accuracy, at a trade-off of high cost. Therefore, those systems are only adopted in specialist motion labs. In fact, clinical observational forms [2] (e.g., WOMAC, IKDC, etc.) are typically considered in clinical practice. Their non-empirical assessments, however, may not be adequate or sensitive enough to detect subtle clinical pathological changes in movement following knee surgery even when utilised by experienced clinicians [3,4]. Thus, small-size low-cost wearable inertial sensors (e.g., accelerometers and gyroscopes) have been representing a more and more practical and viable alternative solution to biomechanical motion capture in sport and healthcare. This is confirmed by the steady growth of works in the area of inertial sensors applied to biomechanics and gait analysis, and more specifically to monitoring of lower-limbs during rehabilitation. In the latter case, the aim of the research is the performance assessment in impaired subjects in a rehabilitation context, and the discrimination between correct and incorrect execution of recommended exercises [5-7].

However, to date, only a limited number of studies have considered the quantitative assessment of patients' lower-limb performance via body-worn sensors during the complete rehabilitation process. This task is indeed 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.

For instance, Lin et al. [8] estimated the joint angles associated with 14 exercises performed by a cohort of elderly patients monitored from the first day of admission until discharge (averagely for 5.7 days). Field et al. [9] investigated the gradual changes of motion with new proposed metrics, by monitoring 14 subjects over repeated rehabilitation exercises in a period of 12 weeks, adopting a cumbersome motion capture suit consisting of 17 sensors. Finally, Houmanfar et al. in [10] showed how the continuous measurement of patient improvement can be obtained via a novel machine learning technique capable of handling a variety of rehabilitative exercises. The approach was tested by adopting two wearables sensors on thigh and shank on clinical data collected on 18 elderly patients involved in rehabilitation following hip and knee replacements for 4-12 days.

The main limitations of those studies are related to the short period for data collection which explores only the initial part of the rehabilitative process without considering the long-term effects or the pre-surgery conditions. Another limitation is the need of a large and specific initial dataset on which the machine learning method has to be trained. Finally, the lack of definition of the impact of the single features on the final outcome was also noticed.

In a previous work [11], the motor performance was evaluated during lower-limb rehabilitation through the considerations of well-known statistical, time-domain related, and kinematic features. Activities targeted considered the

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exercises normally assigned by clinicians for at-home rehabilitation, and the collection was performed via body-worn kinematic sensors over a longitudinal study of nine months on a patient in pre/post-surgery conditions. The results obtained proved the potential of those features to inform qualitatively and quantitatively movement functions in a rehabilitative context. However, several studies [12-17] have already shown that spectral features and time-frequency domain features (such as informatics-theoretic, entropy, etc.), not addressed in [11], may also carry distinct information on the patient-related outcomes. Therefore, the present study will analyze the same data collected in [11] with the aim of establishing if the extracted spectral/time-frequency domain features can also be sensitive and helpful to determine changes in motor capacity and be correlated with rehabilitation progresses. The clinical aim will be to make them potentially beneficial for clinicians when monitoring patients in the course of lower-limb rehabilitation and develop better models for objective assessment. The present work is organized as follows. The description of the methodology adopted during the data collection is described in Section II. The features extracted are illustrated in Section III. The obtained results are shown in Section IV and exhaustively analyzed and discussed. Finally, conclusions are drawn in the last section.

II. Methodology

The biomechanical monitoring system consists of two Tyndall Wireless Inertial Measurement Units (WIMUs) per leg. Each WIMU [11, 18] is equipped with a high-performance low-power 168 MHz 32-bit microprocessor with 1 Mb of flash memory and 192 + 4 Kb of RAM, a communication module (BLE), rechargeable battery, 3D accelerometer and gyroscope. Inertial sensors are wired to the micro-controller through the I2C communication. The platform measures 44 × 30 × 8 mm without battery. Sensor data can be transmitted wirelessly, or logged to a removable Micro SD card with sampling rate of 250 Hz. 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.

