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A statistical approach for functional reach-to-grasp segmentation using a single inertial measurement unit

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Abstract: The aim of this contribution is to present a segmentation method for the identification of 9 voluntary movements from inertial data acquired through a single inertial measurement unit placed 10 on the subject's wrist. Inertial data were recorded from 25 healthy subjects while performing 75 11 consecutive reach-to-grasp movements. The approach herein presented, called DynAMoS, is based 12 on an adaptive thresholding step on the angular velocity norm, followed by a statistics-based post-13 processing on the movement duration distribution. Post-processing aims at reducing the number of 14 erroneous transitions in the movement segmentation. We assessed the segmentation quality of this 15 method using a stereophotogrammetric system as the gold standard. Two popular methods already 16 presented in the literature were compared to DynAMoS in terms of the number of movements iden-17 tified, onset and offset mean absolute errors, and movement duration. Moreover, we analyzed the 18 sub-phase durations of the drinking movement to further characterize the task. Results showed that 19 the proposed method performs significantly better than the two state-of-the-art approaches (i.e., 20 percentage of erroneous movements = 3%; onset and offset mean absolute error < 0.08 s), suggesting 21 that DynAMoS could make more effective home monitoring applications for assessing the motion 22 improvements of patients following domicile rehabilitation protocols. 23

Keywords: Activity of daily living; functional assessment; IMU; movement segmentation; telereha-24bilitation; upper limb25

1. Introduction

Activities of Daily Living (ADLs) are fundamental for independent living and, in this 28 regard, the functionality of the upper limb is crucial for a good quality of life [1,2]. Unfortunately, 28% of the population over 50 years of age and 50% of the population over 80 30 years are affected by movement disorders [3].

To define appropriate interventions for motor disorders management, an accurate 32 clinical assessment sets the basis for designing an effective motor rehabilitation program 33 and for testing its effectiveness. Clinical assessment is usually performed using scales 34 grading functional and movement disorders based on the clinician's evaluation of the ex-35 ecution of a specific task. However, in the last decades, many motion analysis systems 36 have been proposed and used for reducing the subjectivity in patient clinical evaluation 37 and enhancing the effectiveness of rehabilitation outcome evaluation, especially for the 38 upper limb [4–8]. In particular, Inertial Measurement Units (IMUs) have been widely used 39 for the assessment and rehabilitation of movement disorders of the upper limb [9]. IMUs 40 measure acceleration and angular velocity of the body segment they are fixed to, allowing 41 for the quantitative analysis of patient movements based on parameters derived from in-42 ertial recordings [9]. The use of IMUs arose because of their ease of use, portability, and 43 low cost. For example, using IMUs allows clinicians to tailor rehabilitation protocols to 44 the patient's needs [10] and, in the context of therapy delivery systems, allows patients to 45

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Copyright: © 2024 by the authors. Submitted for possible open access publication under the terms and conditions of the Creative Commons Attribution (CC BY) license (https://creativecommons.org/license s/by/4.0/). decide when and where to carry out therapeutic sessions [11]. However, these devices are not yet considered adequate for measuring the quality of movement during functional tasks in a clinical environment [12]. Therefore, there is a need to develop and validate new methods that increase the reliability and validity of IMU-derived evaluation metrics in clinics [12].

Among all the proposed parameters, execution time is one of the most commonly 51 used metrics for the assessment of patient functionality in a clinical context. Hence, it is 52 necessary to precisely identify voluntary movements. To this end, several methods, based 53 on the inertial data, have been presented in the literature. The most straightforward ap-54 proach is to define a threshold that discriminates between voluntary movements and in-55 voluntary ones. For example, Schwarz et al. [13] identified voluntary movements by ap-56 plying a fixed threshold to the angular velocity norm. Voluntary movements were identi-57 fied in correspondence to the time instants above this threshold. Carpinella et al. [14] pro-58 posed a similar approach setting an adaptive threshold at 25% of the maximum of the 59 angular velocity norm during the movement. Setting the threshold value equal to a per-60 centage of the maximum recorded value guarantees that the threshold is more suited to 61 the characteristics of the subject under analysis, reducing the influence of inter-subject 62 variability on the segmentation results. Moreover, Hughes et al. [15] identified voluntary 63 movement onset and offset by applying a kinematic criterion on the linear velocity de-64 rived from the IMU accelerometer. In detail, the onset was determined as the first instance 65 in the time series where the resultant velocity exceeded 1.5% of the first velocity peak, and 66 the offset was determined when the velocity dropped under 1.5% of the velocity peak. 67 The method proposed by Hughes *et al.* presents several challenges. First, the reconstruc-68 tion of the linear velocity relies on numerically integrating the linear acceleration after 69 removing the gravitational bias. This process requires accurately estimating the sensor 70 orientation using a sensor fusion filter. Even with fine-tuning of the filter parameters re-71 sidual errors persist, leading to propagation errors in the numerical integration process 72 [16]. Additionally, the initial conditions of orientation and velocity are critical factors that 73 significantly impact the accuracy of the results. Repnik et al. [17] presented a different 74 segmentation method, based on the biomechanical model reconstruction of the upper 75 limb from multiple IMUs mounted on the patient chest, arm, and forearm. Apart from the 76 approach used by Schwarz et al. [13], all the other methods cannot be used in real-time 77 applications since they need to extract information from the whole IMU recordings before 78 performing movement segmentation. 79

