Movement Smoothness Metrics in Human-Machine Interaction

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Abstract. The evaluation of motion abilities is crucial to rate human movement control performance in several contexts. In the medical field, for example, smoothness, a feature related to the regularity of movement, is assessed through objective metrics during the execution of free movements in order to support the decision based on clinical scales about the impairment severity. Nevertheless, individuals with and without impairment interact daily with machines to improve their well-being in many contexts: rehabilitation, collaborative robotics, and sport exercises, among others. During these activities, they perform movements in a closed-chain, where inertial or resistance forces introduced by an external tool could affect their motion control.

In this study, closed-chain movements performed by three able-bodied and five individuals with coordination impairments were investigated; three different smoothness metrics presented in the literature were applied to analyze the results. The experimental tests consisted in moving a slider mounted on a linear rail with varying velocity and resistance force conditions. Position in the main direction, accelerations and forces in all directions were recorded during the tests.

All the metrics detected a smoothness improvement when velocity increased, while only two metrics found an influence of the resistance force on the smoothness.

Keywords: SDG3, SDG9, Smoothness, Para-athletes, Cerebral Palsy, Collaborative robotics, Closed-chain movement.

1 Introduction

Smoothness is one of the features assessing human movement control performance, related to its continuity [1]. A ‘smooth’ movement is defined by a regular pattern without intermittences. On the opposite, a movement is ‘unsmooth’ when it is characterized by peaks that make the trend less regular and with multiple alternations of accelerations and decelerations [2]. In the medical field, the motion behavior of people with neurological health disorders such as stroke or cerebral palsy has been investigated to assess their impairment severity, relying on movement control capabilities. To quantify smoothness, appropriate metrics should be used to analyze motion signals. Metrics have to be dimensionless (e.g. not influenced by amplitude and duration of movement), have a monotonic response to the motion regularity and be sensitive in the physiological range [3].

Different metrics have been considered to quantify movement smoothness in various contexts [4, 5]. Peak Metrics (PM) technique was adopted for classifying para-swimmers with hypertonia, ataxia and dyskinesis [6]. Log Dimension-Less Jerk (LDLJ) and Spectral-Arc Length (SPARC) metrics were investigated to evaluate upper limb movement smoothness using IMU data [7]. Gait smoothness in patients with Parkinson’s disease was estimated with SPARC in [8].

All these studies have assessed smoothness on movements that could be defined as open-chain (OC), that is, the distal segment has no external constraints and it is free to move. However, several motor activities involve the interaction with a tool or a machine in a closed-chain (CC), where physical interaction between human and machine leads to motion constraints and haptic feedbacks. Conditions of CC occur in daily living activities [9], manufacturing tasks [8] and collaborative robotics [10], functional rehabilitation [11], and sports, including para-sports [12]. Indeed, smoothness may be an evaluation factor to assess and possibly improve individual’s comfort and activity experience in tasks requiring a human-tool interaction. The assessment of movement features can allow for optimized development and control of machines and equipment, according to human-centered design. The enhanced usability and management of machine interfaces are coherent with SDG3 and SDG9 goals, where health-promoting, well-being and inclusive working are addressed.

In this work, three smoothness metrics mainly used in the literature (SPARC, LDLJ and PM) were applied on signals collected during a task realized in CC by able-bodied individuals and individuals with coordination impairments, active in sports. The paper aims were to investigate whether smoothness identified through these methods is related to (i) motion velocities and (ii) resistance forces while performing motion control in CC tasks.

2 Materials and Methods

2.1 Participants

Participants involved in this study were recruited as part of a research project on Paralympic Sports. Two groups of individuals were recruited for the experiment. Group *1* was composed of twenty athletes (18 males, 2 females) with Cerebral Palsy (CP); group *2* consisted of twenty able-bodied reference participants (9 males, 11 females). All participants were active in sports (age 18 to 50 years). In the current study, data from five participants with CP (CP1, CP4, CP6, CP13, CP14) and three able-bodied (REF10, REF15, REF20) were used for statistical analysis. Participants with CP were divided into sub-groups *1a* and *1b* by severity of impairment relying on clinical scales, such as TASC (Test of Arm Selective Control, an upper limb control performance score), MAS (Modified Ashworth Scale, spasticity evaluation), SARA (Scale for the Assessment and Rating of Ataxia) and GMFCS (Gross Motor Function Classification System), as reported in Table 1 [13]. Participants included in the reference group were recruited in the Swedish School of Sport and Health Sciences (GIH, Stockholm, Sweden). The athletes with CP were recruited by the Universitas Miguel Hernandez (Elche/Alicante, Spain). Ethical approval was applied depending on the Swedish and Spanish Ethical Review Authority of each country.

