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Time-independent relationship between digits closure velocity and hand transport acceleration during reach-to-grasp movements

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A R T I C L E I N F O

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A B S T R A C T

Prehension movements in primates have been extensively studied for decades, and hand transport and hand grip adjustment are usually considered as the main components of any object reach-to-grasp action. Evident temporal patterns were found for the velocity of the hand during the transport phase and for the digits kinematics during pre-shaping and enclosing phases. However, such kinematics were always analysed separately in regard to time, and never studied in terms of dependence one from another. Nevertheless, if a reliable one-to-one relationship is proven, it would allow reconstructing the digit velocity (and position) simply by knowing the hand acceleration during reaching motions towards the target object, ceasing the usual dependence seen in literature from time of movement and distance from the target. In this study, the aim was precisely to analyse reach-to-grasp motions to explore if such relationship exists and how it can be formulated. Offline and real-time results not only seem to suggest the existence of a time-independent, one-to-one relationship between hand transport and hand grip adjustment, but also that such relationship is quite resilient to the different intrinsic and extrinsic properties of the target objects such as size, shape and position.

1. Introduction

Hands are essential organic tools for primates. Reach-to-grasp movements have been extensively studied for decades as these represent a stereotypical human-object interaction. Neurophysiological data provide strong evidence about "where in the brain" certain prehension-related processes happen (Oztop and Kawato, 2009). However, the "how" is still quite uncertain and even though several behavioural models were suggested, the complexity of neural circuitries prevents the identification of a clear winner. This uncertainty reflects itself on the challenges posed on control engineering when designing high- and low-level grasping paradigms for robotic limbs. This ultimately translates in poorly performing and poorly accepted robotics assistive devices.

Thanks to the pioneering work of Marc Jeannerod (Jeannerod, 1984, 1981), hand transport and hand grip adjustment are usually considered as the main components of any object reach-to-grasp action. Guided by preliminary observations for which the hand transport component appeared governed by extrinsic properties of the target object (i.e., its location) and the grip adjustment component appeared governed by intrinsic properties of the target object (i.e., its size and shape), Jeannerod argued that the prehension behaviour was shaped by an "open-loop control of two independent visuomotor channels", independent in both terms of anatomy and information processing. Such proposition was quite tempting as it would simplify the brain task of visuomotor coordination to a rather simpler time-synchronization between these two specialized modules. However, for how tempting this simplification was, it shortly became clear that it had to be amended (Smeets et al., 2019). Indeed in the two decades following Jeannerod's early work, new experimental evidence clearly showed considerable coupling between these two visuomotor channels. Specifically, it was shown that hand transport time increased with object distance as expected, but surprisingly also decreased with object size (Marteniuk et al., 1990). It was also shown that maximum grip aperture increased with object size as expected, but surprisingly also increased with object distance (Jakobson and Goodale, 1991). Moreover, it was shown that sudden changes in the location of the target object during reaching produced rapid adjustments in the hand transport as expected, but surprisingly also in the hand aperture (Paulignan et al., 1991). Therefore, the independent visuomotor-channels hypothesis had to be amended by assuming certain level of interaction between the two channels, an interaction perhaps more related to functionality rather than temporality. More recently, Smeets *et Al.* suggested an alternative framework by which the grip

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formation emerges from controlling the movements of the digits in space (Smeets and Brenner, 2001; Smeets et al., 2019). Arguments for this framework are that the individual digits trajectories for reaching-to-grasp an object and for moving-to-tap the same position are remarkably similar (Smeets et al., 2010). Moreover, such similarity holds even under disturbances, i.e., when displacing the object.

Regardless to the underlying theoretical framework, a clear coupling between hand transport and hand grip adjustment was revealed by the abundant experimental data on reaching actions. Evident temporal patterns were found for the velocity of the hand during the transport phase (i.e., ballistic bell-shaped curve), and for the digit kinematics during pre-shaping and enclosing phases. However, such kinematics were always analysed separately in regard to time, and never studied in terms of dependence one from another. Nevertheless, there would be clear benefits from unveiling a potential one-to-one relationship between the kinematics of hand transport and digit closure around the target object. For instance, if a reliable relationship is proven, it would allow reconstructing the digit velocity (and position) simply by knowing the hand acceleration during reaching motions towards the target object, ceasing the usual dependence seen in literature from time of movement and distance from the target. In regard to upper limb prosthetic devices, ultimate focus of the authors, this relationship would allow autonomous object grasping by using the residual limb inertia as the main control input.