Among the aforementioned methods, the most used approaches for voluntary move-80 ment segmentation are those presented by Schwarz et al. [13] and Carpinella et al. [14], 81 due to their simplicity and scalability. Nevertheless, both methods are subject to limita-82 tions. The segmentation method proposed by Schwarz et al. [13] does not present a tech-83 nical validation. Moreover, the application of a fixed arbitrary threshold may strongly re-84 duce the adaptability of the method to different movement and subject characteristics. 85 These limitations have been partially solved by Carpinella et al. [14], who performed a 86 technical validation and employed an adaptive threshold to identify voluntary movement 87 from the angular velocity norm. However, the definition of the adaptive threshold can 88 have a significant impact on the final segmentation results. The choice of a high value 89 (e.g., 25% of the maximum angular velocity norm) could lead to the exclusion of parts of 90 movements or even whole movements. On the other hand, selecting a value that is too 91 low may lead to the inclusion of involuntary movements or background noise. This is 92 especially true when analyzing movements that are composed of sub-phases executed at 93 very different intensity levels. Moreover, the reliability of the segmentation results may 94 be compromised by signal fluctuations around the threshold value, resulting in fast erro-95 neous transitions. 96

To overcome the limitations of the approaches proposed by Schwarz *et al.* [13] and 97 Carpinella *et al.* [14], we developed a new method and performed a technical validation 98 using a StereoPhotogrammetric (SP) system as a gold standard. The newly proposed 99 segmentation method, DynAMoS (Dynamic Adaptive Movement Segmentation), en-100 hances the state-of-the-art adaptive thresholding approach with statistics-based post-pro-101 cessing aimed to reduce erroneous segmentation by applying statistical considerations to 102 the movement duration histograms. In this paper, after the evaluation of the effectiveness 103 of the proposed method against the gold standard and state-of-the-art approaches (i.e., 104 Schwarz et al. [13] and Carpinella et al. [14]), segmentation results are used for the charac-105 terization of a reach-to-grasp movement. With the aim of supporting the adoption and 106 standardization of IMU-derived parameters in clinical environment, we freely distribute 107 the DynAMoS Matlab algorithm, its detailed documentation, and a sample dataset on the 108 BIOLAB GitHub repository (https://github.com/Biolab-PoliTO/DynAMoS). 109

2. Materials and Methods

2.1 Participants

Twenty-five healthy subjects (12 females and 13 males; age: 22.5 ± 2.1 years; 6 left-113 handed and 19 right-handed) participated in the study. To participate, volunteers were 114 required to have no history of physical or neurological pathologies that might interfere 115 with their ability to perform the task. The subject height and weight were recorded by 116 self-report. The dominant forearm length was measured with a flexible measuring tape 117 with the forearm facing downward, measuring from the lateral epicondyle to the ulnar 118 styloid process. 119

This study was approved by the Ethics Committee of Politecnico di Torino (Protocol 120 N. 24766/2022, approved on July 19, 2022). Written informed consent was obtained from 121 each participant before the experimental sessions, and all the acquisitions were performed 122 following the Declaration of Helsinki.

2.2 Acquisition System

Recordings were carried out at the Motion Analysis Laboratory of Polito^{BIO}Med Lab, Politecnico di Torino (Turin, Italy). Inertial data were recorded using an IMU-based wear-127 able device designed and developed at the BIOLAB of Politecnico di Torino (Turin, Italy). 128 This device incorporates an IMU featuring a three-axial accelerometer and gyroscope 129 (LSM9DS1, STMicroelectronics), a Bluetooth Low Energy module, a floating-point micro-130 controller (SAME70, Microchip) to easily install and run custom algorithms onboard, a 131 micro-SD card to store raw and processed data, and an 1 Ah rechargeable battery [18]. All 132 the IMU recordings are acquired at a sampling frequency of 100 Hz. 133

A twelve infrared camera SP system (Vicon T20, Vicon Motion Systems, sampling 134 frequency: 100 Hz) was used to reconstruct the trajectories of 4 photo-reflective markers 135 (diameter: 9.5 mm) attached to the IMU. The IMU was secured to the wrist of the subject using double-sided adhesive tape [19] with its short edge roughly aligned with the wrist's 137 flexion-extension axis. 138

Three RGB cameras integrated with the SP system were used to record the acquisi-139 tions (sampling frequency: 50 Hz). Video recordings were anonymized by blurring sub-140jects' faces. 141

Figure 1a shows a schematic representation of the acquisition system.

