Dimensionality Reduction and Motion Clustering During Activities of Daily Living: Decoupling Hand Location and Orientation

Yuri Gloumakov[®], *Graduate Student Member, IEEE*, Adam J. Spiers[®], *Member, IEEE*, and Aaron M. Dollar[®], *Senior Member, IEEE*

Abstract—This article is the second in a two-part series analyzing human arm and hand motion during a wide range of unstructured tasks. In this work, we track the hand of healthy individuals as they perform a variety of activities of daily living (ADLs) in three ways decoupled from hand orientation: end-point locations of the hand trajectory, whole path trajectories of the hand, and straight-line paths generated using start and end points of the hand. These data are examined by a clustering procedure to reduce the wide range of hand use to a smaller representative set. Hand orientations are subsequently analyzed for the end-point location clustering results and subsets of orientations are identified in three reference frames: global, torso, and forearm. Data driven methods that are used include dynamic time warping (DTW), DTW barycenter averaging (DBA), and agglomerative hierarchical clustering with Ward's linkage. Analysis of the end-point locations, path trajectory, and straight-line path trajectory identified 5, 5, and 7 ADL task categories, respectively, while hand orientation analysis identified up to 4 subsets of orientations for each task location, discretized and classified to the facets of a rhombicuboctahedron. Together these provide insight into our hand usage in daily life and inform an implementation in prosthetic or robotic devices using sequential control.

Index Terms—Hierarchical clustering, manipulation, motion analysis, upper limb, prosthetics, robotics.

I. INTRODUCTION

H EALTHY upper-limb motion is a crucial tool in independent living, indispensable in nearly all tasks under activities of daily living (ADLs). Many efforts have therefore been placed on preserving functional abilities and healthy arm motions in the elderly, rehabilitating stroke victims, and augmenting amputee patients with prosthetic devices. In particular, upper-limb reaching has been the forefront subject of many research endeavors including balance confidence in seniors [1],

Manuscript received May 5, 2020; revised November 9, 2020; accepted November 16, 2020. Date of publication November 26, 2020; date of current version January 29, 2021. This work was supported by the Congressionally-Directed Medical Research Programs (CDMRP) underunder Grant W81XWH-15-10407 and Grant W81XWH-15-C-0125. (Corresponding author: Yuri Gloumakov.)

Yuri Gloumakov and Aaron M. Dollar are with the Mechanical Engineering and Materials Science Department, Yale University, New Haven, CT 06511 USA (e-mail: yuri.gloumakov@yale.edu; aaron.dollar@yale.edu).

Adam J. Spiers is with the Department of Electrical and Electronic Engineering, Imperial College London, London SW7 2AZ, U.K. (e-mail: a.spiers@imperial.ac.uk).

Digital Object Identifier 10.1109/TNSRE.2020.3040716

A subject's motion-centured hand and torso location

Fig. 1. A subject's motion-captured hand and torso locations are superimposed on a skeleton model performing an ADL task, reaching overhead. Redundant markers enabled the prediction of occluded marker locations. Other reaching targets are displayed as well; discretized according to clustering results. Note the hand appears to reach to the side in the torso reference frame.

influence of object presence on motion dynamics [2], developing novel prosthesis control using joint synergies [3], evaluating rehabilitation efforts [4], and ergonomics [5].

These past research efforts have examined specific reaching movements separately. Instead, we investigate reaching motion across a wide range of ADLs. And unlike developments in classifying human motion [6], in which tasks are chosen heuristically, using data driven methods to cluster upper-limb functionality to obtain a representative set of motions related to ADLs, as well as discretization of ADLs, has not yet been done. Whether the research goal is to evaluate rehabilitation outcomes across all tasks or analyze arm movement dynamics for specific tasks, a hierarchical description of the hand workspace can be leveraged to justify these efforts at every subcategory of ADLs.

In this work we investigate decoupled healthy hand use and discretize task locations, hand trajectories, and orientations. Although in the past the hand has been considered to take a straight-line path with a bell-shaped velocity profile that

1558-0210 © 2020 IEEE. Personal use is permitted, but republication/redistribution requires IEEE permission. See https://www.ieee.org/publications/rights/index.html for more information. minimizes jerk [7], [8], it was later shown that this is only the case under certain conditions [9], [10]. We suspect that by analyzing the deviation of the actual hand trajectories from the straight-line approximations, hereafter simply called original paths and straight-line paths, respectively, we will gain insight into why certain motions cluster together. For the path analyses, we use a strictly non-dynamic kinematic model, considering only the three-dimensional coordinate locations of the hand.

Given the significance of hand orientation relative to the forearm (commonly also referred to as wrist angles) in completing ADLs [11] and avoiding compensatory movements [12], we analyze unconstrained hand usage, particularly orientation, during ADLs within a particular task space as defined by clusters of task location. Previous research on wrist orientations include investigating wrist synergies with elbow and shoulder postures [13], [14] and reaching direction [15], as well as obtaining a trajectory of wrist poses used in ADLs [16].

Desired hand positions and trajectories could alternatively be viewed as inputs to a control system, rather than joint positions, as has been neurologically demonstrated [17], and we leverage this to develop a biomechanical analysis of human arm motion to inspire a range of technologies, such rehabilitation programs for stroke patients [18], [19]. One major application of discretization is in a semi-autonomous sequential control of upper-limbs prosthetic devices or wheelchair-mounted robotic arms [20], [21]. In these cases, end-effector locations, trajectories, and orientations can be individually selected from a list and executed using conventional velocity control inputs, such as surface electromyography (sEMG) placed on the residual limb of the amputee [22]. While end-point locations of tasks can be used to reliably discretize the 3-dimensional ADL workspace, path trajectories can be used to recreate motions that appear natural and predictable in prosthetic devices and robotic applications. Trajectories could be implemented either instead of or in addition to using task locations in controlling arm devices whereby unique lists of trajectories are available to a user depending on the current position of the end effector. Hand orientations can subsequently be chosen from one of the available options for the location. We use the term "hand orientation" instead of "wrist angle" in this article given that the wrist is analyzed in various reference frames.

