Movement Analysis Strategies and Applications

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***Abstract*—Movement analysis enables the comprehension of human voluntary movements patterns, crucial in the rehabilitation field or in industrial applications like human-robot collaboration. This paper presents two simplification strategies for the analysis process of human voluntary tasks: the identification of the optimal experimental setup for the validation of a rehabilitation device, and the reduction of the features number for machine learning algorithms applied to human intention prediction.**

Keywords*—*movement analysis, human-robot interaction, optoelectronic acquisition systems, accelerometers, Machine Learning Techniques (MLT)

I. Introduction

A thorough comprehension of human voluntary movements is fundamental in several contexts, like: i) the rehabilitation field, since the comparison between the healthy and the pathological pattern allows monitoring the subject' health condition [1], ii) the design process, and in particular for rehabilitation systems, enabling devices evaluation and validation, or iii) the industrial field, providing precious hints for the optimization of control strategies within the context of human-machine interfaces and human-robot collaboration [2]. Human movement is a complex set of tasks, including postural adjustments performed both before (anticipatory) and during (compensatory) the focal movement. To simplify the analysis process, two complementary strategies can be applied: i) to select and reduce the amount of collected data, defining essential analysis models and instrumental setup, but as much reliable and portable, as well as less invasive as possible. Within this scenario, comparisons among acquisition systems strength points and drawbacks are fundamental to properly chose an optimal solution; ii) to use machine learning (ML) techniques, reducing the number of evaluated features to the minimum. To depict these two strategies, this paper presents two illustrative case studies of movement analysis applied to human voluntary tasks.

II. Movement Analysis Strategies

A. Experimental Setup Simplification

Several evaluation approaches, based on different sensors and acquisition systems, can be adopted to validate rehabilitation devices, like the LEPRE (LEg Programmable REhabilitation) system (PoliBrixia, Italy), depicted in Figure 1. This end-effector-based robotic system presents a compact two Degrees of Freedom (DOFs) differential system and allows implementing every motion profile within a plane.

LEPRE was developed within the SIMeRiON project (Innovative Mechatronics System for Orthopedic and Neurological Rehabilitation), funded by Regione Lombardia (bando FRIM FESR Aggregazioni 2016/18). For the validation campaign, LEPRE was provided by Polibrixia s.r.l..

1) Materials and Methods

To verify the system's effectiveness in imposing an expected training, the movement induced by the device on the upper limb of a healthy subject in a sequence of repetitions was evaluated [3]. The kinematics of specific landmark points of the subject's limb was detected thanks to i) an optical marker-based tracking system with two fixed cameras (DX-100, BTS Bioengineering, Italy) and with eight skin passive optical markers, and ii) two triaxial wireless accelerometers (BeanDevice WiLow AX-3D). The optical markers were located on the subject's acromion, lateral humeral epicondyle, and radial styloid process of the left upper limb. One marker was on the device handle, two on the device cover, and two on the chair. The accelerometers were positioned in two configurations: i) on the medial radius (the upper side of the subject's forearm) and ii) on the medial ulna (beneath the forearm). Accelerometers signals were acquired at 200Hz, and markers displacements at a frequency sample of 100Hz.

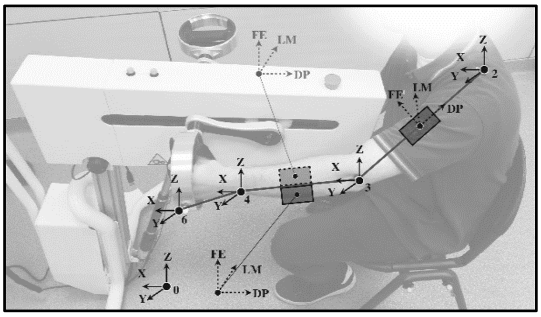

Fig. 1. Positioning of skin passive optical markers and accelerometers, and kinematic model of the subject upper limb.

The subject repeated for 9 cycles a unilateral reaching profile along the sagittal plane (maximum stroke of 0.285m and 0.153m in Z and X direction) according to a passive rehabilitation strategy, with cycle time defined by the operator. Three acquisitions are reported as significant for the comparison of the forearm accelerometer configurations: A) with the sensor in medial radius position, B) with the accelerometer in medial ulnar position, and C) with the same conditions of B.

2) Results and Discussion

To compare the information content provided by the two measurement systems, the absolute acceleration of arm and forearm estimated center of gravity were computed from the marker displacement signals as a_{mrk} and compared with the absolute accelerations a_{acc} acquired by the accelerometers. A fractal dimension analysis was performed on the combined plot of arm versus forearm acceleration of a_{acc} and a_{mrk} to quantify the signal complexity in the synthetic parameter *df* (Table I). Acquisition A (the forearm sensor configuration in the upper position) presents the lowest value of *df*, indicating a smoother and more regular path. If optical markers, with a network of distributed observation units, assure a comprehensive but generic description of the system, accelerometers provide more detailed information at a local level. For this reason, optoelectronic acquisition systems allow implementing complete models for the description of complex kinematic chains, whereas accelerometers are particularly suitable for qualitative analyses of a specific rigid body, e.g. fluency of a limb movement, or smoothness of a device transmission.