The rehabilitation exercises (or scenarios) considered are walking, and hamstring curl, defined by physiotherapists as good indicators of rehabilitation progress. In the walking scenario, the subject walks on a treadmill which is operated at defined speeds (3 and 4 km/h) for approximately one minute per test. In the hamstring curl scenario, the subject stands and bends the knee raising the heel toward the ceiling as far as possible without pain, relaxing the leg after each repetition. This is repeated on both legs.

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 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).

A number of repetitions has been collected for each scenario, so as to provide an accurate picture of the overall conditions, and each scenario taken into account was evaluated during every data capture.

III. Features Extraction

The metrics taken into account for the patient's assessment are divided into two main categories: spectral/energy metrics and information-theoretic/entropy features for indications on the signals complexity. The data analysis is implemented off-line using Matlab.

A. Spectral/Energy Features

This category takes into account various well-known spectral and energy features obtained using the Fast Fourier Transform (FFT). These variables are applied on the raw inertial data collected for both legs on each session without segmenting the walking strides/exercise repetitions. The selected features are shown in Table I, and more details can be found in [12-17]. All these features are calculated for each of the 4 sensors used for data collection.

B. Information-Theoretic/Entropy Features

This category considers several entropy-related and information-theoretic metrics which are described in Table II-III (more details can be found in [12-17]). These variables are applied on the raw inertial data collected for both legs on each session without segmenting the walking strides/exercise repetitions, expect for the Lempel-Ziv complexity which was calculated on the single repetitions/strides and then averaged over the different sessions. All these features are calculated for each of the 4 sensors used for data collection.

TABLE I. Spectral/Energy Features

	Features
Frequency-Domain	Dominant frequency and its width (FWHM), Spectral centroid, Power in 1.5-3 Hz (LFP), Power in 5-8 Hz (MFP), High frequency energy content (HFP), 25-50-75% Quartile frequency, Spectral Edge Frequency (SEF) at 95%, Harmonic ratio (HR), Index of harmonicity (IH), Area under the first 6 harmonics divided by the remaining area (6H), Ratio between the first 4 harmonics and the magnitude of the first 6 harmonics (4-6H), Ratio High-Low bands (RHL)

TABLE II. Entropy Features

	Features
Entropy-related	Frequency-Domain Entropy (FER), Approximate Entropy (ApEn), Shannon Entropy (SE), Conditional Entropy (CondEn), Cross-Conditional Entropy (Cross-condEn)

TABLE III. Information-Theoretic Features

Features	**Description**
Lempel-Ziv Complexity (LZC)	Measures the complexity-predictability of the signal; higher values indicate a less predictable, more complex signal, and *vice versa*
Lyapunov Exponents (short-term - ST, long-term - LT)	Quantifies local dynamic stability; the exponential rates of divergence based on naturally occurring local perturbations

IV. RESULTS AND DISCUSSION

In each session, each scenario was divided into 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 for left and right leg, 478 strides for both legs when walking at 3 km/h, and similarly 544 strides when walking at 4 km/h. Owing to malfunctioning issues during data recording, results from the right leg in the hamstring curl scenario on the first session are not available. For each test, the features described in Section III were extrapolated and compared among the different sessions. Results are summarized in Fig. 1-3, where each plot shows the mean difference (in percentage) between left and right leg (considering the right leg as reference) for some of the parameters throughout the test sessions. The mean difference is an important estimator of the dissimilarities between the two legs which, in an ideal case, should be close to zero in any case for a healthy unimpaired subject. Finally, in order to have the same reference system for the WIMUs worn on the same leg, a virtual rotation around an axis has been applied to the raw inertial data recorded on the shank. As a result, for all the WIMUs involved, the x-axis represents the medio-lateral axis, the y-axis is the anteroposterior one, while the z-axis is the vertical axis. Results for all the scenarios are discussed below.

In the hamstring curl scenario (Fig. 1), most of the detected features are present on the y-, z-axis of the angular rate signals for both shank and thigh. Clear trends are shown by IH, HFP, MFP, spectral centroid, and SE. While most of them are well-defined for the shank data, SE is instead more helpful for data collected on the thigh. Similar results are observed when considering the acceleration signals, especially along the y-, z-axis, for both limbs. Again, HR, SEF, LFP, spectral centroid, FER, ApEn, and short-term Lyapunov exponent are the main parameters that show noticeable trends, in particular when considering shank data. However, the thigh is also characterized by other metrics (in particular, MFP and ApEn measures over the x-axis accelerometry).