In order to directly evaluate motions that are most likely to be a common interaction for most individuals, our experiment set up has participants performing simulated ADLs in a laboratory environment equipped with a motion-capturing system. The tasks selected for analysis are largely inspired by those used in motion rehabilitation evaluations [23], [24] and amputee surveys [25]–[27]; an example of the task *reachingoverhead* is shown in Fig. 1, where the motion capture markers are included for reference. The chosen tasks span food preparation, eating, hygiene, and object transferring, and are crucial for independent living.

In the first paper of the series [28], we clustered 7 degree of freedom (DOF) joint angle trajectories of the arm; 3 DOF for the shoulder, 1 for the elbow, and 3 for the wrist.

TABLE I

Code	Standing Tasks ^a
t2b	(1) reach box on top shelf (2) move box to bottom (3) return hands
b2t	(1) reach box on bottom shelf (2) move box to top (3) return hands
t2m	(1) reach box on top shelf (2) move box to mid (3) return hands
m2t	(1) reach box on mid shelf (2) move box to top (3) return hands
m2b	(1) reach box on mid shelf (2) move box to bottom (3) return hands
b2m	(1) reach box on bottom shelf (2) move box to mid (3) return hands
ke	(1) bring key to keyhole (2) turn key (3) turn back (4) remove key from keyhole and return hand
kn	(1) reach for door knob (2) turn knob (3) turn back (4) return hand
dh	(1) reach for door handle (2) open door (3) return hand
oh	(1) reach for can on top shelf (2) bring can down in front of the body
mp	(1) reach for mug in C1 (2) take a sip (3) return mug (4) return hand
md	(1) reach for mug in C2 (2) take a sip (3) return mug (4) return hand
mc	(1) reach for mug in C3 (2) take a sip (3) return mug (4) return hand
cp	(1) reach for cup in C1 (2) take a sip (3) return mug (4) return hand
cd	(1) reach for cup in C2 (2) take a sip (3) return mug (4) return hand
cc	(1) reach for cup in C3 (2) take a sip (3) return mug (4) return hand
st	(1) reach for suitcase (2) transfer suitcase to table (3) return hands
ax	(1) bring hand to contralateral axilla (2) return hand
pt	(1) bring hand to back pocket (2) return hand
	Sitting tasks ^a
sp	(1) reach for spoon (2) bring spoon to bowl (3) scoop (4) bring to mouth (5) return spoon (6) return hand
fr	(1) reach for fork (2) stab the middle of the plate (3) bring to mouth

sp	mouth (5) return spoon (6) return hand
fr	(1) reach for fork (2) stab the middle of the plate (3) bring to mouth (4) return fork (5) return hand
ms	(1) reach for mug (2) take a sip (3) return mug (4) return hand
cs	(1) reach for cup (2) take a sip (3) return cup (4) return hand
pr	(1) reach for cup (2) pour (3) return cup (4) return hand

^aUnless otherwise specified, standing tasks started and ended with the subjects' hands by their side while for sitting tasks the hands were to start and end on the table palm side down.

One major observation was that clusters seemingly depended strongly on hand location, agreeing with the spatial control hypothesis [8]. Thus, in this work, we aim to recreate and expand on the analysis by decoupling the 7 DOF motion into Cartesian coordinates of hand trajectories and orientations, and explore alternative prosthesis or robotic arm controls. Extensions include a comparison of the hand trajectory with straight-line trajectories and end-point locations, using a data driven approach to identify the number of clusters, and a per-cluster analysis of the distribution of hand orientations.

II. EXPERIMENT PROTOCOL

A. Task Protocol

The protocol was completed by 12 healthy right-handed subjects (6 male, 6 female; 67 ± 3 inches in height) in a single 5 hour visit. Participants were chosen to span 24 to 71 years of age. The set of motions that were analyzed in this study are also the ones used in the first paper of this series [28], albeit with a completely different set of parameters analyzed. These motions are largely based on the functional measure AM-ULA [23], and are listed in Table 1, with the setup described in more detail in Fig. 2. Only the tasks that could be clearly segmented into distinct sub-motions, i.e. clearly identifiable start and



Fig. 2. Depictions of several selected protocol tasks: (a) a box object was to be moved from one specified shelf to another, and the object on the top shelf is the location of the can during overhead reaching tasks, (b) the initial and final locations of the suitcase tasks, (c) simulated door opening task, and (d) simulated door knob and key tasks. (e) The set up for the sitting tasks: the left and right hand start and end in HL and HR, a utensil is placed next to HR, a bowl or plate are placed in P, a cup or mug is placed in C, and a container to collect the water during the pouring task is placed in V. (f) The three target locations of the standing cup and mug tasks, during which the table is elevated to simulate a countertop, where C2 is 25 cm from C1 and C3 is 45 cm from C1. The task conditions for left handed participants are mirrored. Table height is 74 cm, and is elevated to 92 cm to simulate a counter top for the standing cup and mug tasks. The mug (9.5 cm height, 8 cm diameter), can (7.5 cm height, cm diameter), box ($21 \times 37 \times 19$ cm), and suitcase ($43 \times 9 \times 30$ cm) weigh 0.36, 0.09, 0.23, and 1.36 kg respectively. The shelves are 80, 140, and 180 cm above the floor. Door knob and handle are 90 cm above the floor, and the simulated door swivels with an 84 cm radius.

end points, were analyzed, while cyclical tasks and tasks that lacked distinct motion segments, such as dressing, were excluded. The selected 24 tasks were completed 3 times to capture and reduce the effects of natural variability occurring in hand trajectories. No additional normalization of the data or the tasks are made, including not adjusting object locations according to participants' heights, anticipating the results to be more generalizable. This is similar to the motivation of previous research done on reaching motion [12], [29]–[32]. The only given instructions were which 'rest pose' to assume, i.e. standing with hands by their sides or sitting with palms on a table surface, and which task to perform. Tasks and experimental set-up were inverted for left-handed participants.