Table 1. Clinical data grouping participants with CP by severity of impairment.

Participant	TASC	MAS	SARA	GMFCS	Sub-group
CP 1	0	0	0	1	**1a**
CP 4	0	1.5	0	1	**1a**
CP 6	6	8.5	2	4	**1b**
CP 13	9	3	4	1	**1b**
CP 14	4	2.5	3	1	**1b**

2.2 Test bench and protocol

The test bench was composed of a slider with a handle, that could be moved along the longitudinal X axis of a linear rail (Fig.1a). The handle is free to rotate around the Z axis. A magnetic brake provides a resistance force opposing the sliding movement through a timing belt transmission.

(a) (b)

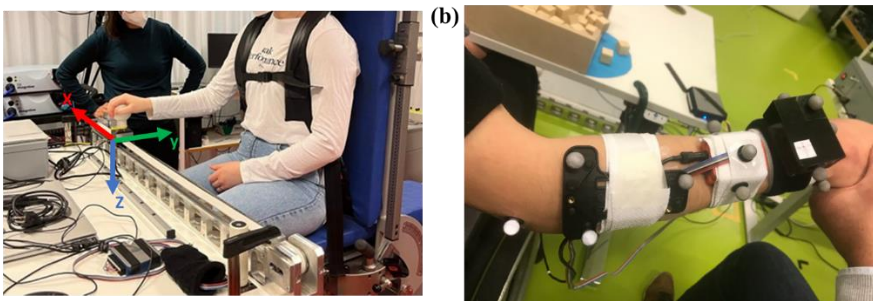

Fig. 1. a) Test bench with the linear rail, slider and handle. b) The instrumentation worn by the participant (inertial sensor and reflective markers).

The instrumentation adopted consisted of a 3D force transducer K3D120 (ME-Meßsysteme, Germany) interposed between the handle and the slider to measure forces in the X, Y and Z axes (Fig.1a). An encoder PM325 (Elcis, Italy) was positioned on the brake axis to record the slider position during the tests. In addition, the participant wore an MTx inertial sensor (Xsens, Netherland) placed on the wrist measuring linear accelerations in the three directions, and some reflective markers for motion tracking used for tests not reported in this paper.

During the test, individuals sat in front of the table, with the trunk secured to the backrest with straps. They were asked to grasp the handle with the dominant or stronger hand and move the slider along the rail for at least 8 repetitions with different test conditions. The movement consisted of an alternate back and forth displacement with a spatial range of 50 cm self-controlled. A pre-test has been performed to measure the personal maximum velocity (V_{max}) of movement with a minimum resistance force, i.e. 5 N bench friction. The tests protocol included nine different conditions by combining three velocities (35%, 50% and 65% of V_{max}) and resistant forces at three different constant levels (5 N, 10 N, and 20 N). At the beginning of each trial a series of intermittent LEDs were used to guide the range of the displacement and the pace. When the recording started, the lights went off and the velocity was self-maintained by each individual.

2.3 Data collection and signals processing

Different signals were recorded during the test: position of the slider along the X axis, forces and accelerations in all directions. As regards the accelerations, the inertial sensor (IMU) was placed only in the CP group test, so inertial data could be compared just within the CP group. Furthermore, the velocity and the derivatives of the forces were post elaborated using Matlab by MathWorks (USA).

Based on the displacement trend, signals were segmented into cycles, where a cycle corresponded to the trajectory of the slider from the right to the left end and back to the right. Eight complete cycles were considered for each trial.