In this study, we sought to precisely analyse reach-to-grasp motions to explore whether a relationship between hand transport and hand grip adjustment existed and how it can be formulated. To this goal, an extensive human-object interaction dataset was collected, aiming to wide data diversity regarding target objects size, shape, weight, and position in respect to the participant. Offline and real-time results not only seem to suggest the existence of a time-independent, one-to-one relationships, but also that such relationships are quite resilient to the different intrinsic and extrinsic properties of the target objects.

2. Methods

2.1. Human-object interactions dataset

The analyses reported in the following were performed on the HANDdata dataset (Mastinu et al., 2023), a data collection specifically tailored for autonomous grasping of a robotic hand and with particular attention to the reaching phase.

29 healthy adults participated to the data collection (ethical approval 12/2022 by the Ethical Committee of the Scuola Superiore Sant'Anna). Participants were asked to reach-grasp-lift-and-replace different target objects while wearing an instrumented glove that could track digits and forearm kinematics (Fig. 1, top-left). The instrumented glove was based on a CyberGlove II (CyberGlove Systems, USA) to which an inertial sensor was added via a custom circuit board mounted on a customizable wrist band. The CyberGlove included 18 strain gauges and data acquisition electronics which allowed tracking the joints angles of the digits with a resolution of less than one degree and a frequency of 90 Hz. Fingertips were not occluded to prevent non-normal human-object interactions. Forearm kinematic was tracked via 3-axes accelerometer and gyroscope inertial sensor acquiring at 120 samples-per-second.

Ten different target objects were used in the data collection protocol and each object required a certain grasp pattern (Fig. 1, top-right). Specifically, abstract objects like a sphere, a cylinder, a triangular prism, a cuboid with a thin rectangular prism 'handle' and a thin rectangular prism were meant to trigger the spherical, power, tri-digit, lateral and pinch grip pattern, respectively. Each object was available in two materials, wood or aluminium. Objects dimensions, materials and weights are standardized within the Southampton Hand Assessment Procedure (Light et al., 2002), a well-established clinically validated functional assessment tool, in the field of prosthetics. All objects were manipulated over one or two instrumented platforms (Fig. 1, bottom), to detect instants of contact. Each was 9 cm tall from the support desk and with landing areas of 60 cm^2. When two platforms were used, their landing areas were spaced out by 40 cm. Each platform was instrumented by a strain gauges-based load cell to allow tracking the instant of first contact with the object as well as lift off and replace from/to the platforms. Data was streamed at 80 Hz and acquired via wired USB connection.

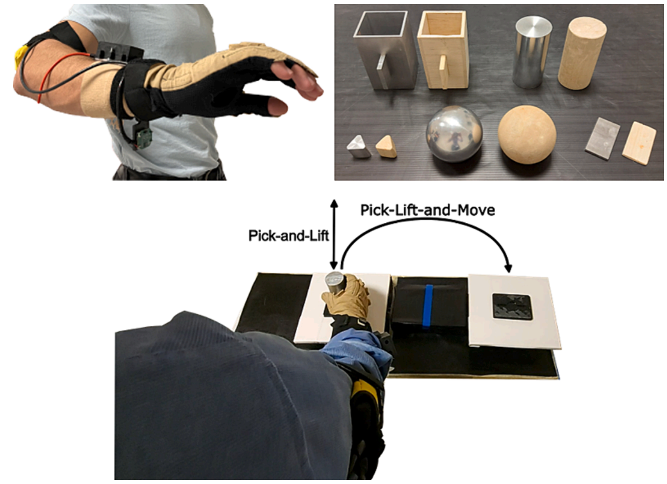

Fig. 1. Instrumented glove, target objects and object manipulation with the instrumented platforms. The dataset analysed in this study includes human-object interaction data acquired from 29 participants manipulating 10 different objects while wearing an instrumented glove. The instrumented glove (top-left) was based on a CyberGlove to which an inertial sensor was added via a custom circuit board mounted on a customizable wrist band. Ten different target objects were used (top-right), each linked to a particular hand grasp. Abstract objects like a sphere, a cylinder, a triangular prism, a cuboid with a thin rectangular prism 'handle' and a thin rectangular prism were meant to trigger the spherical, power, tri-digit, lateral and pinch grip pattern, respectively. All objects were manipulated over one or two instrumented platforms (bottom) in two human-object interaction scenarios with increasing complexity, pick-and-lift and pick-lift-and-move.

The dataset included human-object interactions from two scenarios with increasing complexity (Fig. 1, bottom), namely:

1) Pick-and-lift: participants were asked to reach the target, pick it, lift it about 10 cm, and then reposition it on the same start-area.
2) Pick-lift-and-move: participants asked to reach the target, pick it, lift it about 10 cm while transporting it to a land-area different from the start-area, 40 cm away. Start- and land-area were alternated at each trial ultimately providing data for pick-and-lift from two different approach directions.