This study protocol was approved by Yale University Institutional Review Board, HSC# 1610018511.

B. Data Acquisition

All tasks were recorded with a Vicon Motion Capture System (Oxford Metrics Limited, Oxford) using 12 infrared 'Bonita' model cameras, 1 video reference camera (synchronized with the Vicon system), at a rate of 100 frames/second. 2 markers were placed on either side of the wrist, and the mid-point served as the hand location. 5 markers on the back of hand were used to compute hand orientation. 20 additional markers were placed around the torso and arm to define the body and forearm reference frames according to [33]. Synchronized video from the reference camera was used to aid in marker identification in the Vicon Nexus software.

III. DATA ANALYSIS

The goal of this work is threefold: gain insight into reaching motions, reduce the ADL hand motion space to representative groups, and identify subsets of hand orientations within clusters using data driven approaches. The flowchart of the analysis is summarized in Fig. 3. After task segmentation, which yielded a total of 85 distinct motion segments per subject, representative end-point locations and trajectories were obtained by averaging across subjects and repetitions. Using the start and end points of each segment, a straight line was generated using the same number of time steps as the original path and likewise averaged. For generalizability, locations and trajectories are all described using the subject's torso as the reference frame.

A divergence is computed between each pair of segments followed by a clustering step. Cluster results obtained from the three representations are then evaluated and compared. Coordination between task location and hand orientations are then analyzed. All analysis methods used on the trajectory path data have been demonstrated to work well with similar data and are described in detail in previous work by the authors [28], and are therefore only briefly summarized.

A. Motion Segmentation

Hand motions during ADLs, whether reaching or manipulating an object, can be seen as a composite of a series of individual sub-motions through which generalized tasks, such as drinking from a cup, are accomplished. Motion segments were extracted manually each time the hand reached zero velocity, which occurred when contact was made with an object or a transfer task was accomplished. Although more quantitative approaches to task segmentation exist, such as using principle component analysis [34] or a Hidden Markov Model [35], all rely on heuristic ground truths for verification.

B. Divergence Measure

Unlike end-point locations, hand trajectories vary in length (both distance and time) and a divergence cannot be directly computed. Therefore we use dynamic time warping (DTW) [36], a lossless algorithm that better aligns epochs between pairs of time-series data than linear resampling, and



Fig. 3. Flowchart outlines the steps in the analysis. (a) Cartesian marker data is recorded and analyzed using either the trajectory or the end-point location of the hand. Additional markers are presented for reference. (b) The recorded tasks are then segmented into sub-movements and averaged across repetitions and individuals to obtain individual representations of each motion. (c) A distance matrix is obtained for each data representation, using either DTW for the trajectory data (top) or a Euclidean distance (bottom) for the end-point locations, followed by (d) a clustering step using agglomerative hierarchical clustering, in which the number of clusters is selected using the L method. (e) Hand orientations are classified to discrete orientations using the categorization obtained from end-point location clustering. (f) Subsets of hand poses are extracted from the orientation distributions. Steps (a)-(d) are repeated for each of the three motion representations, while (e)-(f) are repeated 3 times for each coordinate frame for one of the motion representations, namely end-point location.

compute the average frame distance. Divergence was also recalculated with one of the motions moving in reverse in order to capture similarity between trajectories that happened to move in opposite directions, with the smaller of the values two saved. Finally, divergence values are normalized by the resulting time duration obtained during DTW, such that they are comparable across both short and long segments. Alternatives to length normalization were considered, such as normalizing by the root of the time duration [37], but were ultimately excluded due results remaining largely unchanged.

C. Averaging

While averaging end-point locations is done using a straightforward mean calculation, averaging of time-series data is performed using DTW barycenter averaging (DBA) [38]. Unlike linear resampling and averaging, DBA effectively aligns all trajectories' epochs, and thus computes a more representative average. DBA uses the DTW alignment between all the segments and a consensus segment and computes each frame of the consensus segment to be the average of the associated frames. This is iteratively performed until no new associations are made. The consensus segment was initialized as the longest trajectory in the group. While more complex algorithms exist that attempt to deal with local minima identified in DBA [39], we simply limited the amount of frames that can be warped to the minimum amount possible when DTW is performed between the shortest and longest trajectory pair in each group.

D. Agglomerative Hierarchical Clustering

Each data representation yielded a divergence matrix that can be used to create clusters using any compatible clustering algorithm [40]. Agglomerative hierarchical clustering [41] with Ward's linkage is chosen due to its ability to create "spherical" clusters by minimizing variation within clusters while maximizing the differences between clusters. The agglomerative algorithm iteratively merges clusters based on smallest Ward's linkage until one cluster containing all members is left, outputting a dendrogram of the data. Ward's linkage between a pair of clusters is calculated as the difference between the sum of squares of each individual cluster and the combine cluster.

A set number of clusters is obtained from the dendrogram using a straight-line cut. A data driven approach is implemented to identify at which level to cut the dendrogram, namely the L method with the greedy evaluation approach [42], by looking at the diminishing returns with respect to within-cluster variance. Unlike other approaches that evaluate local mergings, the L method considers the entire merging data set to identify the transition between internally homogenous and non-homogenous phases. Ward's linkage values at each merging are first plotted against number of clusters and the transition between the internally homogenous and non-homogenous cluster merging phases is then identified. Each phase is linearly fit and the number of points that belong to each phase is varied according to

$$RMSE_{tot} = \frac{c-1}{b-1} \times RMSE(L_c) + \frac{b-c}{b-1} \times RMSE(R_c) \quad (1)$$

where *c* and *b* correspond to the partitions of the data that belong to the non-homogenous and homogenous phases, respectively, while L_c and R_c are the lines of best-fit, respectively. The value of c corresponds to the "knee" of the plot which minimizes $RMSE_{tot}$.