The IMU and SP signals were then imported into MATLAB release r2023b (The Math-Works Inc., Natick, MA, USA) to be offline processed through custom routines.

2.3 Experimental Protocol

Volunteers were seated at a table (distance between the tabletop and the seat: 30 cm; 147 table height: 70 cm) and were asked to perform a drinking task using their dominant up-148 per limb. The bottle was positioned in front of the subject sternum at a distance from the 149 table edge equal to 1.5 times the forearm length. The drinking task consisted of reaching 150

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Figure 1. Panel (a): Representation of the acquisition setup composed by the SP system and the IMU (in dark blue color) and a picture of the wrist-worn IMU with 4 photo-reflective markers. Panel (b): Representation of the drinking task sub-phases. The drinking task consisted of reaching and grasping the bottle (step 1 and 2), lifting the bottle simulating drinking (step 2 and 3), placing the bottle back on the table (step 3 and 2), and returning to the resting position (step 2 and 1).

and grasping the bottle (Phase I), lifting the bottle simulating drinking (Phase II), placing
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Figure 1b schematically represents the experimental protocol with the indication of the
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three task sub-phases. The investigated task represents a typical ADL and is part of the
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Frenchay Arm Test, which is commonly used to evaluate upper limb function [20]. The
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position of the bottle on the table and the wrist resting position were marked using adhesive tape, to ensure the repeatability of the movement.

At the start of each trial, subjects were requested to perform a 30-second static acqui-158 sition, after which they were instructed to raise the instrumented arm (dominant side) and 159 perform three rapid rotations along the forearm longitudinal axis before returning to the 160 resting position for 30 seconds. This movement was necessary to synchronize the SP sys-161 tem and the wrist-worn IMU. Subsequently, subjects were required to perform 25 repeti-162 tions of the drinking task. The drinking task sub-phases were executed following verbal 163 instructions from the investigator. Between consecutive drinking tasks belonging to the 164 same trial, a resting period of 4 seconds was performed. In conclusion, a single trial con-165 sisted of a 30-second static acquisition, a synchronization movement, another 30-second 166 static acquisition, and 25 consecutive repetitions of the drinking task. Each volunteer com-167 pleted three consecutive trials with a 2-minute rest in between. For each trial, considering 168 the sub-phases as separated movements, 100 movements are expected. 169

2.4 Data Pre-Processing and Synchronization

The IMU position in space was reconstructed using the Vicon Nexus 2.12 software. 172 The marker trajectories were visually checked and possible gaps were manually filled. To 173 remove random noise, marker trajectories were low-pass filtered using a 2nd-order zerolag Butterworth filter with a cut-off frequency of 6 Hz. A Marker-cluster Local Frame 175 (MLF) was defined using the markers attached to the IMU to determine its reference orientation with respect to the SP system global reference frame. The orientation of the MLF 177 was performed using the Singular Value Decomposition (SVD) [21]. Then, the angular 178

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velocities were obtained from the orientation data [22]. The angular velocities estimated 179 from the SP system were cross-correlated with the angular velocities recorded through the IMU to synchronize the two systems. 181

To reduce rapid signal fluctuations that could lead to inaccurate movement segmen-182 tation, marker trajectories and IMU recordings were further smoothed by means of a 4th-183 order zero-lag low-pass Butterworth filter with a cut-off frequency of 1.5 Hz. 184

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2.5 Movement Segmentation

2.5.1 Stereophotogrammetric-based segmentation

Considering the SP system, voluntary movements were identified based on linear 188 rather than angular velocity. Tri-axial linear velocity and its norm (|v|) were calculated 189 from the marker trajectories. Each linear velocity norm was normalized in amplitude be-190 tween 0 and 1 considering the absolute maximum value recorded over the task duration 191 $(|v_max|)$. To determine voluntary movement onset and offset, an adaptive threshold was 192 implemented, defined as the average over trials of the optimal thresholds computed 193 through Otsu's method from the linear velocity norm of each trial [23,24]. Otsu's method 194 is an unsupervised threshold selection method developed in image processing for the sep-195 aration of objects from the background using the image gray-level histogram. In our case, 196 Otsu's method was applied to the normalized linear velocity norm to identify the thresh-197 old that best distinguishes between the "background" (i.e., involuntary movements or 198 background noise) and the "main object" (i.e., voluntary movements). Based on Otsu's 199 method, the optimal threshold is selected as the one maximizing the inter-class variance. 200 In this study, the adaptive threshold for the SP-based segmentation (Th_{SP}) was set equal 201 to $0.11 \cdot |v_max|$. 202

Additionally, the results of the SP-based segmentation were manually checked by an 203 expert operator, using the videos of the acquisitions as a reference. These segmentations 204 were considered the Gold Standard (GS) for the IMU-based segmentation approaches. 205

Figure 2a shows an example of voluntary movement segmentation obtained considering the SP-derived linear velocity norm.