For each scenario, the participants were asked to start and end each trial with the arm in rest position. The rest position was defined as the upper arm adjacent to the body trunk, with elbow joint bent at 90degrees, and with the hand palm perpendicular to the floor. Moreover, the participant's alignment in respect to the target object changed depending on the scenario. For the pick-and-lift scenario, the subject's arm in rest position was aligned on the single area of interest where the target objects were located (i.e., straight prehensive motion). Instead, for the pick-lift-and-move scenario, the subject's arm in rest position was aligned with the centre of the two start and land areas (i.e., slightly curved leftwards and rightwards prehensive motion).

2.2. Data temporal analysis

All analyses reported in the following were performed via MATLAB

(R2022b, MathWorks) on the HANDdata files in *.mat format.

An initial data analysis was performed on the dataset trying to characterize the temporal evolution of the pick-and-lift trials for three different hand grasps:

- *power grasp*, including data from the sphere and the cylinder in both wood and metal materials,
- *precision grasp*, including data from the triangular prism and the thin rectangular prism in both wood and metal materials,
- *lateral grasp*, including data from the cuboid with a thin rectangular prism 'handle' in both wood and metal materials.

The temporal evolution of the pick-and-lift trials was characterized in terms of:

- *Reaching time*, as the time needed to reach and touch the target object.
- *Reaching onset*, as the time needed to start the positive acceleration towards the target object.
- *Deceleration onset*, as the time needed to start the deceleration phase while approaching the target object.
- *Closure onset*, as the time needed to preshape the hand for the correct grasp and thus start the digits closure.

The reaching time to touch the target was found as the first maxima within the normalized, zero-offset instrumented platform data.

The reaching onset was found as the first minima of the normalized, Gaussian smoothed z-axis acceleration curves, aiming for the start of positive acceleration towards the target object and thus neglecting the earliest portion of the arm movement typically including some elbow backward swing for wrist height adjustments in respect to the target.

The deceleration onset was found as the first maxima of the normalized, derived and Gaussian smoothed z-axis acceleration curves, aiming for the instant of change of the acceleration towards the target.

The closure onset was found for all different objects as the absolute minima of the participant-normalized, Gaussian smoothed sum of the angular positions of thumb-index abduction and index proximal joints, thus aiming for the instant of maximum hand aperture.

The rationale for grouping considerably different objects within the same grasp was to collocate the modelling part in a worst-case scenario, and thus to show model performance to a preliminary objects categorization which will be mandatory in any future real application. Indeed, grouping different materials (i.e., different weights and frictions) as well as different shapes expectedly induced high variability in the timing of the major grasping events considered. In order to understand such variability, statistical tests were performed on the distributions of deceleration and closure onsets as percentages of the whole movement time (two-sided Wilcoxon rank sum test with significance for $p < 0.05$).

2.3. Data extraction and modelling

The steps reported in the following were meant to extract the relevant data from the HANDdata dataset, namely kinematic channels of the digits (i.e., CyberGlove readings) and acceleration of the forearm (i.e., inertial sensor readings). Here, the aim was to create an input–output data structure composed of length-consistent, time and amplitude max–min normalized, smoothed curves of acceleration towards the object (i.e., input) and digits angular velocity (i.e., output) during reach-to-grasp motions.

Only a subset of the available kinematic channels of the digits was considered. Specifically, the thumb-index abduction joint and the four metacarpal-phalangeal joints (i.e., proximal joint between hand palm and the long fingers), as these were found via principal component analysis to have the most informative content (Ingram et al., 2008). Moreover, only the z-axis accelerometer channel was considered, approximately parallel to the direction of reaching towards the object at trial start. Lastly, only pick-and-lift trials were considered for modelling leaving the pick-lift-and-move trials for inference testing.

The CyberGlove readings were considered to be linearly proportional to the angular position of the digit joints. Subject-specific baseline values of the hand starting position were used to remove readings offsets. Angular velocities were calculated from the first difference of the angular position data divided by the time step. The end of each trial was redefined as the instant of contact with the target object. Trials in which the contact occurred earlier than 0.5 s or later than 1.5 s were considered as outlier thus discarded. Then, the start of each trial was redefined as the reaching onset (see temporal analysis section). Digits angular velocities and z-axis acceleration data were Gaussian smoothed, max–min normalized and resampled (modified Akima cubic interpolation + antialiasing filter) to have same length across all trials.

The following steps were meant to create models from time and amplitude max–min normalized, smoothed curves of acceleration towards the object (i.e., input) and digits angular velocity (i.e., output) during reach-to-grasp motions for each hand grasp (i.e., power, precision and lateral grasp). At first, the extracted data was divided into training and testing sets for each hand grasp with percentages of 70 % and 30 %, respectively. Then, empirical models were created by fourth-order polynomial fitting of the median of the training set (*Polyfit* Matlab built-in function).