Certain improvements to the L method have been suggested in [42]. Including too many merging points in the evaluation can skew the "knee" towards one end of the plot yielding too many clusters. Limiting the analysis to 25 merging points ensures the "knee" is located approximately in the range of 3-20 clusters. Additionally, as recommended in [37], merging points to the left of the largest merging distance have been removed; in this case only the left most merging point for each data representation has been removed.

E. Cluster Quality

A clustering quality measure is computed by clustering all of the end-point and trajectory data, prior to averaging and using the same methods described above, and evaluating how often repetitions are clustered together at every merging [28]. A quality score is increased by one for every pair of repetitions that appear in the same cluster, and is computed for every number of clusters for each representation method. The score is then described as a percent of the maximum possible score. The score starts at 100% with the largest single cluster, which contains all data, and monotonically decreases with every additional cluster. We primarily hoped to gain insight into



Fig. 4. X_H is normal to the palm and always faces the center of the rhombicuboctahedron while the thumb, Y_H , indicates the orientation around the palm axis; Z_H is aligned with the direction of the fingers. Example hand orientations are shown for some of the bins (highlighted). The hedron is displayed in two orientations (a) and (b), such that all sides can be visible. A dotted line and a circle are added to aid in visualizing the rotation. (c) Reference coordinate axes, global, torso, forearm, and hand, with respective subscripts, are all aligned such that the displayed hand is classified to the same bin.

methods representing hand use during ADL, and subsequent analysis is not contingent on these results.

F. Orientation Classification

After considering a number of possibilities, we decided to represent the large distribution of hand orientations via a grid of square faces on a rhombicuboctahedron (with eight triangular and eighteen square faces, Fig. 4a and 4b): a spherical like geometric object whose facets represent a classification of hand orientations. Each of the 18 main square faces can be thought of as a palm plane (i.e. the palm of the hand is placed coplanar with the surface), and within each of those main squares, the 8 smaller squares represent an orientation of the hand in that plane (with the thumb aligning with that square, with the central square of the 3×3 grid empty). This yields 18×8 (144) hand orientation axes. The number of bins is chosen by balancing coarseness and usefulness in control; too

few (such as the facets of a cube) and the bins might not be useful, too many and the bins lose their intuition.

In human-robot collaboration, object manipulation and sensing requires a careful consideration of a reference frame, which may simplify computation and improve accuracy [43]. Therefore, we analyze and compare hand orientations in three reference frames: global, torso, and forearm, with each being useful in different applications. While the global reference frame is fixed to the room, the torso and forearm reference frames are defined according to [33]. In order for the classified distributions to be comparable across reference frames, the axes are aligned such that the hand orientation is classified to the same bin as seen in Fig. 4c. Although orientations can be transformed between reference frames, each reference frame representation encodes the data differently such that each will yield a different number of hand orientation clusters, thus we evaluate orientations in each reference frame independently.

G. Obtaining a Subset of Hand Orientations

In order to identify a representative set of hand orientations in each set of task locations we evaluate the dispersion of hand orientations, divide the distribution into smaller sets until a target dispersion is reached, and calculate an average orientation for each set. Dispersion is calculated by averaging the distances between pairs of orientations,

$$d_{ij} = 2 * \cos^{-1} \left(|\langle q_i, q_i \rangle| \right) \tag{2}$$

$$Dispersion = \frac{\sum_{i,j=1}^{n} d_{ij}}{n}$$
(3)

where d_{ij} is the distance between a pair of orientations, q_i is the quaternion representing a hand pose in an end-point location, and n is the number of hand orientations in a location cluster. The dispersion value is reduced by re-clustering the set of orientations into smaller groups until a threshold of 22.5° is achieved; such that the cluster average represents a dispersion equivalent to a bin on the rhombicuboctahedron, i.e. orientations that exceeded a distance of 22.5 degrees would be classified to a different bin. Because calculating the pairwise distance for every splitting permutation is computationally infeasible, divisive hierarchical clustering is performed using k-means; k-means was rerun 1000 times to avoid local minimums. Cluster averages are computed using a quaternion averaging algorithm developed in [44]. The algorithm works by identifying an orientation that minimizes the total rotation from all other orientations. Additionally, clustering ensures that the obtained average hand orientations are as distinct as possible. For brevity, analysis is performed on end-point location clusters only. Orientation distribution of trajectory clusters and orientation trajectories will be explored in future work.

H. Orientation Distribution Comparison

In order to identify similarity between different distributions of hand orientation, we use a histogram distance calculation [45]. A distance matrix is created by calculating the



Fig. 5. Visual representations of the end-point locations (top) and the averages (bottom). The end-point locations of the un-averaged repetitions are classified according to average results. Centroids (red) are included in the top results. The origin is located halfway between markers placed on the C8 spinal segment and at the top of the sternum.

summed absolute difference between classifications normalized by the size of the distribution,

$$S_i = \sum_{a=1}^n A_{ia} \tag{4}$$

$$D_{ij} = \sum_{a=1}^{n} \left| \frac{A_{ia}}{S_i} - \frac{A_{ja}}{S_j} \right|$$
(5)

where A is a vector representing the results of the classification, i and j are the distributions being compared, and nis the number of bins. Although a statistical significance is not associated with this distance, a sense of relative similarity between distributions can nonetheless be obtained.