Gait tests have been analyzed by using those variables (Fig. 2-3). Generally, there is a certain similarity among the features considered at different speeds. For example, considering angular rate signals, most of the measures showing specific trends can be seen on the anteroposterior and vertical axis (for both shank and thigh) and include IH, 6H, SEF, HFP, LFP, spectral centroid, FER, CondEn, Cross-condEn, short-term and long-term Lyapunov exponents. However, ApEn is an additional metric noticed, in particular, at lower speed also on the x-axis and, vice versa, MFP has a more evident tendency at higher speed.

Likewise, regarding the acceleration signals, shank measures related to the medio-lateral axis are highly informative at every speed, especially if considering IH, SEF, MFP, CondEn, and Cross-condEn. Additional shank features can be more evident at lower speed, e.g., 4-6H, HFP, spectral centroid, and RHL, while, on the other side, FER provides a clearer trend at higher speed. In a restricted manner, also some of the shank measures over the y-axis can be helpful at 3-4 km/h, in particular when considering IH and Lyapunov exponents, while results on the vertical axis are more spread.

In summary, it is evident how most of the studied frequency-/entropy-/information-theoretic features are able to show a quantification of the progressive improvements of patients over rehabilitation. In particular, IH, SEF, HFP, MFP, LFP, spectral centroid, ApEn, CondEn, Cross-condEn, and Lyapunov exponents. Unfortunately, LZC did not show any clear trend in any of the selected scenarios, probably because of the number of adopted levels used for quantization (e.g., 90). The improvement trends are highlighted in Fig. 1-3 via fitting curves (in dashed lines), which can show linear or cubic relations for the different parameters underlying that this trend can be monotonic or presenting a plateau in some occasions. The fitting curves indicate moderate-to-high agreement with the data, demonstrated by R^2 value between 0.56 and 0.855.

V. CONCLUSIONS

The present study proved that spectral and time-frequency domain features extrapolated from inertial data collected on the lower-limbs can be used for a quantitative biomechanics monitoring and assessment over the course of a nine month rehabilitation program involving different exercises, also providing feedback on which of those features should be taken into account by clinicians during their analysis. Even though this paper reviewed a large number of features, there remain opportunities for further analysis, by considering other mathematical metrics. Fractal dimensions, wavelet transform, Hilbert-Huang transform, recurrence quantification analysis, multiscale entropy, are some of the examples which could be also evaluated in future studies to develop a complete framework for collecting data and monitoring patients' progress over rehabilitation. An enhanced number of subjects, with homogeneous characteristics, will also be tested in future so as to have a more robust base for the study and further validate the developed model in statistical terms. Additional clinical trials are, thus, currently being planned.

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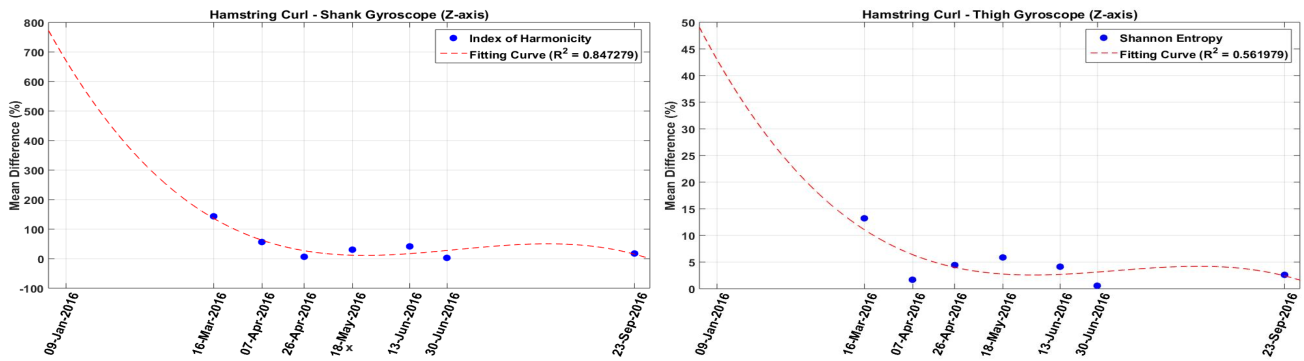

Fig. 1. Hamstring curl scenario. Mean difference for two metrics. Gyro z-axis shank Index of Harmonicity (left); gyro z-axis thigh Shannon Entropy (right).