2.4. Model offline testing and inference

The quartic models were offline tested for each hand grasp at two different levels:

- via the test set previously partitioned from the pick-and-lift processed trials (i.e., model testing),
- via an additional test set extracted from the pick-lift-and-move processed trials (i.e., model inference).

In both cases, the Root-Mean-Square-Error was calculated between the predicted values of the max–min normalized angular velocity of the digits and ground-truth observed ones. Such RMSE is to be intended as unitless and normalized between 0 and 1.

The pick-lift-and-move trials were processed with same methods as above. These trials ultimately provided a complementary test set of unseen pick-and-lift trials with several fundamental differences from the training data:

- Two different, alternating target object positions, forcing the participant to proceed with slightly curved leftwards and rightwards prehensive movements. Curved prehension was shown to delay the hand aperture kinematics (Haggard and Wing, 1998).
- Different task presentation and goal, arguably influencing the participant's grasping kinematics (Ansuini et al., 2008, 2006).

2.5. Model online bench-validation

Aiming to a preliminary practical validation, the models were further online tested with an experimental bench setup (Fig. 2). More details can be found in the Supplementary Material b. The setup consisted of:

- a prosthetic hand (Mia Hand, Prensilia SRL, Italy) mounted on a bench support,
- six couples of test objects, three from the HANDdata dataset and three from domestic environment,
- an instrumented bracelet to measure acceleration during hand transport towards the target,
- two instrumented platforms to measure instants of contact with target objects,
- a real-time Matlab app for data acquisition, normalization, models evaluation and prosthesis control.

Fig. 2. Experimental setup for online bench-validation (top). Via an instrumented bracelet (bottom-left), the acquired hand transport acceleration was real-time translated into speed commands to the hand prosthesis. Then, the delay between the instants of contact of the human and robotic hands was measured via two instrumented platforms. Six couples of test objects were used (bottom-right), three from the HANDdata dataset and three from domestic environment. Each couple was assigned to the testing of a particular hand grasp.

Three healthy adults participated to the experiment. Participants stood in front of the target object and were asked to reach-grasp-lift-and-replace it while wearing the instrumented bracelet. Each couple of test objects was divided between the two instrumented platforms, one for the participant and one for the hand prosthesis. The prosthesis was mounted on a bench support and aligned with its target object so to correctly grasp it with the pre-assigned hand posture. The acquired hand transport acceleration was real-time translated into velocity closure commands to the hand prosthesis. Then, the delay between the instants of contact of the human and robotic hands was measured via the instrumented platforms.

Six experimental conditions were defined, with 10 trials for each target object.

Three pick-and-lift scenarios, namely:

- scenario0, straight prehensive motion similarly to the training data;
- scenario1, curved leftwards prehensive motion with the target positioned at 20 cm higher position;
- scenario2, random standing positioning of the participant, without restrictions.

Two hand control conditions, namely:

- grasp control, in which the model of the thumb digit controlled the entire grasp closure;
- digit control, in which the models of the thumb, index and middle digits controlled the respective closure in the prosthetic hand digits. By design, on the prosthesis the ring and little digits were mechanically coupled to the middle digit.

3. Results

3.1. Data temporal analysis

The aggregated times of reaching onset and reaching time were 0.31:0.12 (MEDIAN:IQR) and 0.99:0.24 s, respectively (Fig. 3). The aggregated times of deceleration onset and closure onset were 0.48:0.13 and 0.66:0.23 s, respectively. As seen in previous literature, the peak wrist velocity (deceleration onset, DO) was on average reached at about a third of the transport phase and the maximum hand grip aperture (closure onset, CO) was on average reached at about midway into the transport phase (Fig. 3). The dataset proved consistent with previous literature.

Regarding the within-grasp timings variability, the object material had statistically significant effect on the distributions of the deceleration and closure onsets for the cuboid with handle (p_{DO}=0.011, p_{CO}<0.001), for the cylinder (p_{DO}=0.034, p_{CO}<0.001) and for the triangular prism (p_{DO}<0.001, p_{CO}=0.003). On average, participants behaved slower when handling the heavier metallic objects. Additionally, the different shapes of the sphere and cylinder grouped within the same power grasp also significantly affected the timing of the deceleration and closure