Recorded data were filtered using a second Butterworth filter with a 20 Hz low-pass cut-off frequency [3, 14]. The smoothness was evaluated according to the three metrics: SPARC [14] and LDLJ [7], mainly in support of medical decision-making; and PM [6], adopted as a comparison method in para-athletes to assess severity of the impairment. Equation (1) describes the SPARC index η_{SPARC} calculation, where $\hat{S}(\omega)$ is the Fast Fourier Transform (FFT) of the signal profile in time $s(t)$, normalized with respect to its maximum and ω_c is the cut-off frequency; equation (2) represents the LDLJ index η_{LDLJ} formula, where t_1 and t_2 are the start and end instants of the movement, $a(t)$ is the acceleration profile and a_{peak} corresponds to the maximum acceleration peak between t_1 and t_2; PM index η_{PM} is the total number of signal maximum local peaks s_{peak} in the studied interval according to equation (3):

$$\eta_{SPARC} = -\int_0^{\omega_c} \sqrt{\left(\frac{1}{\omega_c}\right)^2 + \left(\frac{d\hat{S}(\omega)}{dt}\right)^2}\, d\omega \tag{1}$$

$$\eta_{LDLJ} = -\ln\left(\frac{(t_2-t_1)}{a_{peak}^2}\int_{t_1}^{t_2}\left|\frac{da(t)}{dt}\right|^2 dt\right) \tag{2}$$

$$\eta_{PM} = \sum s_{peak} \tag{3}$$

Metrics algorithms were implemented in Matlab and applied to all signals. In addition, the SPARC metric includes the calculation of the FFT, that shows a power dispersion around the main frequency if applied on finite time sinusoidal signals. For this reason, the Chebyshev window [15] is introduced to reduce the amplitude and maximize the decreasing velocity of the FFT secondary lobes.

The three metrics provide indices in different scale ranges, therefore, in order to compare the results consistently, the values were normalized in the range 0-1 applying the min-max scaling method; index decreases when smoothness increases.

3 Results and discussions

The smoothness metrics Spectral-Arc Length, Log Dimension-Less Jerk and Peak Metrics technique were applied to the recorded signals. The smoothness indices values were compared inter-participants. The results presented in previous work [6, 16] showed a smoothness improvement trend when the OC movement velocity increased. According to the first aim of this study, the smoothness variability with respect to velocity in a CC movement at a fixed resistant force value equal to 10 N was investigated.

Table 2 summarizes smoothness results for each signal, where '*Yes*' indicates improved smoothness when velocity increases, coherent with the literature related to OC movements; '*No*' means no impact or no monotonic trend; '*/*' means not applicable. In the table, **A**, **F**, **S** and **V** are acceleration, force, displacement and velocity respectively, and subscripts **x**, **y**, **z** represent axes components. The last row collects the number of participants analyzed for each signal, highlighting that inertial data are examined only for the CP group.

Table 2. Metrics reliability for closed-chain movement.

	$\mathbf{A_x}$	$\mathbf{A_y}$	$\mathbf{A_z}$	$\mathbf{F_x}$	$\mathbf{F_y}$	$\mathbf{F_z}$	$\frac{dF_x}{dt}$	$\mathbf{S_x}$	$\mathbf{V_x}\left(\frac{dS_x}{dt}\right)$
SPARC	*Yes*	*No*	*No*	*No*	*No*	*No*	*Yes*	*No*	*No*
LDLJ	*Yes*	*No*	*No*	/	/	/	/	/	/
PM	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*	*Yes*
Participants	5	5	5	8	8	8	8	8	8

SPARC reveals improved smoothness vs velocity only if applied to acceleration and to the force first derivative signals only along the x-axis. LDLJ metric outcomes present a significant trend considering the x-axis acceleration signal recorded on the CP group and it is not applicable to the other signals. Finally, the PM metric returns the expected trends for all the measured signals. Figure 2 illustrates examples of the smoothness trends for each metric.