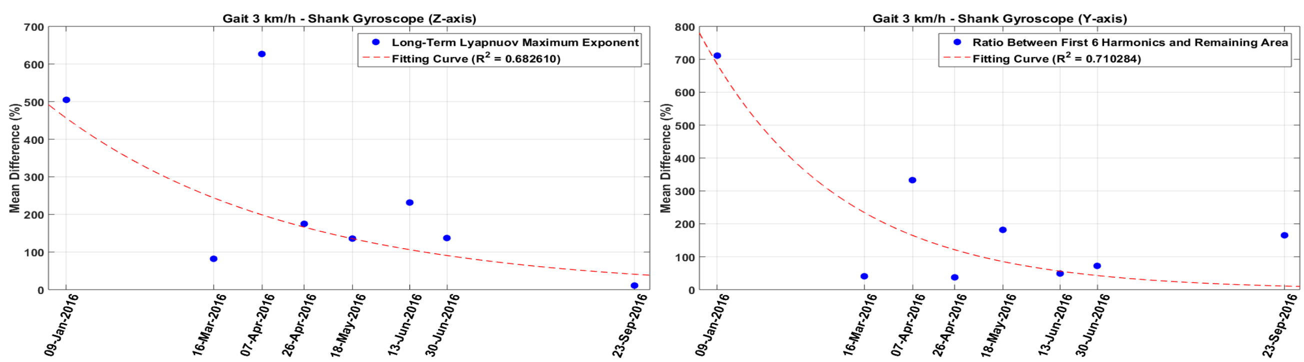

Fig. 2. Gait scenario (3 km/h). Mean difference for two metrics. Gyro z-axis shank Long-term Lyapnunov exponent (left); gyro y-axis shank 6H (right).

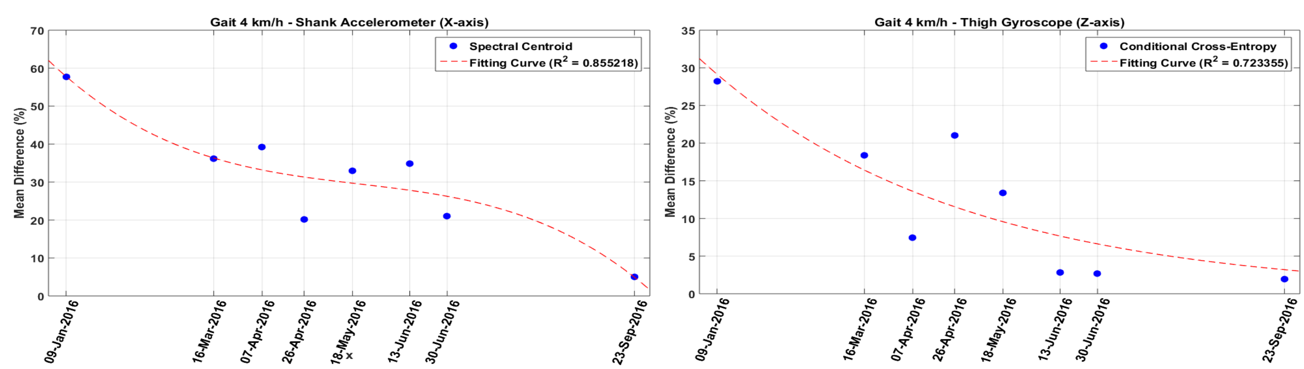

Fig. 3. Gait scenario (4 km/h). Mean difference for two metrics. Accelerometer x-axis shank Spectral Centroid (left); gyro z-axis thigh Conditional Cross-Entropy (right).