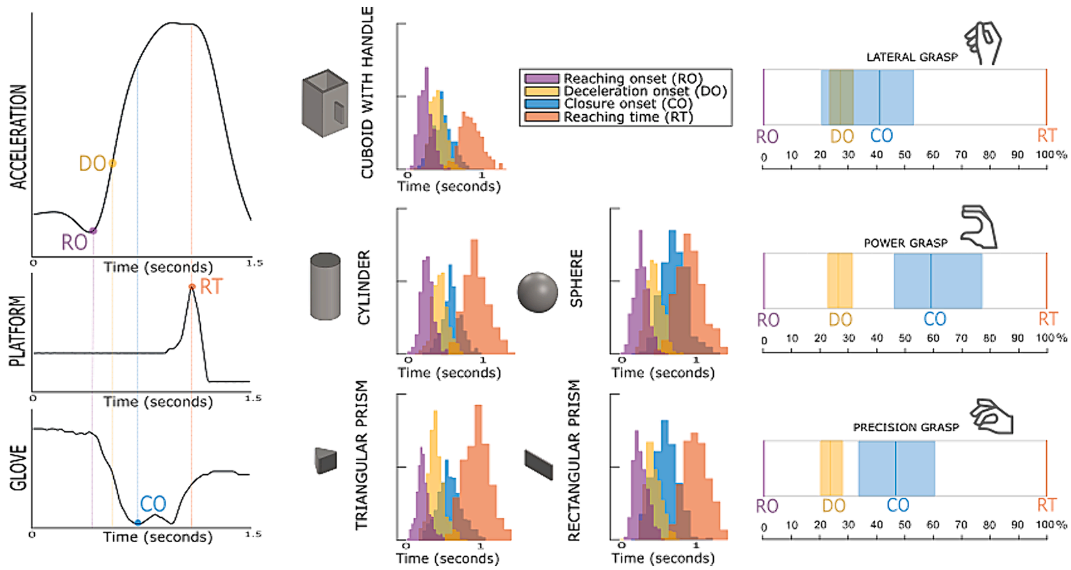

Fig. 3. Temporal analysis of pick-and-lift trials. The temporal evolution of these trials was characterized in terms of Reaching onset (RO, purple), Deceleration onset (DO, yellow), Closure onset (CO, blue) and Reaching time (RT, orange). These events are highlighted in a representative trial along the data from the acceleration, instrumented platform and glove (left panel). These same events are shown also as time-distributions for the five differently shaped objects (mid panel) as well as movement completion percentage-distributions for the three different hand grasps (right panel). The completion percentage-distributions are shown as thick lines and coloured areas for the median values and for the interquartile ranges, respectively. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

onsets (p_{DO}=0.020, p_{CO}<0.001). Similar results were found also for the shapes of the triangular and rectangular prisms grouped within the precision grasp (p_{DO}=0.001, p_{CO}<0.001). A considerably slower behaviour was observed when preshaping the hand for grasping the sphere compared to grasping the cylinder. These significant differences underline the temporal diversity purposely included within the three hand grasps considered here, arguably collocating the modelling part in a worst-case scenario.

3.2. *Model offline testing: Can models properly reconstruct pick-and-lift trial?*

A total of 2211 trials (85 % of available pick-and-lift trials) were considered for the analysis, of which 1549 trials for training and 662 trials for testing. Regarding the training set, Fig. 4 depicts the relationship between the curves of acceleration towards the object and digits angular velocity. Even though large data variability can be observed, the median proved considerably stable across different joints and grasps. During fitting, the coefficients of determination R^2 for power, precision and lateral grasp were remarkably high, 0.97:0.01, 0.91:0.04 and 0.94:0.04, respectively. Testing RMSEs were also quite promising (Fig. 5, upper panel). The aggregated RMSE (i.e., for all outputs and all grasps) were 0.26:0.16, 0.25:16 and 0.31:12 for power, precision and lateral grasp, respectively. Commonly, relative RMSE values lower than 0.2 are considered good, and between 0.2 and 0.3 are considered satisfactory. These results would imply that, knowing a priori the