2.5.2 IMU-based segmentation

The performance of the Dynamic Adaptive Movement Segmentation (DynAMoS) 209 method was compared against two of the most widely used approaches: the fixed thresh-210 olding approach proposed by Schwartz et al. (M1) [13] and the adaptive thresholding ap-211 proach proposed by Carpinella et al. (M2) [14]. All the tested methods were based on the 212 application of a threshold on the angular velocity norm (Ω) . In the following, the three 213 tested segmentation approaches are described: 214

a) Fixed thresholding by Schwarz et al. (M1): The method consists of the application of a sin-215 gle threshold (Th_{M1}) whose value was set equal to 0.1 rad/s. Ω values higher than the 216 threshold are identified as voluntary movements. This empirically selected threshold rep-217 resents a reasonable value for discriminating between stationary and non-stationary 218 states. Figure 2b represents the segmentation results obtained by applying the M1 method 219 to the angular velocity norm of a representative healthy subject during a drinking task; 220

b) Adaptive thresholding by Carpinella et al. (M2): The method consists of the application of 221 an adaptive threshold defined as $Th_{M2} = 0.25 \cdot \Omega_{max}$, where Ω_{max} represents the maxi-222 mum value of the angular velocity norm recorded over task duration. Setting the thresh-223 old to 25% of the maximum value of the angular velocity norm represents a more con-224 servative approach to the segmentation task, ensuring that all the segmented sections are 225 actual movements. Figure 2c represents the segmentation results obtained by applying 226 the M2 method to the angular velocity norm of a representative healthy subject during a 227 drinking task; 228 c) Dynamic Adaptive Movement Segmentation (DynAMoS): This newly proposed algorithm 229 is based on an adaptive threshold and statistics-based post-processing applied to the du-230 ration of the identified movements to compensate for erroneous segmentations. The post-231 processing step implemented in DynAMoS was originally developed for clinical gait anal-232 ysis to improve gait cycle segmentation [25]. First, movement onset and offset are identi-233 fied through the application of an adaptive threshold to the angular velocity norm Ω . In 234 particular, the adaptive threshold was defined as $Th_{DynAMoS} = 0.11 \Omega_{max}$, where Ω_{max} 235 represents the maximum value of the angular velocity norm recorded during the task and 236 the multiplicative constant was defined through Otsu's method [23,24] as detailed in sec-237 tion 2.5.1 Stereophotogrammetric-based segmentation. Then, the duration of each segmented 238 movement was calculated as the difference between the offset and onset time instants. 239 Finally, the statistics-based post-processing is iteratively applied to the movement dura-240 tions according to the following steps: 241

- 1. Definition of the movement duration histogram (see **Figure 3**) and computation 242 of the median (*M*) value; 243
- 2. From the median value *M*, the lower threshold αM (with $0 < \alpha < 1$) and the 244 upper threshold βM (with $1 < \beta < 2$) are obtained. The two thresholds will be 245 used to identify data distribution outliers (i.e., movements characterized by 246 "atypical" durations). The algorithm analyzes movements with "atypical" dura-247 tions. If a movement has a duration lower than the threshold αM , the algorithm 248 tries to merge it with the preceding or following movement. Meanwhile, if a 249 movement has a duration longer than the upper threshold βM , the algorithm 250 tries to split it into two movements. In the case of a duration lower than the 251 threshold αM , the algorithm attempts to merge the movement under analysis 252 with the preceding or the following, separately. The first attempt is performed 253 with the merging candidate closest in time. If it fails, the other movement is con-254 sidered. Merging fails if the new movement duration is lower than αM or 255 higher than the βM thresholds. If none of the attempts satisfies the thresholds, 256



Figure 2. Example of segmentation results obtained through the application of the the gold standard and three tested methods (i.e., the method by Schwarz *et al.* – M1, the method by Carpinella *et al.* – M2, and the newly proposed method - DynAMoS) on inertial data acquired during drinking tasks. Dotted horizontal lines represent the threshold values of each method, while colored binary masks represent the segmentation output of each method.

