From Mocap data to inertial data through a biomechanical model to classify countermeasure exercises performed on ISS

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***Abstract*— On board the International Space Station (ISS) resistive training is essential to reduce the effects of musculoskeletal system deconditioning due to weightlessness. However, it could be equally dangerous or not useful if performed with inappropriate techniques. Thus, a system based on inertial sensors able to monitor astronauts has been thought. In this work, an OpenSim biomechanical model was used to reproduce motion of countermeasure target exercises and to simulate inertial sensors put on the model. This was done starting from kinematic data collected with motion capture system (mocap), because no inertial data were available. Then, it was explored a possible approach to build the classifier able to automatically recognize 'correct' and 'wrong' techniques of execution. Two machine learning algorithms were compared and results in terms of accuracy were encouraging.**

***Keywords*— Microgravity, biomechanics, inertial sensors, machine learning**

I. Introduction

During space missions astronauts are inserted in an environment that significantly differs from that on Earth. Weightlessness induces a series of human body changes and adaptations involving different systems: cardiovascular, respiratory, visual and, especially, musculoskeletal. The unloading of bones and muscles in microgravity produces rapid and severe mineral loss and reduction of muscle mass and muscle strength [1]. In current flights, recovery time is not critical, but space agencies are planning long-duration missions (LDMs) to Moon and Mars [2], so these physiological effects must be considered. To prevent deconditioning, crewmembers perform resistive exercises on board the International Space Station (ISS) thanks to the Advance Resistive Exercise Device (ARED). It simulates the use of weights in microgravity generating a constant load that can be changed from 0 to 272 kg [3]. Currently, ground teams communicate with crew by using a real-time audio/video system to ensure correct lifting technique. However, the more the distance from the Earth, the longer the communication delay. Therefore, feedback during LDMs to Moon and Mars will become more difficult to receive. Wrong techniques of execution, especially by using high loads, could decrease efficacy of training and may involve risk of injuries, as well documented in literature [4]-[6]. This study is inserted in a project that aims to design a biofeedback system based on a small set of wearable inertial sensors, suitable in microgravity, and machine learning algorithms to supervise crew members during their daily training. Currently, no inertial sensor data of exercises performed with ARED are available, but only kinematic and dynamic experimental data collected by using a motion capture system and force plates at NASA Johnson Space Center (JSC) in Houston, where the on-ground ARED model is installed. For this reason, it is needed to use a personalized biomechanical model in order to extract acceleration signals in different virtual body points, where real inertial sensors would be put. The model is inserted in a virtual environment where target exercises, proposed on ISS, are simulated in microgravity or weightlessness conditions. Executions in different configurations, both correct and wrong ones, are required and a set of biomechanical variables associated with a musculoskeletal risk level should be extracted. Thus, corrective information must be provided with different types of biofeedback easy to interpret.

This work was focused on: (a) the extraction of acceleration signals by using a biomechanical model in OpenSim virtual environment. This was done starting from data collected with motion capture system related to correct and wrong exercise techniques. This point is necessary because, currently, no real data acquired with inertial sensors are available; (b) the development of a classifier able to automatically classify a technique between correct and wrong. This was done starting from simulated inertial data. At the moment, these analyses were completed with data collected at Luigi Divieti laboratory at Politecnico di Milano of two subjects performing target exercises, in correct and wrong forms, with barbell and weights. Currently, the study is going on by elaborating kinematic data collected at NASA JSC of six subjects performing target exercises in correct form. Exercises under analysis are normal stance squat (NS), wide stance squat (WS) and normal deadlift (ND). Currently, on board the ISS it is installed the motion capture system ELITE S2 [7] that is going to be substituted because it is now obsolete. As soon as a new system will be available, in-flight data collection will be planned in order to enlarge our dataset and to improve the classifier.

II. Materials and methods

A. Participants

Two voluntary athletes (one man, 170 cm, 65 kg, 30 year; one woman, 164 cm, 54 kg, 25 year) participated to the data collection at Politecnico di Milano. Six non-astronaut subjects (three women, 161.8±7.2cm, 60.0±7.8kg, 31.3±6.8year; three men, 174±8.5cm, 70.8±13.2kg, 31.8±4.8years) were recruited at NASA JSC. All subjects were healthy and had experiences with the proposed resistance exercises.