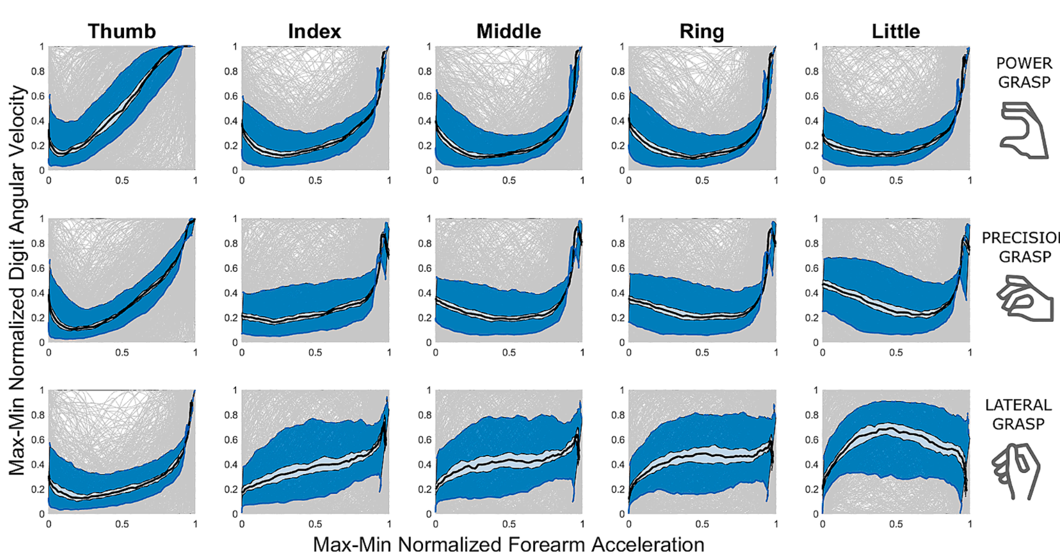

Fig. 4. Relationship between acceleration towards the object and digits angular velocity. The relationship is qualitatively shown on max–min normalized values for all considered digits joints and hand grasps. The thin grey lines depict all training set trials and provide an idea of the large data variability. The blue areas depict the interquartile area of data dispersion. The thick black lines depict the median of the trials, and the white area around its 95% confidence interval. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

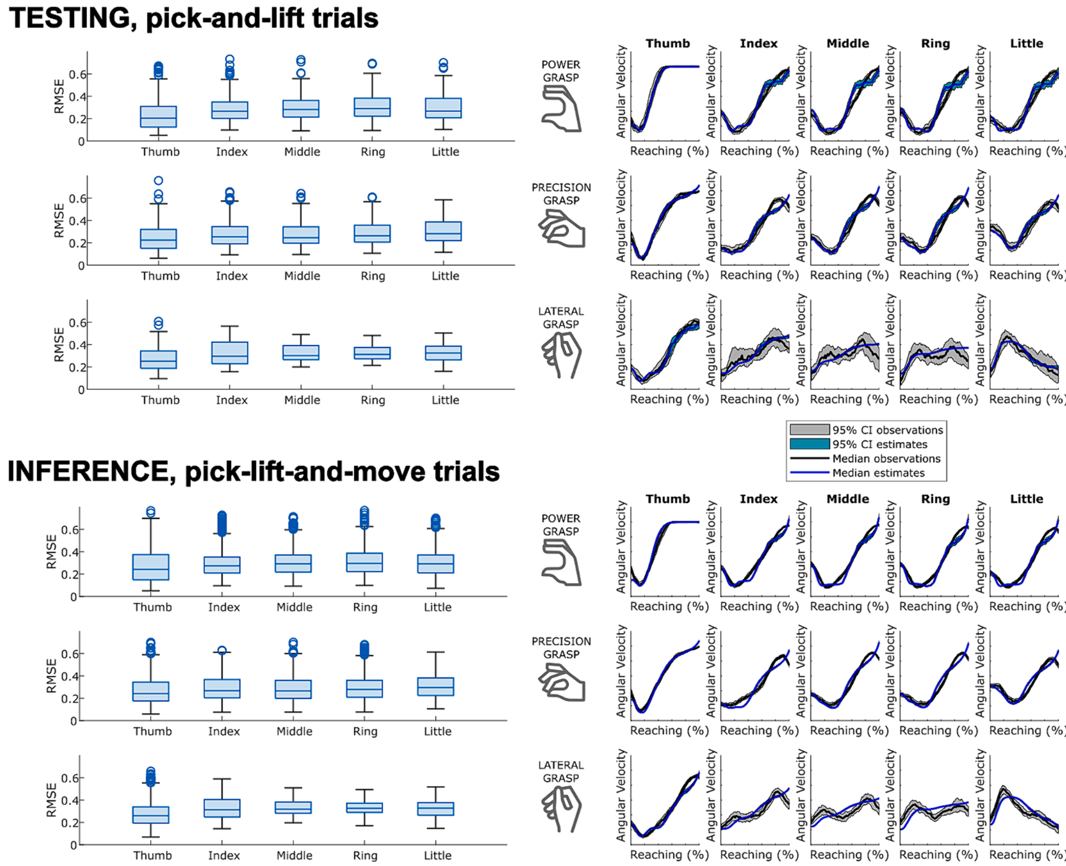

Fig. 5. Models testing results on unseen data. Tests were performed on both pick-and-lift trials (upper panel) and on pick-lift-and-move trials (lower panel). The left side of each panel represent the RMSE boxplots of the estimates. For qualitative evaluation, the right side of each panel represents the median trajectory of the normalized estimates (blue thick line) and its 95% confidence interval (cyan area), as well as the median trajectory of the normalized observations (black thick line) and its 95% confidence interval (grey area). (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

intended hand grasp, the sole acceleration towards the target can be sufficient to reconstruct stereotypical prehension movement of the most important digits joints.