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Figure 3. Example of movement duration histograms before (left side) and after (right side) the application of the statistics-based post-processing.

the movements are not merged. In case of merging success, the extremities of 257 the "parent" movements are used as starting and ending points. In the case of a 258 movement with a duration longer than the upper threshold βM , the algorithm 259 tries to split it into two movements. To this purpose, the algorithms use local 260 minima points in the signal as possible splitting points. From the minimum 261 point with the lowest value, it splits the movement in two, with the new ending 262 and new starting at the identified minimum. If these movements have a length 263 longer than αM and shorter than βM thresholds, the split is accepted and the 264 two new movements are created. Otherwise, the algorithm moves to another 265 minimum point, if it exists; 266

- 3. After each splitting or merging event, *M*, αM , and βM values are updated considering the new movements;
- 4. The algorithm runs iteratively until all the movement duration outliers are processed.

Further details about DynAMoS functioning are freely available on the BIOLAB GitHub repository (<u>https://github.com/Biolab-PoliTO/DynAMoS</u>).

Figure 2d represents an example of segmentation obtained using the previously described method.

The optimization of the parameters α and β was performed using a grid search approach on all the acquired IMU data. Specifically, the value of α was chosen between 0.5 276 and 0.95 with steps of 0.05. Similarly, β was chosen between 1.05 and 1.5 with steps of 277 0.05. To find the best pair of parameters the following cost function (*Fc*) was defined as 278 detailed in **Eq. (1)**: 279

$$F_{c} = \frac{Extra_{IMU}}{Total_{IMU}} + \frac{Missing_{IMU}}{Total_{IMU}} + \overline{\Delta Onset} + \overline{\Delta Offset} + \overline{\Delta Duration}$$
(1)

where $Extra_{IMU}$ represents the number of "extra" movements obtained from the IMU 280 data compared to the number of movements identified by the GS. $Missing_{IMU}$ represents 281 the number of missing movements compared to the number of movements identified by 282 the GS. $Total_{IMU}$ is the total number of movements obtained from the IMU data. $\overline{\Delta Onset}$ 283 and $\overline{\Delta Offset}$ represent the onset and offset mean errors (expressed in seconds) between 284 the movements obtained from IMU data and the GS, respectively. $\overline{\Delta Duration}$ represents 285 the mean duration difference (expressed in seconds) between the movements obtained 286 from IMU data and the GS. The best pair of parameters α and β was determined by finding the minimum value of the cost function *Fc*.

2.6 PerformanceAssessment

To evaluate the performance of each of the presented methods, several parameters 291 have been used. For each trial, it has been calculated whether the specific method detected erroneous movements (N_{mov}) compared to the GS, the percentage of erroneous move-293 ments (Err_{Mov}) with respect to the GS, the onset and offset Mean Absolute Error (MEA_{onset} 294 and MEA_{offset}, respectively) against the GS. Notice that MEA_{offset} and MEA_{offset} were 295 calculated only for those movements that were consistent between the GS- and the IMUbased segmentation. Additionally, the duration of each movement (T) was calculated as the difference between the offset and onset time instants. 298

In the following analyses, the average over the three trials of the temporal parameters (i.e., percentage of erroneous movements, onset/offset mean absolute error, and movement duration) was considered.

2.7 Drinking Task Characterization

After the evaluation of the effectiveness of the identification of voluntary movements 304 from the inertial data, the drinking task was characterized in terms of the duration of each 305 sub-phase. First, each repetition of the drinking task was split using the longer resting 306 time (approximately 4 s) between consecutive movements. Then, the single sub-phases 307 were identified and classified using the SP as a reference. For each segmentation method, the mean duration of each sub-phase over trials was calculated as the difference between the offset and onset time instants and compared against the GS. 310

2.8 Statistical Analysis

We applied the Kolmogorov-Smirnov test to assess the data distribution normality 313 of the percentage of erroneous movements, the onset and offset mean absolute error, and 314 the movement duration. Based on the Kolmogorov-Smirnov test results, a 1-way ANOVA 315 (in case of normal distributions) or a Kruskal-Wallis test (for non-normal distributions) 316 was used followed by *post-hoc* analysis with Bonferroni adjustments for multiple compar-317 isons. All the analyses were performed setting the significance level (α) at 0.05. Parameter 318 estimates are represented as mean ± standard error over the population. The effect size of 319 the statistically significant differences was calculated through the Hedges' g statistic [26]. 320 A g value of 0.2, 0.5, and 0.8 are considered a small, medium, and large effect size, re-321 spectively. 322

The statistical analyses were performed using the Statistical and Machine Learning Toolbox of MATLAB release r2023b (The MathWorks Inc., Natick, MA, USA).