B. Experimental protocol

Motion data at Politecnico di Milano were collected using motion capture system SMART DX 400 (BTS Bioengineering S.p.A, Milan, Italy), composed by 8 TV cameras with 100 Hz sampling frequency; Ground Reaction Forces (GRFs) were measured by 2 force plates (AMTI, USA). The marker-set was chosen according to the one previously used for data collected at NASA JSC. A total of 43 retro - reflective markers were placed on body excluding upper limbs (fig. 1) and 2 on the extremities of the bar. Placement were as follow, considering both sides: dorsal margin of first and fifth metatarsal heads, lateral midfoot, most posterior aspect of calcaneus, most lateral and medial point of malleolus, bank of 3 markers on lateral thigh, lateral knee, bank of 3 markers on lateral shank, prominence of greater trochanter, most anterior and most posterior superior iliac spine (ASIS, PSIS), xiphoid process, supraclavicular notch, 10^{th} thoracic vertebrae, vertebra prominens, 3 markers on head.

Fig. 1: marker placement for data collection at Politecnico di Milano

Each subject performed one set of 4 repetitions of normal squat, wide stance squat and normal deadlift with correct execution, similarly to that collected at NASA JSC. Additionally, they performed one set of each kind of wrong technique with a number of repetitions varying from 2 to 4 basing on the individual sensations, to avoid injuries. External loads were in the range of 75-80% of maximal isometric strength (ISO-MAX).

The experimental data prior collected at NASA JSC with ARED were acquired at 250 Hz by 11 cameras SMART-D (BTS Bioengineering S.p.A., Milan, Italy) and GRFs were collected at 1000 Hz by 2 force plates incorporated in the ARED foot platform (Model 9261, Kistler). All subjects involved in the experiment performed one set of four repetitions of the target exercises in correct configuration, with an external load of 75% ISO-MAX.

The protocol adopted, the correct and wrong techniques, were reviewed and approved by NASA Astronaut Strength, Conditioning and Rehabilitation (ASCR) specialists.

C. Correct and wrong techniques

The good form of normal squat requires to start from a standing position and to maintain the trunk straight. Moving down, knees are flexed to reach an angle equal or greater than 90° and then extended to return to the starting position. Wide squat differs from normal squat in placement of feet that show a separation 1.5-2 times larger. To minimize risk of trauma and ensure maximal lower limb muscles activation, optimal squat technique requires: upright trunk to maintain spine in a neutral position, with a slightly lordotic lumbar spine; knees tracking over toes, so without bring them closer and avoiding to overcome the toes; heels in contact with the floor, to prevent forward lean of the trunk; tibiae parallel to the upright torso; gaze forwards or upwards [5],[8],[9]. The deviations from the correct techniques were: rounded back (RB), valgus knees (KV), knees overcoming toes (KOT), raised heels (RH) and shallow squat (SQ).

As concern normal deadlift, the optimal technique requires to start in partial squatting, with natural width of feet and with arms coming down outside the legs to reach the bar. Then, hip and shoulders have to be lifted at the same time maintaining a natural position of the spine. It is necessary to respect some features to avoid inefficacy of training and/or injuries: hip joints have to be maintained higher than knees, to prevent forward lean of the trunk; upright trunk to maintain spine in a neutral position; shoulder blades adduced, slightly in front of bar; gaze forwards [4], [10]. Wrong executions were: rounded back (RB), bar over shoulders (BOS) and hyperextension of the back at the end of lifting (HB).

D. Data analysis and biomechanical simulation

OpenSim [11] is an open-source software used to build individual biomechanical models and to compute joint angles and moments. The model used for the analysis was the published skeletal model with 12 segments and 23 degrees of freedom (dof). Hip joint was modelled as a ball-and-socket joint with 3 dof, while knee and ankle as single dof hinge joints. The same model was utilized by DeWitt et al. [12] and Mummidivarapu et al. [13] to identify the optimal body weight replacement in weightlessness during squat. Fregly et. Al [14] combine the published extension of the same model, which includes also all upper-body joints [15], with three-dimensional computer-aided design (CAD) geometry of ARED to simulate squat exercise in microgravity. Custom script using Matlab R2019a were used to pre-process data, to create files in compatible format with OpenSim and to elaborate its output. Raw data were interpolated with a cubic spline function to fill gaps and filtered with a 6^{th} order Butterworth low pass filter with a cut-off frequency of 5 Hz. External loads were added by considering a constant vertical force applied on the shoulders of the model, on the mid-point of the barbell (fig. 2).