TABLE I. FRACTAL DIMENSION OF THE COMBINED ACCELERATION SIGNALS ARM VERSUS FOREARM FOR THE TWO MEASUREMENT SYSTEMS, FOR THE THREE ACQUISITIONS

Absolute Arm vs Forearm Acceleration	**Fractal dimension *df***		
	Acquisition A (medial radius)	***Acquisition B (medial ulna)***	***Acquisition C (medial ulna)***
Optical Markers	1.1487	1.1961	1.2264
Accelerometers	1.4091	1.4113	1.4144

B. *Adoption of Machine Learning Techniques*

ML techniques are particularly suitable to predict subjects' intention of moving towards specific directions.

1) Material and Methods

A campaign on ten healthy subjects performing a reaching movement with the upper limbs was carried out in collaboration with ISIR (Institut Systèmes Intelligents et de Robotique, Sorbonne Université, France). Subjects were asked to reach six targets at three directions, i.e. internal, middle, external, and two distances, i.e. i) far, at 90% of arm length, and ii) close, at 65% of arm length. With each hand, three repetitions were recorded for each target, following a standardized order: close-middle, far-internal, high-external, far-middle, close-external, high-internal, close-internal, far-external, high-middle.

An electromagnetic tracking device (Polhemus FASTRAK) was used to collect data, with four sensors located at the subject's manubrium, acromion process, upper third of humerus, and dorsum of the wrist splint. Minimum, maximum, and root-mean-square of sensors i) position components, ii) velocity modulus, iii) acceleration modulus, and iv) Euler angles, were evaluated as features of a multiclass ML problem, considering as output classes the targets' positions. The performance of Random Forest (RF) and Linear Discriminant Analysis (LDA) as intention predictors was compared with respect to observation window size (1/10 and 1/7 of the total motion time length) and considered features [4]. For RF the Out-of-Bag (OOB) error was computed. For the comparison, RF and LDA were trained using the 90% and 85% of data, randomly selected with a cross-validation approach, on 200 testing cycles.

2) Results and Discussion

Better accuracy is achieved with wider observation windows, and without the distinction of which hand is performing the motion (Figure 2). LDA achieves better results, and highest accuracy in the tests considering sensors position and velocity. No significant accuracy increasing is obtained including Euler angles-related features in the evaluation (Figure 3). LDA requires shorter training times and faster prediction times ($1.1 \cdot 10^{-4}$ [s] vs $3.1 \cdot 10^{-3}$ [s]).

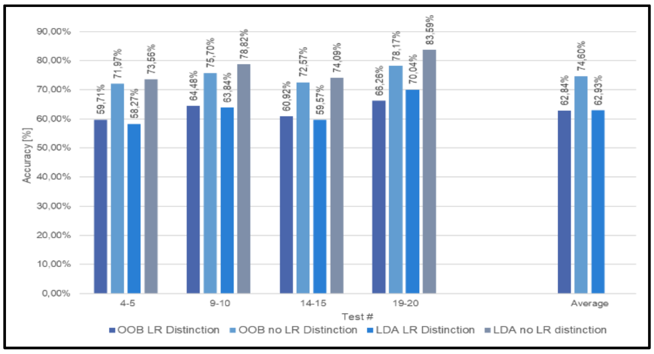

Fig. 2. Comparison of RF's out-of-bag (OOB) error and LDA accuracy with respect to the left-right hand (LF) distinction.

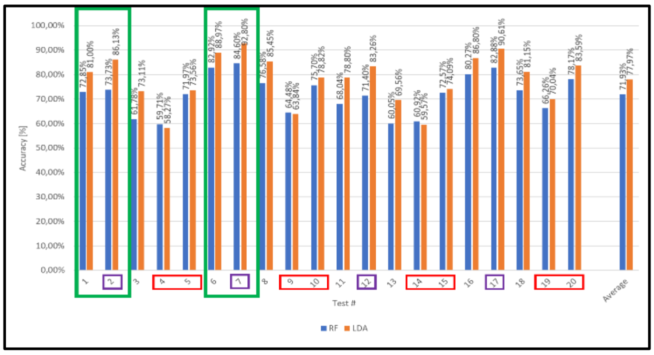

Fig. 3. RF vs LDA accuracy. Red squares indicate tests with acceleration-related features, purple ones acceleration- and Euler angles-related features.

III. CONCLUSIONS

The complexity of human voluntary movements analysis can be effectively simplified if the evaluation efforts are focused on the essential data. This goal can be for instance achieved by properly designing the data collection campaigns, e.g. keeping the acquisition system as essential as possible, or performing preliminary investigations on the measured data, e.g. highlighting the most significant features for specific ML algorithms.

ACKNOWLEDGMENT

For the support in the data collection and analysis, the authors thank: Manuela Ghidoni, Paolo Gaffurini, and Luciano Bissolotti (LEPRE device), and Leonardo Archetti, Ludovic Saint-Bauzel, Agnès Roby-Bramy, and Johanna Robertson (multi-target reaching task).

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