3.3. Model offline inference: What happens if we change the start/end position?

The trained models were further inference tested on a diverse test set

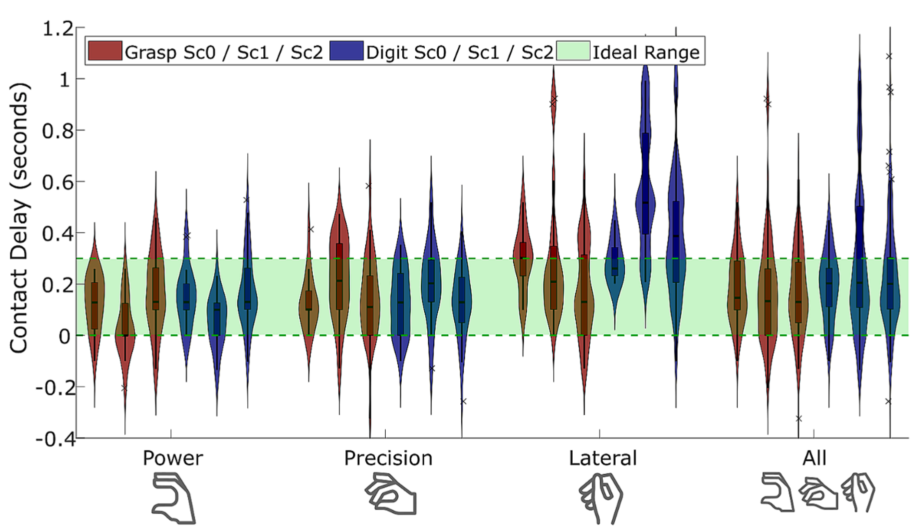

Fig. 6. Distributions of the delay between the instants of contact of the human and robotic hands for the bench-validation. The delays are shown here for all bench-testing conditions, thus control strategies (i.e., grasp vs digit in red and blue colour, respectively), scenarios (i.e., 0 vs 1 vs 2) and grasps (i.e., target objects). The ideal range of 0 ÷ 300 ms for the delay is shown as a green area. (For interpretation of the references to colour in this figure legend, the reader is referred to the web version of this article.)

based on pick-lift-and-move trials. A total of 2190 trials (84 % of available trials) were considered. The models proved impressive resilience (Fig. 5, lower panel). The aggregated RMSE were 0.28:0.17, 0.27:16 and 0.31:11 for power, precision and lateral grasp, respectively. These results are particularly remarkable considering the diversity of such test set (i.e., two different target positions, and different task presentation and goal), and although preliminary they nevertheless offer a quite promising insight on the generalizability of the models: models trained on stereotypical pick-and-lift actions can be sufficient to reconstruct prehensions in less controlled scenarios.

3.4. Model online bench-validation: Does it work in real-time?

A total of 480 trials were performed and analysed. Again, the models proved feasibility and potential (see Movie 1). Overall, the distributions of the delay between the instants of contact of the human and robotic hands were in large part contained within the ideal range of 0 ÷ 300 ms (Fig. 6). Such range was deemed as the target because negative delays would imply a too early closure of the prosthesis, likely interfering with the grasp of the target; and 300 ms is the conventional threshold for human perceivable lag in prosthetics (Englehart and Hudgins, 2003). Beside certain distribution divergence for the lateral grasp (especially in digit control condition), the aggregated delays were 0.13:0.17 and 0.20:0.20 s for grasp and digit control, respectively. Moreover, the weak correlation found between contact delay vs estimated input range would suggest overall robustness with respect to normalization errors (Fig. 4Sb, bottom-panel).

4. Discussion

This study aimed to investigate reach-to-grasp actions so to unveil whether a time-independent, one-to-one relationship existed between the digits angular velocity and the acceleration towards the target object. To this aim, an extensive human-object interaction dataset was collected and analysed, and different model formulations were evaluated. The evaluation was performed on unseen data at two different levels: at first, with data collected from same conditions of training data, and secondly, with data collected with target objects placed at different positions. At first, a temporal dataset validation showed grasping execution timings aligned with the literature (Haggard and Wing, 1998; Jakobson and Goodale, 1991; Paulignan et al., 1990; Rand et al., 2006; Santello et al., 2002; Santello and Soechting, 1998; Smeets et al., 2010). Then, results for fourth-order models fitting and evaluation proved to be considerably promising towards the main hypothesis of existence of a time-independent, one-to-one relationship between digits angular velocity and forearm reaching acceleration. Further, results improved by simplifying the fourth-order models to simpler sequentially-activating linear models (see Supplementary Material a). Interestingly, these relationships appeared quite resilient to the different intrinsic and extrinsic properties of the target objects. Our results showed accurate model performances even when dealing with considerably different objects (i.e., different material, weight, size and shape) categorized together within the same hand grasp. Such results enclose a double-folded potential benefit: 1) a short-term potential to automatise reach-to-grasp actions in prosthetic arms by using reaching inertia as the main control input; 2) a long-term potential to revisit historical reach-to-grasp behavioural models by incorporating the apparent strong time- and object-independent relationship between hand transport and hand grip adjustment parameters.