IV. RESULTS

Cluster results and accompanying descriptions for each representation method is shown in Fig. 5 and Fig. 6 corresponding to end-point locations and trajectory data, respectively. Scatter plot of the un-averaged end-points, grouped according to the clustering performed on the averages, are shown in the Fig. 5 as well. An additional third-person view for the averaged locations is shown in Fig. 1. Un-averaged trajectories were not visually informative and were thus excluded. Skeleton models were created using an online animation tool, KineMan (http://www.kineman.com), and inserted into the figures for reference.

The L method identified 5 clusters for the end-points of motion segments, 5 clusters for the original-path trajectories, and 7 clusters for the straight-line path trajectories (Fig. 7). Detailed results depicting the results of hierarchical clustering are shown in Fig. 11 in the Appendix.

Evaluation of the clustering quality of each representation method is shown in Fig. 8. The number of clusters is varied from 1, containing all data, to 25 clusters. Evaluation could theoretically go on up until all data points belong to their own cluster, but results are less informative at that range. Original-path trajectory clustering outperformed the other methods while end-point locations performed the worst at almost every number of clusters.

Distribution of hand orientations are presented in Fig. 9 using the rhombicuboctahedron representation shown in the global, torso, and forearm coordinate frames for each of the 5 end-point location clusters for a total of 15 distributions. The initial dispersion, based on the average pairwise distance between orientations, is displayed at the top right of each distribution. Sets of hand orientations are additionally shown below each distribution that represent the average hand poses for the sub-clusters that reduced dispersion below 22.5°. Note that for three of the of forearm locations, the subsets are identical, suggesting that distribution differences were not significantly different.



Fig. 6. Visual representations of the original-path trajectories (top) and straight-path trajectories (bottom). Clusters are identified with unique line patterns and colors. Cluster labels are additionally included. The origin is located halfway between markers placed on the C8 spinal segment and at the top of the sternum.



Fig. 7. L method results for each data representation. An example of the identified "knee" for end-point locations is included in the top right.

A distance half matrix is shown in Fig. 10, highlighting the relative similarity between distributions. The range is normalized from 0, assigned to identical distributions, to 1, as identified by the most dissimilar pair of distributions. Note that the global and torso reference frames are more similar across than between clusters, indicated by the light diagonal.



Fig. 8. Evaluation of clustering for each of the representation methods across a range of number of clusters. Scoring assessed how frequently repetitions clustered together.

V. DISCUSSION

End-point locations, path trajectories of the hand, and generated straight-line paths of the hand performing a battery of ADL tasks were used to discretize the ADL workspace using data driven approaches. End-point representation identified the following discretization: *in-front-low*, *in-front-mid*, *overhead*, *mouth and axilla*, and *hand-by-side and pocket*. The original-path trajectory on the other hand identified the following discretization: *reach-to-pocket*, *reach-to-front*, *motions-in-front*, *drink-utensil-to-mouth*, and *reach-overhead*. Straight-line path clusters further differentiated some motions



Fig. 9. Distributions of the hand orientations are shown in each of the three reference frames (right column), as well as within each end-point location cluster. Subsets of the distribution, found by re-clustering, are shown below each respective distribution. Some subsets are identical across distributions, as is seen for three of the clusters in the forearm reference frame. Dispersion values are displayed at the top right of each distribution.

and merged others into the following groups: *reach-to-body*, *reach-to-front*, *reach-overhead*, *far-to-mouth*, *close-to-mouth*, *motions-in-front*, and *move-box*.

Differences between original-path and the straight-line path clusters includes a merging of *reach-to-pocket* with reaching to axilla motions, and differentiation of the *drink-utensil-tomouth* cluster into motions that began closer to or further from the body. Unlike straight-line path clusters, original paths that pass by the mouth, such as transferring the box from the bottom to the middle shelf and transferring the suitcase, clustered with drinking and eating motion segments. Original-path clusters also grouped *reach-overhead* with transferring a box task. These observations are largely impacted by a significant overlap that is not present when considering the straight-line path. This suggests that ADL tasks are not as distinguishable as they appear and that finer task segmentation could be more appropriate, for example, by splitting a transferring motion around the mid-point when the object is closest to the body.

Although many tasks included an object that was centered and placed in front of the subject, the end-point locations of the hand were primarily situated to one side of the body. This suggests that reaching motions were coordinated with the



Fig. 10. Relative similarity between hand orientation distributions across clusters and reference frames. Reference frames are indicated by G, T, and F, for global, torso, and forearm respectively. Cluster indices 1-5 refer to clusters *in-front-low, in-front-mid, overhead, mouth/axilla,* and *hand-by-side and pocket*, respectively.

motion of the torso such that the arm did not move directly in front of the body; this was even the case for the door opening task when the hand was expected to come across the body when reaching for the door handle. An example of this can additionally be seen in Fig. 1. Trajectory plots further verified this observation by demonstrating that the paths seldom traversed in front of the torso. Although it may seem trivial, many experiments and evaluations have consistently centered the testing platforms with respect to the center of the subjects' bodies. If we accept that in the body reference frame the arm indeed predominately appears to reach to one side, then results of those tests fail to account for the significance of body compensation due to the torso and potentially misevaluate upper-limb prosthesis or rehabilitation outcomes.

When evaluating the quality scores, we observe that endpoint location clustering performs worse than path clustering for every number of clusters. This could be due to trajectories having more degrees of freedom than individual points in Cartesian space, and therefore contain sparser data. This is consistent with the original-path clustering also outperforming the generated straight-line paths at every number of clusters. Additionally, straight-line paths fail to capture characteristic hand motions and could therefore be the reason for its lower clustering quality. We also observe that path trajectories are more uniform between individuals and repetitions than end-point locations alone. Differences between methods are generally negligible for a few number of clusters, and selection of the representation is therefore highly application dependent. We proceed with analyzing the hand orientations within the end-point location clusters as they generalize to either of the trajectory representations while enabling an intuitive control interface as is discussed below.