3. Results and Discussion

3.1 DynAMoS Optimization Process

Figure 4 shows the results of the DynAMos optimization process aimed at selecting the optimal α and β values. The optimal parameters selected were $\alpha = 0.8$ and $\beta =$ 1.4. All DynAMoS results described in the following sections were obtained using these optimal parameter values.

3.2 Performance Assessment

The performance of IMU-based segmentation approaches against the stereophoto-334 grammetric system (i.e., gold standard) is represented in Table 1 with the indication of 335 the statistically significant differences. 336

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Figure 4. Values assumed by the cost function F_c when considering different α and β . The red dot identifies the minimum of the cost function F_c found when $\alpha = 0.8$ and $\beta = 1.4$.

The SP-based segmentation identified, on average, 100 ± 4 voluntary movements 337 (mean ± standard error) per trial. Considering the IMU-based segmentation approaches, 338 168 ± 24 movements, 101 ± 7 movements, and 103 ± 5 movements were obtained consid-339 ering M1, M2, and DynAMoS methods, respectively. Overall, the newly presented algo-340 rithm identified only 3% erroneous movements (i.e., 2.8% extra movements and 0.2% 341 missed movements) compared to the GS. M1 resulted in 39.8% erroneous movements (i.e., 342 39.8% extra movements) compared to the GS, while M2 gave significantly better results, 343 revealing only 3.7% erroneous movements (i.e., 2.5% extra movements and 1.2% missed 344 movements). As shown in Figure 5, in some cases, the percentage of missed and extra 345 movements per trial is relatively high, with a maximum of 51.5% and 15.1% of the move-346 ments, respectively. Statistically significant differences in the percentage of erroneous 347 movements were detected among all the tested approaches (p < 0.0001). In particular, the 348 worst performance was obtained considering the M1 approach. Even if no statistically 349 significant differences in the percentage of erroneous movements were detected between 350

Performance Assessment		Kruskal-Wallis			
	GS	M1	M2	DynAMoS	<i>p</i> -value
N _{mov}	$100 \pm 4^{*,+,\ddagger}$	$168 \pm 24^{*,*}$	$101 \pm 7^{+,*}$	$103 \pm 5^{\ddagger, *}$	< 0.0001
Err _{Mov} (%)	N/A	39.8% ^{*,†}	3.7%*	3.0% [†]	< 0.0001
MAE_{Onset} (s)	N/A	$0.22 \pm 0.05^{*,+}$	$0.10 \pm 0.04^{*,\ddagger}$	$0.07 \pm 0.02^{+,\ddagger}$	< 0.0001
MAE_{Offset} (s)	N/A	$0.29 \pm 0.07^{*,+}$	$0.20 \pm 0.04^{*,\ddagger}$	$0.08 \pm 0.03^{+,\ddagger}$	< 0.0001
<i>T</i> (<i>s</i>)	$0.97 \pm 0.08^{*}$	$0.98 \pm 0.17^{+}$	$0.67 \pm 0.08^{*,+,\ddagger}$	$0.98 \pm 0.11^{\ddagger}$	< 0.0001

 Table 1. Performance assessment of the three tested approaches against the stereophotogrammetric system.

Parameters are represented as mean \pm *standard error over the population.*

N/A: Not Applicable; GS: Gold Standard.

Asterisks (*), double asterisks (*), daggers (†), and double daggers (‡) represent statistically significant differences between methods.



Figure 5. Boxplots representing the percentage of erroneous movements computed between each tested segmentation approach (M1, M2, and DynAMoS) and the gold standard. Statistically significant differences are represented through asterisks (*** p < 0.0001).

M2 and DynAMoS, it is noticeable the difference in the number of outliers (i.e., DynAMoS 351 revealed a reduced number of outliers compared to M2). 352

These results confirm that the application of a low threshold, as employed by M1, 353 can result in the detection of an excessive number of voluntary movements, which may 354 be attributed to noise or involuntary movements. In contrast, the detection method M2 is 355 characterized by a high number of missing movements, despite the adaptive threshold. 356

Considering the onset mean absolute errors, statistically significant differences were 357 detected between all the tested approaches (p < 0.0001). *Post-hoc* analysis identified signif-358 icant differences between DynAMoS and M1 (p < 0.0001; g = 3.9), between DynAMoS and 359 M2 (p < 0.0001; g = 1.3), and betwen M1 and M2 (p < 0.0001; g = 2.5). **Figure 6a** represents 360



Figure 6. Boxplots representing (a) the MAE_{onset} and (b) the MAE_{offset} computed between each tested segmentation approach (M1, M2, and DynAMoS) and the gold standard. Statistically significant differences are represented through asterisks (*** p < 0.0001).