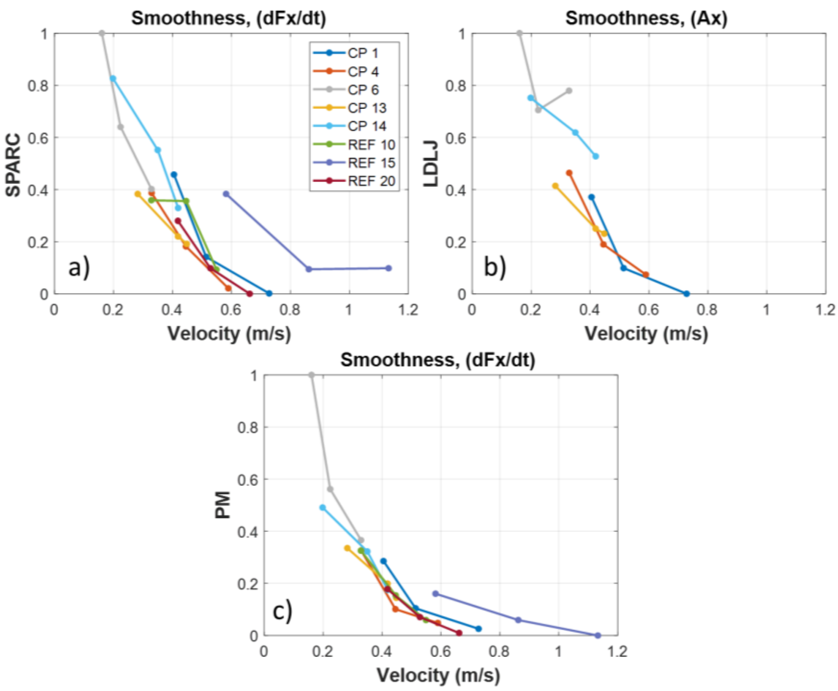

Fig. 2. a) SPARC applied to the force first derivative along the X axis. b) LDLJ applied to the acceleration signal along the X axis. c) PM applied to the force first derivative along the X axis.

The second aim of this study was to investigate the relationship between smoothness and resistance force. For each participant and for all metric-signal combinations marked '*Yes*' in Table 2, smoothness values were collected in a 3x3 matrix, aggregating all the velocity-force combinations.

Results show that smoothness values evaluated with SPARC and LDLJ metrics vary with the force: in most of the cases the movement smoothness decreased monotonically with increased resistance force; however, some tests have more chaotic variation. The third metric PM does not produce evidence related to the force change.

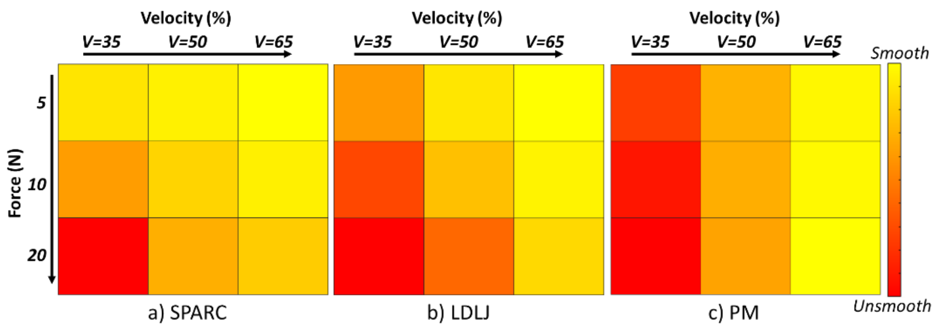

Fig. 3. Maps with results obtained using a) SPARC metric, b) LDLJ metric, c) PM metric.

As an example, Fig. 3 shows the matrices for the acceleration component $\mathbf{A_x}$ along the motion axis, recorded in participant CP 4 for the three metrics. The columns of each matrix represent the velocity conditions and the rows the constant resistance force values. The color of the cells depicts the smoothness level according to the color scale on the right. In this case, two trends characterize the matrices. The first one is a smoothness improvement increasing the movement velocity; this is confirmed for all three metrics. The second one emerges looking at Fig.3a (SPARC) and Fig.3b (LDLJ), in which the smoothness decreased with higher forces. On the contrary, PM is not affected by the changing force (Fig.3c).

4 Conclusion

Smoothness is an important movement control feature and it can be assessed using different metrics. These methods are mainly used in literature on OC tests, however, many activities in daily life are CC, due to the interaction with tools and instruments.

The experimental tests carried out in this study point out the influence of movement velocity on smoothness in CC tasks, as already stated in previous work for OC, according to SPARC, LDLJ and PM metrics. In addition, SPARC and LDLJ are influenced by a variation of resistance force in most of the tests; this evidence is not depicted with PM.

The analysis here presented will be extended systematically to all the participants to access the correlation between force and smoothness using SPARC and LDLJ metrics.

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