A semi-autonomous control application of this work would enable users to operate multiple DOF without the associated increase in cognitive burden. For example, a 7 DOF (shoulderelbow-wrist) prosthetic device could be first controlled by selecting one of the 5 desired locations followed by a selection of hand orientations; automatically selected when there is one associated orientation. Switching from one location to another or moving within the same location would then correspond to which trajectories are available; e.g. starting with *hand-byside*, there are 3 possibilities, *reach-to-front*, *reach-overhead*, and *reach-pocket*. This particular implementation could take advantage of already existing myoelectric interfaces on the market and simultaneously operate multiple DOF rather than just one at a time. With capable location sensing, a prosthetic wrist device could likewise reorient itself from one 3 DOF hand orientation directly to another by providing users a succinct list of orientations to pick from. The user control process could be streamlined for locations that had an orientation dispersion value below 22.5°, such as *hand by side/pocket*, by coupling the location to a single hand orientation. Various other permutations of location and trajectory sequential control are possible, and can be explored in future iterations.

Relative distances demonstrated that the distribution of hand orientations is more similar across global and torso frames than between clusters. While this may not be surprising, this reaffirms the potential interchangeability of the two reference frames; an important feature in modeling the world space in mobile robots and prosthetics. One application is the implementation of an IMU in a prosthetic device [46] to orient it either with respect to gravity or the torso, which may include other hardware considerations.

While similar, the two references still have certain noteworthy differences that do not make them completely interchangeable, so while a robotic arm is generally fixed to a base normal to the ground, a prosthetic arm could either be assumed to be on a moving base in some scenarios and not in others. Given that the global reference frame places no restrictions on hand orientation, we suspected that it would always have a more dispersed distribution than the torso or forearm reference frame, however, the opposite was the case for the two clusters. This suggests that the distribution of hand orientations of some objects or locations is more consistent in the global reference frame. One way to exploit this is to use the more compact reference frame that includes the fewest representative hand orientations for different tasks.

The forearm reference frame orientation distribution is the most compact of the three, and would likely be the best control option for transradial amputees looking to use a wrist prosthesis device. Most bins are anatomically impossible to reach, and the vast majority of orientations appear to lie within a narrow range along the pronation-supination axis of rotation; this may explain why the first three location clusters have the same set of representative hand orientations. One implementation may include interpolating the current orientation and the desired final orientation, rotating as the hand traverses its trajectory. However, it might not be appropriate in prosthetic devices for transhumeral and shoulder disarticulate amputees since positioning of the end effector would highly depend on device capability. Specifically, setting the position and orientation of the forearm would have to be a precursor to positioning of the hand, which is not a challenge for transradial devices. Additionally, since the global and torso reference frame distributions are generalizable, these are likely to be more useful for non-anthropomorphic robotic arms that may have an unconventional forearm or forearm control [47]. For



Fig. 11. Hierarchical clustering is displayed and a sets of clusters are numbered and colored and are extracted using horizontal cuts according to the L method.

example, while reaching for an object, it may be necessary for a robotic arm to position the forearm in extreme orientations in order to avoid an obstacle, or in the case of hyper-redundant manipulators that lack a well-defined forearm altogether.

The focus of this work is on positioning the end effector, therefore motions that involve ongoing coordination of joints throughout the trajectory would require a separate controller, such as the drinking mode in the JACO arm [21], and are analyzed in the first paper of this series. In the future, the efficacy of a decoupled sequential control in upper-limb devices will need to be tested. Initial tests would demonstrate whether torso compensation could account for the variability within a location and orientation. In wheelchair-mounted applications the cluster locations will most likely need to be dynamically adaptive to account for the variance, which could come in the form of a second input or computer vision. While the choice of references frames was based on the perspective of a prosthesis user, various other custom reference frames considerations [48] should be made depending on the application. The results of this article are also dependent on the selected task list, which by no means is exhaustive, hence the framework could be extended to other applications by the inclusion of relevant tasks.

VI. APPENDIX

Hierarchical clustering results for each of the representation methods is displayed in Fig. 11. Number of clusters for each method was selected using the L methods and demonstrated in the plots using a horizontal cut. Tasks segments and end-point locations are listed according to Table 1.

REFERENCES

- B. S. Row and P. R. Cavanagh, "Reaching upward is more challenging to dynamic balance than reaching forward," *Clin. Biomechanics*, vol. 22, no. 2, pp. 155–164, Feb. 2007, doi: 10.1016/j.clinbiomech.2006. 06.003.
- [2] K. J. Wisneski and M. J. Johnson, "Quantifying kinematics of purposeful movements to real, imagined, or absent functional objects: Implications for modelling trajectories for robot-assisted ADL tasks," *J. NeuroEngineering Rehabil.*, vol. 4, no. 1, pp. 1–14, Dec. 2007.
- [3] R. R. Kaliki, R. Davoodi, and G. E. Loeb, "Prediction of distal arm posture in 3-D space from shoulder movements for control of upper limb prostheses," *Proc. IEEE*, vol. 96, no. 7, pp. 1217–1225, Jul. 2008.
- [4] S. Li, P. N. Pathirana, M. P. Galea, G. Ottmann, and F. Khan, "Quantitative assessment of ADL: A pilot study of upper extremity reaching tasks," *J. Sensors*, vol. 2015, pp. 1–13, 2015, doi: 10.1155/2015/236474.
- [5] D. B. Chaffin, "On simulating human reach motions for ergonomics analyses," *Hum. Factors Ergonom. Manuf.*, vol. 12, no. 3, pp. 235–247, 2002, doi: 10.1002/hfm.10018.
- [6] H. F. Nweke, Y. W. Teh, G. Mujtaba, and M. A. Al-garadi, "Data fusion and multiple classifier systems for human activity detection and health monitoring: Review and open research directions," *Inf. Fusion*, vol. 46, pp. 147–170, Mar. 2019, doi: 10.1016/j.inffus.2018.06.002.
- [7] T. Flash and N. Hogan, "The coordination of arm movements: An experimentally confirmed mathematical model," *J. Neurosci.*, vol. 5, no. 7, pp. 1688–1703, Jul. 1985.
- [8] P. Morasso, "Spatial control of arm movements," *Exp. Brain Res.*, vol. 42, no. 2, pp. 223–227, Apr. 1981.
- [9] J. J. Faraway, M. P. Reed, and J. Wang, "Modelling three-dimensional trajectories by using Bézier curves with application to hand motion," *J. Roy. Stat. Soc. C, Appl. Statist.*, vol. 56, no. 5, pp. 571–585, Nov. 2007.
- [10] A. Spiers, S. G. Khan, and G. Herrmann, *Biologically Inspired Control of Humanoid Robot Arms: Robust and Adaptive Approaches*, 1st ed. Cham, Switzerland: Springer, 2016.
- [11] F. Montagnani, M. Controzzi, and C. Cipriani, "Is it finger or wrist dexterity that is missing in current hand prostheses?" *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 23, no. 4, pp. 600–609, Jul. 2015.