the *MAE*_{onset} distributions with the indication of the statistically significant differences. 361 Similarly, when considering the offset mean absolute error, significant differences were 362 detected between DynAMoS and all the tested approaches (p < 0.0001). Bonferroni adjust-363 ments for multiple comparisons revealed significant differences between DynAMoS and 364 M1 (p < 0.0001; g = 3.7), between DynAMoS and M2 (p < 0.0001; g = 3.7), and between 365 M1 and M2 (p < 0.0001; g = 1.4). Figure 6b represents the MAE_{offset} distributions with 366 the indication of the statistically significant differences. The distributions of the onset and 367 offset mean absolute errors obtained using DynAMoS are largely concentrated below 0.1 368 s., a value that deviates considerably from those obtained considering M1 (mean absolute 369 error higher than 0.2 s). In contrast, M2 errors have a different behavior. The mean onset 370 error is 0.1 s, with the major part of the distribution lower than 0.15 s, whereas the mean 371 offset error is 0.2 s. 372

Considering the movement durations, the tested approaches showed statistically sig-373 nificant differences (p < 0.0001). In particular, statistically significant differences were de-374 tected between M2 and the GS (p < 0.0001; g = 3.6), between M2 and M1 (p < 0.0001; g =375 2.3), and between M2 and DynAMoS (p < 0.0001; g = 3.3). The mean duration of the move-376 ment, as identified by M2, is approximately 30% shorter than the one identified by the GS. 377 Although there was no statistically significant difference in the mean durations, the dis-378 tribution obtained applying M1 is notably more variable than the one obtained consider-379 ing the GS and DynAMoS. A lower and fixed threshold results in longer movements and 380 fast transitions given by small fluctuations around the threshold level, increasing the var-381 iability in the results. Figure 7 shows the distributions of the movement duration for all 382 the tested approaches, with the indication of the statistically significant differences. 383

3.3 Drinking Task Characterization

Figure 8 and **Table 2** report the drinking task characterization results for all the tested methods.

For all the sub-phases, a statistically significant difference in sub-phase duration was observed. Multiple comparisons resulted in a significant difference between the M1 and 389



Figure 7. Boxplots representing the movement durations (*T*) computed considering the GS (yellow), M1 (red), M2 (blue), and DynAMoS (green) methods. Statistically significant differences are represented through asterisks (*** p < 0.0001).

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Sub-phase		Kruskal-Wallis			
duration (s)	GS	M1	M2	DynAMoS	<i>p</i> -value
Phase I	$0.97 \pm 0.11^{*,*}$	$1.44 \pm 0.19^{*,+,\ddagger}$	$0.59 \pm 0.14^{*,+,\bullet}$	$1.01 \pm 0.14^{\ddagger, \bullet}$	< 0.0001
Phase II	$0.98 \pm 0.13^{*,*}$	$1.47 \pm 0.17^{*,+,\ddagger}$	$0.79 \pm 0.08^{*,+,\bullet}$	$1.02 \pm 0.13^{\ddagger, \bullet}$	< 0.0001
Phase III	$0.98 \pm 0.10^{*,*}$	$1.44 \pm 0.20^{*,+,\ddagger}$	$0.77 \pm 0.07^{*,+,\bullet}$	$1.01 \pm 0.13^{\ddagger, \bullet}$	< 0.0001
Phase IV	$0.98 \pm 0.09^{*,*}$	$1.54 \pm 0.22^{*,+,+}$	$0.58 \pm 0.14^{*,+,\bullet}$	$1.00 \pm 0.13^{\ddagger, \bullet}$	< 0.0001

Table 2. Drinking task sub-phase durations.

Parameters are represented as mean \pm standard error over the population. GS: Gold Standard.

Asterisks (*), double asterisks (*), daggers (†), double daggers (‡), and point (•) represent statistically significant differences between methods.

M2 methods, and between both the M1 and M2 methods and the GS and DynAMoS (p < p390 0.0001; g > 1.7). In particular, the data distribution obtained considering M2 is below the 391 lower quartile of the other distributions, while the data distribution obtained considering 392 M1 is above the upper quartile of the other distributions. On the other hand, for all the 393 sub-phases, there was no statistically significant difference (p > 0.8) between the timings 394 obtained through the GS and those obtained through DynAMoS. The application of M2 395 results in a mean duration of the sub-phases that deviates downward from that obtained 396 through the GS of approximately 20%, for Phase II and III, and 40%, for Phase I and IV. It 397 is worth noting that similar sub-phases, in terms of the range of motion but opposed in 398 terms of the goal of the movement, present similar timings and errors. In contrast, the 399 result obtained by applying M1 overestimates movement sub-phase durations by approx-400 imately 45%. The estimates obtained by means of DynAMoS align with the GS results. 401