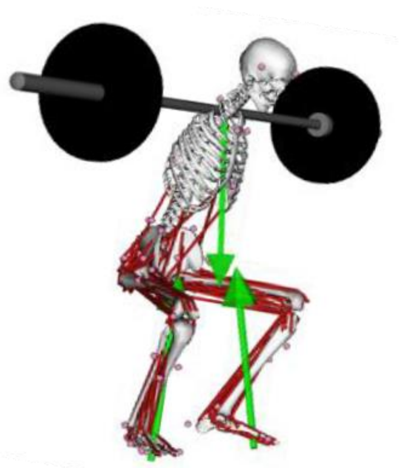

Fig. 2: screenshot of the model during simulation of correct squat. GRFs and external force due to the barbell are shown in green.

Output coming from OpenSim were elaborated in order to compare results between correct and wrong techniques with non-parametric Wilcoxon-Mann-Whitney test. For each exercise and each subject, joint angle and joint moment average and standard deviation of all repetitions were computed. For squat and wide squat, one cycle begins (0%) with hip and knee joints extended, it continues with their flexion and terminates (100%) returning to the initial position. For deadlift is the opposite: the cycle starts with knee and hip joints flexed, it proceeds with their extension and ends returning to the initial position.

E. *Inertial sensors simulation and classifier development*

The Analyses Tool of OpenSim was used to simulate inertial sensors, so to extract acceleration data in different body points related to each kind of training exercise and execution. This tool allows to compute trajectory, velocity and acceleration of body points properly specified by user. To do this, it is needed to specify the coordinates of the points involved, the name of the segment in which they are located and the reference system in which they are expressed. The chosen points were sternum, sacrum, mid-thigh and mid-shank. Despite the few simulated acceleration data available, it was explored a method to build a classifier based on machine learning algorithms. The classification was limited to a binary one in order to distinguish performance between correct and wrong, without differentiating the various mistakes. Two supervised learning methods were compared: Artificial Neural Network (ANN) and Support Vector Machine (SVM). Four sensors were simulated, each one gave three acceleration signals, one per axis. Accelerations related to each repetition were extracted, filtered with a 2nd order Butterworth low-pass filter with cut-off frequency of 2 Hz and normalised in time. Basing on works in literature [16], [17], features both in time domain (e.g. mean, max, min, variance, standard deviation, etc.) and frequency domain (e.g. energy, mean, max, min, band power, etc.) were extracted. Principal component analysis (PCA) [18] is one of the most used techniques for dimensionality reduction. It was chosen in this work to reduce the feature set and, thus, to facilitate the subsequent learning and generalization steps of machine learning algorithms. Workflow can be seen in the scheme below (figure 3).

III. Results

A. *Comparison between correct and wrong techniques*

The hypothesis of not equality of joint angles and joint moments in the sagittal plane between correct and wrong techniques was statistically demonstrated with Wilcoxon-Mann-Whitney test ($p<0.05$).