When it comes to the potential benefit for the development of semi-autonomous upper limb prosthetic components, ultimate focus of the authors, the one-to-one relationship explored here would allow reconstructing the end-effector digits velocity (and position) simply from the reaching acceleration of the residual limb towards the target object, heavily reducing the usual dependence of prosthetic devices from the myoelectric signals alone. As demonstrated in the bench-validation (Movie 1), the digits actuation for grasping can be derived from the intuitive reaching movement towards an object. Such route will soon be tested in a more realistic prosthetic application. Lastly, we cannot exclude that a similar reasoning of proximal-to-distal escalation of actuation could also benefit the control of other kinds of robotic arms in industrial or domestic applications.

Prehension movements in primates have been extensively studied for decades, and hand transport and hand grip adjustment are usually considered as the main components of any object reach-to-grasp action. Initially conceived in literature as two independent but time-synchronized black-boxes (Hoff and Arbib, 1993; Jeannerod, 1981), these are now largely considered to have a strong interplay. Such interaction between hand transport and hand closure is imperative to match experimental evidence. The results from our study seem to endorse such strong interaction, actually elevating it to an unprecedented level in literature. Indeed, our results would imply the existence of a time-independent, one-to-one, strong relationship between digit angular velocity and forearm acceleration during reaching movements, a relationship that appears to be independent also from intrinsic and extrinsic properties of the target object (i.e., its size, shape and location). Arguably, such direct relationship does not find an easy interpretation within the classic visuomotor channels behavioural framework. Rather, it would call for alternative frameworks, such as the digit-in-space framework proposed by Smeets *et Al.* (Smeets et al., 2019). Indeed, a framework of proximal-to-distal harmonized movements of the upper limb would better explain such digit aperture vs transport acceleration direct mapping, as well as the better results for sequentially-activating linear models (e.g., relative digits independence when moving in space). Moreover, our results are also aligned with classic synergies theories (d'Avella et al., 2003; Grinyagin et al., 2005). There is no debate on the fact that digits move in harmony when grasping an object: PCA analyses indicated strong linear relationships between digits angular positions during reaching motions, where over 70 % of the variance could be explained by 2 principal components (Ingram et al., 2008; Santello et al., 2002). Moreover, even anatomy points towards the same direction: cadaver studies found clear mechanical linkages between digits for which inter-tendons connections act limiting digits independence (von Schroeder and Botte, 1993). Perhaps, such synergistic harmony of movements could start and be governed by more proximal limb parts when considering a reach-to-grasp task. Surely, our results call for further in-depth investigations including also controlled disturbances to the reaching motion as well as more variations on the target position.

CRediT authorship contribution statement

Enzo Mastinu: Writing – original draft, Visualization, Supervision, Software, Project administration, Methodology, Funding acquisition, Formal analysis, Data curation, Conceptualization. **Anna Coletti:** Writing – original draft, Visualization, Software, Resources, Methodology, Formal analysis, Data curation. **Carlo Preziuso:** Visualization, Software, Methodology, Formal analysis. **Christian Cipriani:** Supervision, Resources, Project administration, Funding acquisition, Conceptualization.

Declaration of competing interest

The authors declare the following financial interests/personal relationships which may be considered as potential competing interests: [Prof. Christian Cipriani (last author) is the founder of Prensilia SRL, a university spin-off that develops multi-articulated and sensorized robotic hands. All authors declare this research was conducted in the absence of any commercial or financial relationships that could constitute a potential conflict of interest].

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Author contributions

EM and CC conceptualized and received the funding for the autonomous hand research project; EM ideated and supervised the dataset collection, analysis and bench-testing; CP, AC and EM designed and performed the analysis; CP and AC performed the bench-tests; EM and AC drafted the manuscript; CC supervised the whole research project; all authors reviewed and approved the submitted manuscript.

Appendix A. Supplementary data

Supplementary data to this article can be found online at https://doi.org/10.1016/j.jbiomech.2024.112262.

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