4. Final Considerations

This study presents a novel segmentation method developed to overcome the limita-403tions of the most popular existing methods published in the literature. In particular, the404presented algorithm was compared with the threshold-based segmentation approaches405proposed by Schwarz *et al.* [13] (M1) and Carpinella *et al.* [14] (M2).406

Although the mean number of movements identified by M2 was the closest to that 407 obtained by the GS, it is worth noticing from the Err_{Mov} distribution represented in Fig-408 ure 5 that in numerous instances the number of missing movements was significant. While 409 selecting an adaptive threshold may be more appropriate for different movements, a high 410 threshold can result in a higher percentage of missed movements (51% in the case of the 411 M2 approach), especially when the movement consists of different sub-phases with vary-412 ing intensities. In contrast, results obtained through the M1 approach indicate a consistent 413 over-detection of voluntary movements, revealing that the threshold is too low and likely 414 influenced by small signal fluctuations close to the threshold (see Figure 2). As can be seen 415 from Figure 5, DynAMoS Err_{Mov} distribution is similar in variability to the results ob-416 tained with M2. However, the number of outliers and the percentage of missed move-417 ments are considerably reduced, revealing the reliability of the segmentation. 418

Focusing on movement onset and offset detection, the method presented in this study 419 was more accurate than the other tested approaches when compared to the GS. In fact, the 420 movement durations of the 4 sub-phases obtained through DynAMoS were closer to the 421 GS (with an average difference of 0.04 s). Previously published research reports that a 15% 422 variation in movement performance metrics is considered a clinically important differ-423 ence [12]. In our study, movement durations obtained by means of M1 and M2 methods 424 differ from the GS from a minimum of 20% to over 40%, whereas a maximum of 3% vari-425 ation was obtained considering the newly proposed method. Therefore, the difference in 426

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Figure 8. Distribution of the mean duration of the sub-phases of the drinking task for the sample population for the tested methods and the SP Gold Standard. Statistically significant differences are represented through asterisks (*** p < 0.0001).

movement timing between the two tested state-of-the-art methods and the GS is consid-427erably higher than 15%, suggesting that the use of these segmentation methods may428strongly impact the clinical assessment. In contrast, the small differences in movement429timings between DynAMoS and the GS make the proposed method considerably more430reliable and potentially applicable in the clinical assessment of patients.431

Even though a clinical validation of the method was not performed, it is possible to 432 compare the obtained results with similar results presented in the literature. For example, 433 Patterson et al. [27] evaluated post-stroke patients and healthy controls reaching a target 434 at a comfortable speed by using a SP system. On average, the duration of the movements 435 was 0.96 ± 0.27 s and 0.67 ± 0.12 s considering the post-stroke patients and the healthy 436 controls, respectively. The difference in movement durations between the stroke survi-437 vors and the healthy controls is lower than the difference in durations observed in our 438 data. Thus, the application of different segmentation approaches may not be able to dif-439 ferentiate between a healthy and a pathological population. Furthermore, Carpinella et al. 440[14] demonstrated a statistically significant difference of approximately 0.4 s in grasp 441 movement duration between Multiple Sclerosis patients and healthy controls. This differ-442 ence is not substantially larger than the sub-phase duration error between M1, M2, and 443 the GS. 444

Although the results are promising, there are some limitations associated with the 445 method. The first is the impossibility of applying the algorithm in real-time, due to the 446 adaptive thresholding and the post-processing step. Both these steps require the whole 447 inertial data to compute the required parameters (i.e., the maximum angular velocity 448 norm and the movement duration distribution). Moreover, this study was carried out on 449 healthy subjects only. Further studies are needed to validate this approach for patient assessment in a clinical environment. 445

5. Conclusions

In this study, we compare a new IMU-based segmentation method for upper limb 456 movements with two popular segmentation methods [13,14]. The movement herein con-457 sidered is the reach-to-grasp movement, because of its frequent use in the clinical evalua-458 tion of patients suffering from upper limb motion disorders. Results show that the pro-459 posed method performs significantly better than the two implemented ones. According 460 to Kwakkel et al. [12], the segmentation accuracy of DynAMoS could make it available for 461 clinical applications. Using IMU for motion detection and the proposed algorithm for time 462 segmentation of upper limb voluntary movements could make more effective home mon-463 itoring applications for assessing the motion improvements of patients following domicile 464 rehabilitation protocols. 465

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Data Availability Statement: DynAMoS algorithm, detailed documentation, and a sample dataset are freely available on the BIOLAB GitHub repository (<u>https://github.com/Biolab-PoliTO/DynA-MoS</u>).

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