B. *Comparison between ARED and barbell kinematics*

Both correlation and the hypothesis of equality of joint

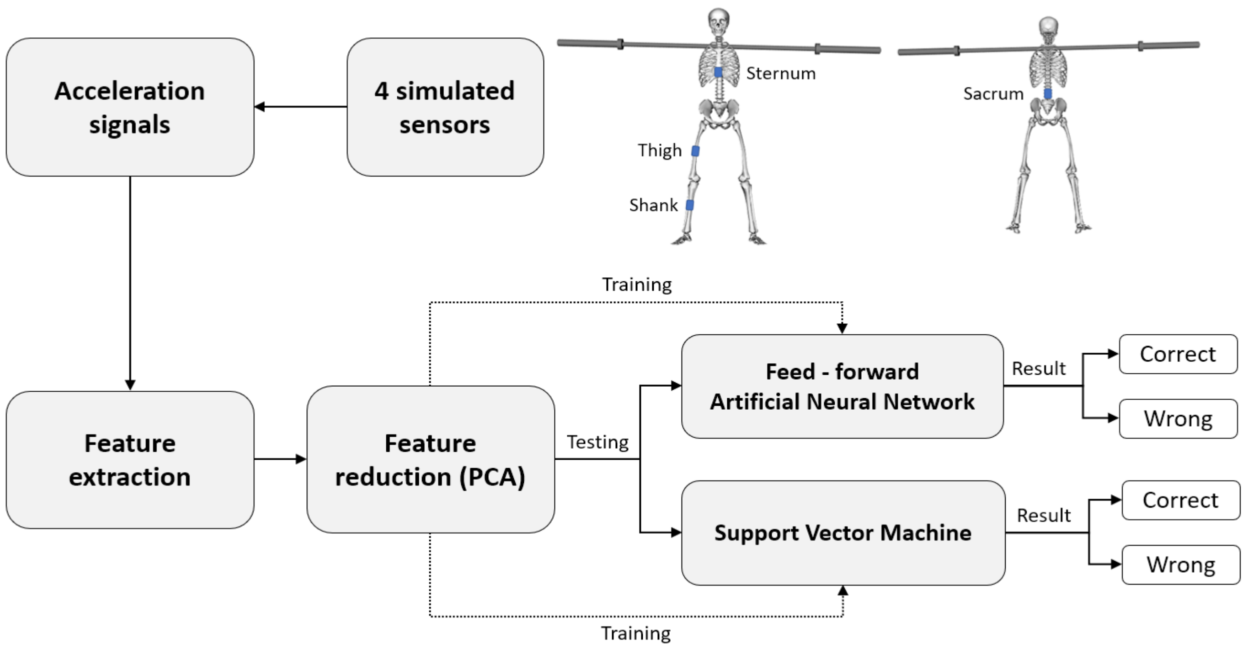

Fig. 3: workflow from sensor simulation to binary classification.

angles in the sagittal plane between ARED kinematics and barbell kinematics were statistically demonstrated with Wilcoxon-Mann-Whitney test ($p < 0.05$). Thus, no statistical differences were observed between kinematics of exercises performed with ARED and barbell.

C. *Performance of the classifier*

From each simulated acceleration signal, a total of 304 features per single repetition were extracted. For example, considering normal squat, dataset was composed by 40 rows, given that two subjects performed 4 repetitions of correct and each type of wrong technique, and 304 columns. PCA reduced the original datasets, composed by 304 features, to 12 for normal squat, 9 for wide squat and 10 for normal deadlift. Then, rows were labelled as 1 for correct execution and 0 for wrong. Datasets were divided to create subsets needed to train, validate and test the machine learning algorithms, considering a percentage of 80%, 5% and 15% of observations respectively. ANN and SVM performance were compared computing accuracy according to the formula Eq. (1) (TP = true positive, TN = true negative, FP = false positive, FN = false negative).

$$Accuracy = \frac{TP+TN}{TP+TN+FP+FN} \qquad (1)$$

As shown in table I, for squat and deadlift SVM was more accurate, instead ANN showed better results for wide squat.

TABLE I
ACCURACY OF MACHINE LEARNING ALGORITHMS

	SQUAT	*WIDESQUAT*	*DEADLIFT*
ANN	83.3%	75%	60%
SVM	88%	71.4%	85.7%

IV. Conclusions

The procedure adopted in this work to simulate inertial sensors, given that no acceleration data related to exercise preformed with ARED were available, was effective despite the small amount of available data. Further investigations are needed to enlarge datasets and to improve the performance of the classifier, but these preliminary results could be seen as encouraging to consider this approach as working solution. Currently, the study is going on by analyzing data collected at NASA JSC and it will be supported by in-flight data, once available.

Acknowledgement

This work has been funded by Italian Space Agency (ASI) in the frame of the ‘BANDO ASI’ DC-VUM-2017-006 “Marcatori biologici e funzionali per la biomedicina astronautica di precisione – MARS-PRE”.

Authors want to thank Prof. Veronica Cimolin and Alessandro Russo for supporting in the data acquisition.

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