2965

- [12] A. J. Spiers, Y. Gloumakov, and A. M. Dollar, "Examining the impact of wrist mobility on reaching motion compensation across a discretely sampled workspace," in *Proc. 7th IEEE Int. Conf. Biomed. Robot. Biomechatronics*, Aug. 2018, pp. 819–826.
- [13] F. Lacquaniti and J. Soechting, "Coordination of arm and wrist motion during a reaching task," J. Neurosci., vol. 2, no. 4, pp. 399–408, Apr. 1982.
- [14] F. Montagnani, M. Controzzi, and C. Cipriani, "Exploiting arm posture synergies in activities of daily living to control the wrist rotation in upper limb prostheses: A feasibility study," in *Proc. 37th Annu. Int. Conf. IEEE Eng. Med. Biol. Soc. (EMBC)*, Aug. 2015, pp. 2462–2465.
- [15] A. Roby-Brami, N. Bennis, M. Mokhtari, and P. Baraduc, "Hand orientation for grasping depends on the direction of the reaching movement," *Brain Res.*, vol. 869, nos. 1–2, pp. 121–129, 2000, doi: 10.1016/S0006-8993(00)02378-7.
- [16] T. A. Lenssen, L. Cappello, D. H. Plettenburg, C. Cipriani, and M. Controzzi, "Principal orientations of the wrist during ADLs: Towards the design of a synergetic wrist prosthesis," in *Proc. Int. Conf. NeuroRehabilitation*, Oct. 2018, pp. 339–343, doi: 10.1007/978-3-030-01845-0-68.
- [17] L. Paninski, "Superlinear population encoding of dynamic hand trajectory in primary motor cortex," J. Neurosci., vol. 24, no. 39, pp. 8551–8561, Sep. 2004, doi: 10.1523/JNEUROSCI.0919-04.2004.
- [18] N. Hogan, G. Kwakkel, S. Wood-Dauphinee, H. J. M. Hendriks, P. J. Van der Wees, and J. Dekker, "Motions or muscles? some behavioral factors underlying robotic assistance of motor recovery," *J. Rehabil. Res. Develop.*, vol. 43, pp. 605–618, Aug./Sep. 2006.
- [19] Y. Mao and S. K. Agrawal, "Design of a cable-driven arm exoskeleton (CAREX) for neural rehabilitation," *IEEE Trans. Robot.*, vol. 28, no. 4, pp. 1–10, Aug. 2012.
- [20] V. Maheu, J. Frappier, P. S. Archambault, and F. Routhier, "Evaluation of the JACO robotic arm: Clinico-economic study for powered wheelchair users with upper-extremity disabilities," in *Proc. IEEE Int. Conf. Rehabil. Robot.*, Jun. 2011, doi: 10.1109/ICORR.2011. 5975397.
- [21] A. Campeau-Lecours et al., "JACO assistive robotic device: Empowering people with disabilities through innovative algorithms," in Proc. Annu. Conf. Rehabil. Eng. Assistive Technol. Soc. North America (RESNA), Washington, DC, USA, 2016.
- [22] A. Fougner, Ø. Stavdahl, P. J. Kyberd, Y. G. Losier, and P. A. Parker, "Control of upper limb prostheses: Terminology and proportional myoelectric control—A review," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 20, no. 5, pp. 663–677, Sep. 2012.
- [23] L. Resnik *et al.*, "Development and evaluation of the activities measure for upper limb amputees," *Arch. Phys. Med. Rehabil.*, vol. 94, no. 3, pp. 488–494, 2013.
- [24] C. M. Light, P. H. Chappell, and P. J. Kyberd, "Establishing a standardized clinical assessment tool of pathologic and prosthetic hand function: Normative data, reliability, and validity," *Arch. Phys. Med. Rehabil.*, vol. 83, no. 6, pp. 776–783, Jun. 2002.
- [25] E. A. Biddiss and T. T. Chau, "Upper limb prosthesis use and abandonment: A survey of the last 25 years," *Prosthetics Orthotics Int.*, vol. 31, no. 3, pp. 236–257, Sep. 2007.
- [26] C. H. Jang *et al.*, "A survey on activities of daily living and occupations of upper extremity amputees," *Ann. Rehabil. Med.*, vol. 35, no. 6, p. 907, 2011, doi: 10.5535/arm.2011.35.6.907.
- [27] C.-S. Chung, H. Wang, and R. A. Cooper, "Functional assessment and performance evaluation for assistive robotic manipulators: Literature review," *J. Spinal Cord Med.*, vol. 36, no. 4, pp. 273–289, Jul. 2013, doi: 10.1179/2045772313Y.0000000132.
- [28] Y. Gloumakov, A. J. Spiers, and A. M. Dollar, "A clustering approach to categorizing 7 Degree-of-Freedom arm motions during activities of daily living," in *Proc. Int. Conf. Robot. Autom. (ICRA)*, May 2019, pp. 7214–7220.
- [29] D. Popovic and M. Popovic, "Tuning of a nonanalytical hierarchical control system for reaching with FES," *IEEE Trans. Biomed. Eng.*, vol. 45, no. 2, pp. 203–212, Feb. 1998.

- [30] S. D. Iftime, L. L. Egsgaard, and M. B. Popovic, "Automatic determination of synergies by radial basis function artificial neural networks for the control of a neural prosthesis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 13, no. 4, pp. 482–489, Dec. 2005.
- [31] Z. Kadivar, C. Sung, Z. Thompson, M. O'Malley, M. Liebschner, and Z. Deng, "Comparison of reaching kinematics during mirror and parallel robot assisted movements," *Stud. Health Technol. Inform.*, vol. 163, no. 18, pp. 247–253, 2011. [Online]. Available: http://ebooks.iospress.nl/volume/medicine-meets-virtual-reality-18, doi: 10.3233/978-1-60750-706-2-247.
- [32] C. F. Yeong, A. Melendez-Calderon, R. Gassert, and E. Burdet, "Reach-MAN: A personal robot to train reaching and manipulation," in *Proc. IEEE/RSJ Int. Conf. Intell. Robots Syst.*, Oct. 2009, pp. 4080–4085, doi: 10.1109/IROS.2009.5354837.
- [33] G. Wu *et al.*, "ISB recommendation on definitions of joint coordinate systems of various joints for the reporting of human joint motion—Part II: Shoulder, elbow, wrist and hand," *J. Biomechanics*, vol. 38, no. 5, pp. 981–992, May 2005, doi: 10.1016/j.jbiomech.2004.05.042.
- [34] J. Barbic, A. Safonova, J.-Y. Pan, C. Faloutsos, J. K. Hodgins, and N. S. Pollard, "Segmenting motion capture data into distinct behaviors," in *Proc. Graph. Interface*, May 2004, pp. 185–194.
- [35] D. Kulic, C. Ott, D. Lee, J. Ishikawa, and Y. Nakamura, "Incremental learning of full body motion primitives and their sequencing through human motion observation," *Int. J. Robot. Res.*, vol. 31, no. 3, pp. 330–345, Mar. 2012, doi: 10.1177/0278364911426178.
- [36] H. Sakoe and S. Chiba, "Dynamic programming algorithm optimization for spoken word recognition," *IEEE Trans. Acoust., Speech, Signal Process.*, vol. ASSP-26, no. 1, pp. 43–49, Feb. 1978.
- [37] M. Linardi, Y. Zhu, T. Palpanas, and E. Keogh, "Matrix profile X: VALMOD-scalable discovery of variable-length motifs in data series," in *Proc. Int. Conf. Manage. Data–SIGMOD*, May 2018, pp. 1053–1066.
- [38] F. Petitjean, A. Ketterlin, and P. Gançarski, "A global averaging method for dynamic time warping, with applications to clustering," *Pattern Recognit.*, vol. 44, no. 3, pp. 678–693, Mar. 2011.
- [39] M. Cuturi and M. Blondel, "Soft-DTW: A differentiable loss function for time-series," in *Proc. 34th Int. Conf. Mach. Learn.*, Mar. 2017, pp. 894–903.
- [40] S. Aghabozorgi, A. S. Shirkhorshidi, and T. Y. Wah, "Time-series clustering—A decade review," *Inf. Syst.*, vol. 53, pp. 16–38, Oct. 2015.
- [41] B. S. Everitt, S. Landau, M. Leese, and D. Stahl, *Cluster Analysis*, 5th ed. West Sussex, U.K.: Wiley, 2011.
- [42] S. Salvador and P. Chan, "Determining the number of clusters/segments in hierarchical clustering/segmentation algorithms," in *Proc. 16th IEEE Int. Conf. Tools Artif. Intell.*, Nov. 2004, pp. 576–584, doi: 10.1109/ICTAI.2004.50.
- [43] A. Borboni, G. Carbone, and N. Pellegrini, *Reference Frame Identifica*tion and Distributed Control Strategies in Human-Robot Collaboration, vol. 84. Cham, Switzerland: Springer, 2020.
- [44] F. L. Markley, Y. Cheng, J. L. Crassidis, and Y. Oshman, "Averaging quaternions," J. Guid. Control. Dyn., vol. 30, no. 4, pp. 1675–1682, 2007.
- [45] Y. Cao and L. Petzold, "Accuracy limitations and the measurement of errors in the stochastic simulation of chemically reacting systems," *J. Comput. Phys.*, vol. 212, no. 1, pp. 6–24, Feb. 2006.
- [46] N. A. Alshammary, D. A. Bennett, and M. Goldfarb, "Synergistic elbow control for a myoelectric transhumeral prosthesis," *IEEE Trans. Neural Syst. Rehabil. Eng.*, vol. 26, no. 2, pp. 468–476, Feb. 2018.
- [47] H. Su, C. Yang, G. Ferrigno, and E. De Momi, "Improved Human–Robot collaborative control of redundant robot for teleoperated minimally invasive surgery," *IEEE Robot. Autom. Lett.*, vol. 4, no. 2, pp. 1447–1453, Apr. 2019, doi: 10.1109/LRA.2019.2897145.
- [48] H. Nguyen, M. Ciocarlie, K. Hsiao, and C. C. Kemp, "ROS commander (ROSCo): Behavior creation for home robots," in *Proc. IEEE Int. Conf. Robot. Autom.*, May 2013, pp. 467–474, doi: 10.1109/ICRA.2013.6630616.